

Application for Breast Cancer Detection Based on Convolutional Neural Network

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Abstract

Breast cancer starts in breast cells when they grow out of control. It is life-threatening and is common among women. Diagnosis of breast cancer is a challenging task as well as time consuming. In this paper, a new idea for breast cancer diagnosis is discussed. Namely, a convolutional neural network (CNN) method is proposed to assist classification of breast cancer. Two different models are discussed in this paper. Testing results is done using performance metric for all models. On top of the models that classify breast cancer, a practical application is also discussed and implemented that utilized the proposed model. It is not only capable of breast cancer diagnosis but delivers the results flexibly with an AI chatbot. The proposed model performs well with testing accuracy of 98%. The application is also well tested that can perform automated breast cancer diagnosis quickly to reduce the work of the clinic significantly.

Keywords: *Invasive Ductal Carcinoma, Breast cancer, Convolutional Neural Network*

1 INTRODUCTION

Breast cancer is a type of cancer that grows in the breast. It starts when the cells increase out of control and eventually spread outside the breast. It is the second-leading cause of cancer death among women in the United States. Invasive Ductal Carcinoma (IDC), the most common subtype of breast cancer which takes up about 80% of all cases [1]. Practical methods for detecting breast cancer could be done with clinic examination. The method usually needs screening tools. Patients need to perform tests such as Positron Emission Tomography (PET) or Magnetic Resonance Imaging (MRI). However, it is a really difficult task to accurately classify between benign and malignant tumours with information from scans of those tools. To make a definitive analysis, the patient needs to perform a biopsy. It is a procedure to extract cells from the tissues of the breast. These cells will be investigated on a microscopic level by a histopathologist. It is a time-consuming task that the histopathologist need to analysing hostile ductal carcinoma tissue zones of the cell images. However, this task can be automated with the help of deep learning.

Histopathology, the study of disease of the tissues under a microscope can be now fully digitized. High resolution cell images make it possible for computer assisted diagnosis (CAD) with large amount of image

patches of cells. Combining digitized histopathology with deep learning is a trending direction in medical industry, especially convolutional neural networks (CNN), which shows great potential in different fields e.g. medical fields [3] [6] [7] [10] and automatic driving [5] [9] [16]. Hence, it is a popular topic that a lot of scholars are working on. From the paper [11], the researchers tried several methods to detect IDC from histopathology images including logistic regression, K-Nearest Neighbour (KNN) as well as CNN, they achieved a final accuracy about 86%. In Breast Cancer Histopathology Image Classification Using an Ensemble of Deep Learning Models [4], the researchers tried different CNN architecture for detecting IDC and achieved 95% of accuracy. Both papers had a great discussion of how to use CNN to analyse benign and malignant tumours of breast cancer. However, they have not touched in detail about how to combine the proposed method in a practical application.

The aim of this paper is to create a method that can effectively differentiate between benign and malignant breast tissues using several different CNNs including fine-tuned MobileNet and EfficientNet. Moreover, a practical implementation about how to apply this method in a real-world application will be discussed as well. More specifically, the contribution of the paper is first, creating an effective automated method for detecting IDC

from breast histopathology images using CNNs, and creating a real-world web application that applies that method using Next JS and Flask that significantly reduces the workload of clinic.

2 METHOD

2.1 Data description and pre-processing

All data of this paper come from the ‘Breast Histopathology Images’ dataset from Kaggle [8]. However, the dataset is not well distributed. It contains much more benign images than the malignant images. To cope with this problem that the model may see too little malignant images if random images are selected from the dataset. In the study, 6,000 malignant images and 7,000 benign images are taken from the dataset (total 13,000). These 13,000 consists of the training and validation dataset. All image patches from the dataset has the dimension of the $50 \times 50 \times 3$ (height \times width \times RGB). While the size of the image is too small for the model to train. Then an image resizing is performed using python Pillow library. The images are resized to be $224 \times 224 \times 3$ (height \times width \times RGB) that shows more details and meet the input dimension requiremntn of the proposed model. Here are some examples of malignant and benign breast histopathology images from the dataset after resizing to $224 \times 224 \times 3$:

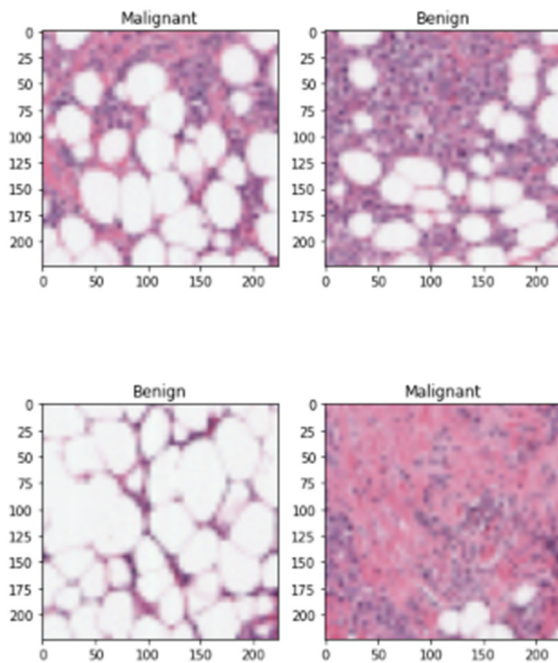


Figure 1: Example Breast Histopathology Images

2.2 Proposed Model

Convolutional Neural Network is a class of artificial neural network (ANN). It is most used in image analysis. It usually consists of convolutional layers, pooling layers,

and fully connected layers. A convolutional layer is the core of a CNN. It contains a set of learnable filters. Those filters will be applied the input and feature maps will be derived from matrix computations [15]. Output of the convolutional layer is the feature maps of different parts of the input images.

Pooling layer is another important block in CNN. It can provide spatial variance which means that the model can recognize an object when the appearance changed in some way [12]. It also works to reduce the parameters of the CNN model that can reduce overfitting. It is usually added after the convolutional layer. It works independently on each slice of the input. For example, a MAX pooling with filter of 2×2 applied stride of 2 by 2 that takes of the MAX value of the input so that 75% of the activations are discarded [2].

In this study, two different CNNs are implemented to tackle this task. Both are build based on a pre-trained CNN model with weights from ImageNet. Since the weights from ImageNet does not train on medical images. Additional layers will be added to the CNN model to create a new one specifically for classify breast cancer, it is also called transfer learning. The first model is based on MobileNetV2 [13]. Namely, it utilized MobileNet as the backbone of the model, then add additional layers after. The layer right after the MobileNetV2 is an average pooling layer that can provide spatial variance. It also can help reducing parameters to overcome overfitting. Then a dropout layer is applied after the pooling layer that drops 50% of the neural which reduce the size of parameters further. To stabilizing the learning process and reduce the number of training epochs for the model, and batch normalization layer is added after the dropout layer. In the end, a fully connected layer is added with output dimension of two since this study have 2 different classes, benign and malignant. The output will return the probability of malignant and benign respectively. The second one is based on EfficientNetB2 [14]. The structure of the model is similar to the previous one. Even though both models share the same architecture, the entire architecture of the model differs due to the internal difference of MobileNet and EfficientNet. However, EfficientNetB2 is a bigger network, and it contains about 4 time of the parameter of MobileNetV2. Hence, it takes longer time to train the model for one epoch.

2.3 Implementation Details

Since both CNN share similar architecture, the hyper parameters are set to be the same for them as well. The learning rate of the model is 0.0001, the loss function is binary cross entropy, to accelerate the training process, Adam is chosen as optimizer in both models. The evaluation metrics of the model is accuracy. To calculate the probability of malignant or benign, both models apply SoftMax activation function in the very last fully connected layer with output dimension of two. After

testing, the models achieved convergency around 20 epochs, both models are trained for 20 epochs. Also, to achieve the best performance, only the improved weights will be saved while training over epochs.

2.4 Application Development

The web application made of two parts, a front-end UI interface and the backend server. The frontend UI is implemented using Next JS and Chakra UI. It can ask user to upload an image. Then it will make request to backend server to get service. Once the server gets the request, it will specify the request type and endpoint, then provide the corresponding response to the frontend application. For example, if the frontend asks for image classification, it will make request to `/api/predict` to get the service, and after the request the processed, it will return the response back to the frontend with different responses based on if the request is processed successfully. If the front-end want to get chatbot service, it will make request to `/api/chat` to get the service. If the response is successfully sent back to front-end, the application will be responsible to display the result to the user. If there is error occurring during the process, it will be displayed in the front-end interface as well.

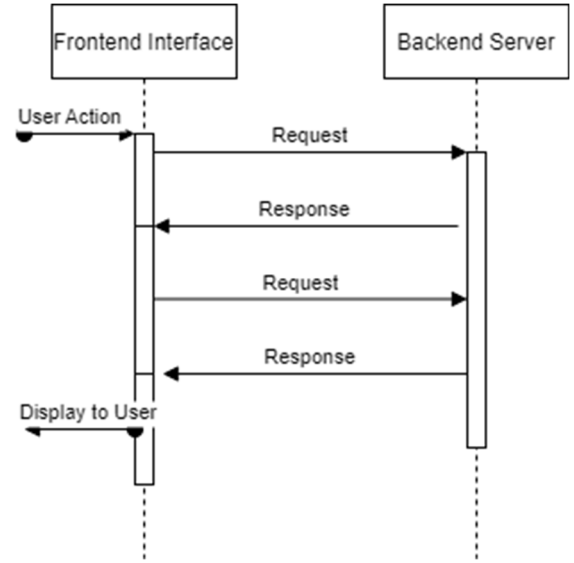


Figure 2: Application Architecture Diagram

3 RESULT & DISCUSSION

By changing the backbone of the CNN from EfficientNetb2 to MobileNetV2, testing accuracy increased to 98.2% of random 1000 benign and 1000 malignant breast histopathology image patches in the test.

Table 1: Performance of Different CNN Models on Breast Histopathology Images

	Training Loss	Training Accuracy	Testing Loss	Testing Accuracy
CNN (MobileNetV2)	0.009	0.991	0.301	0.982
CNN (EfficientNetb2)	0.018	0.993	0.267	0.935

From Table 1, it is shown that EfficientNetb2 has lower accuracy than MobileNetV2 even though it has more parameters. The reason could be that the model does not get enough data to get fully trained. Also, it could be that the model is overfitted as more epochs training on the dataset. MobileNetV2 has better testing accuracy hence it has less overfitting over the training process.

In addition to making classification on breast histopathology image diagnosis, a web application is also implemented using the proposed classification methods. It is shown in Figure 3, Figure 4, Figure 5 and Figure 6. Different parts of the app will be described as follows.

The frontend App is created using Next JS and Chakra UI. The landing page of the app has an upload icon that users can click to choose a breast histopathology image. After the image is chosen, it will be uploaded to Firebase storage and returned an image URL. Then the user can see a button called Start with AI. After clicking

the button, an http POST request will be sent to the backend server and trigger the function to make prediction based on the image URL of the uploaded image.

After the prediction is made, it will be directed to the result page that displays the result of the model's prediction. It will display the probability of having IDC or not having IDC in this image patch. The user can click Talk with AI to go to the chat page where the user can talk to the AI chatbot.

In the chat page, the user can send general sentences as well as medical relevant questions to the chat-bot. After each sentence is sent, it will make a http POST request to the backend server. The sentence will be tokenized, stemmed, and fed into the Natural Language Processing model to identify the intent. Once the intent is identified, it will return a corresponding response in JSON to the frontend. After the frontend received the message, it will be displayed on the page.

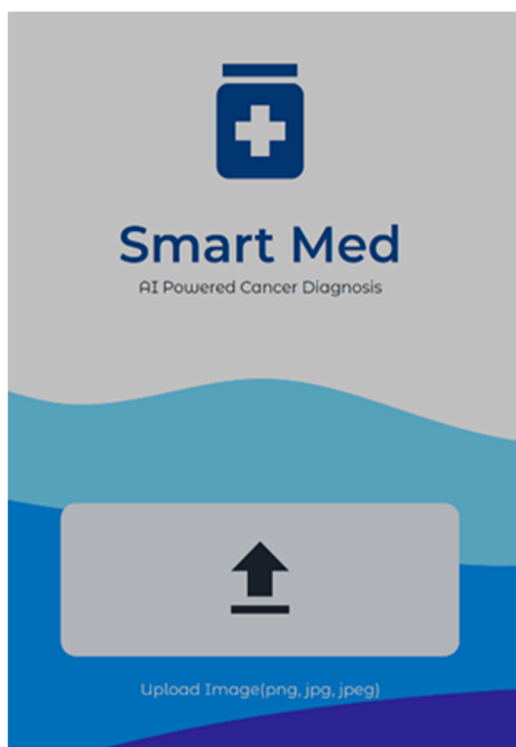


Figure 3: Upload page of the application.

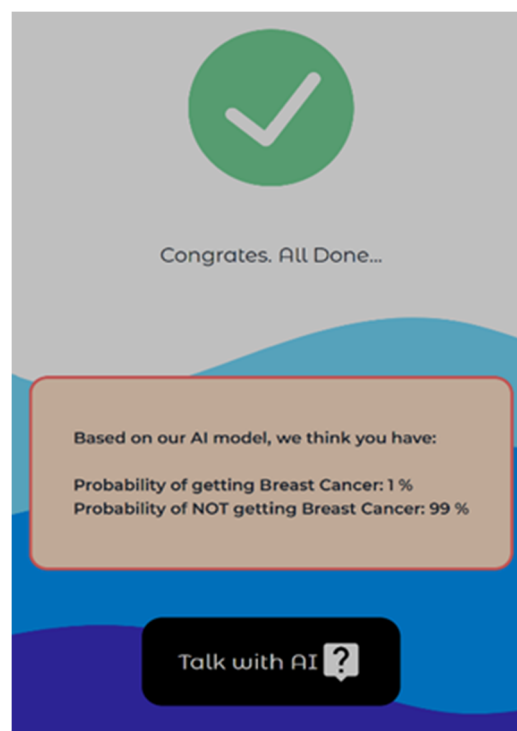


Figure 5: Result Page of the application.

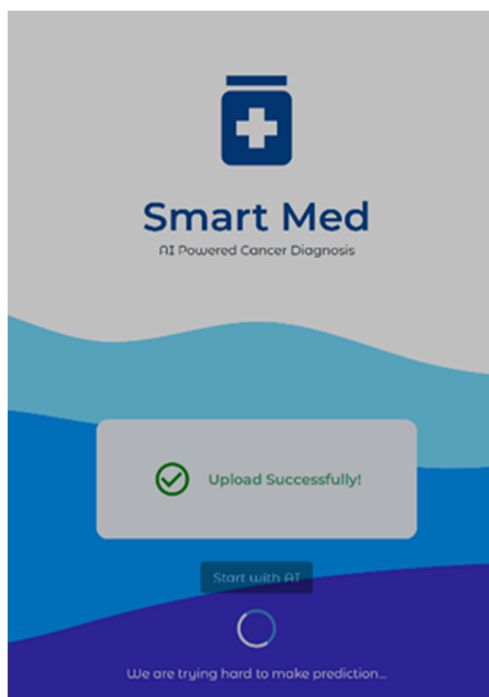


Figure 4: Processing Page of the application.



Figure 6: Chat page of the application.

4 CONCLUSIONS

Accurately classifying breast cancer is a difficult task. To boost the process, the study of this paper proposed an automated method to classify IDC subtype breast cancer from breast histopathology images with a CNN model.

Two different CNN models have been discussed with proper description of the difference. The first CNN model achieved 98% testing accuracy. Although the second model has more layers and parameters, it only achieves accuracy of 93% with much longer time of training. Moreover, a practical web application is implemented to provide a user-friendly interface that can perform the diagnosis of breast cancer using proposed CNN models. It includes breast cancer classification as well as a chat-bot to deliver the result. The web application along with the proposed model can be helpful to reduce the workload of the doctors in clinic as well as reducing mistakes. However, the limitation of the study could be that only a small amount of data from the dataset and are used in the study while those data may not be representative of all the images. In the future study, more data should be used to provide better results of the breast cancer diagnosis of the proposed model.

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