Predicting Invasive Ductal Carcinoma by Using Deep Convolutional Neural Network

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Abstract:
Due to the nature of Breast Cancer, it is challenging to make correct diagnosis based on histopathology images. And it is crucial to make early diagnosis for a complete cure. In this paper, a Neural Network algorithm was proposed to train on sets of breast histopathology images. Based on Convolutional Neural Network (CNN), it can be realized to detect and extract spatial features of images. A deep Convolutional Neural Network architecture similar to VGGNet is proposed for this study, which contains 6 3×3 layers of depth-wise Convolutional layers, 3 pooling layers and 1 fully connected layer. The proposed model was trained using Kaggle dataset of breast histopathology images, 50 epochs, with batch size of 250. The model utilizes Adagrad optimizer with learning rate of 1×10-2, decay equal to value (i.e. learning rate/number of epochs), and Binary Crossentropy as loss function. The proposed model results in 91.28% accuracy and 0.22 loss.

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

1 INTRODUCTION

Breast cancer is the most common type of cancer occurred among women; it accounts for a third of newly diagnosed cancers in women each year [1]. Invasive Ductal Carcinoma is the most common type of breast cancer, recognized for over 80% of all breast cancer diagnosis. It occurs when abnormal cells in the lining of the milk ducts grows and invade breast tissue [16]. Early detection of breast cancer is critical to a cure, as well as reducing mortality rate in the long term [9]. Various methods and techniques have been developed to help breast cancer detection, including Computer-Aided Diagnosis (CAD), or deep learning algorithms [3] [5].

CAD have been used with Breast mammograph earlier in aid of radiologist's diagnostic. However, mammographic images are highly sensitive in nature, which given rise to the problem of false diagnosis. Lesions detected and diagnosed with more than 2% chances of being invasive are recommended for biopsy, subjected to the bias of radiologist; even with the help of CAD, accuracy remains low and subjected to unnecessary procedures [6] [14].

In recent years, digital pathology become a major revolution in modern medicine. With the development of high-resolution digital cameras, digit slide scanners slowly made the alternatives to the conventional microscopes, able to produce high resolution high resolution digital photomicrograph of an entire histology or cytology slide at low cost and time. With this notion, given the rise of deep learning techniques, studies have shown that medical image processing with deep learning algorithms in breast cancer detection have been outperforming traditional radiologist detection with aid of CAD.

Convolutional Neural Network (CNN) is a branch of deep learning algorithms that is designed for spatial hierarchies of feature extraction, including convolution layer, fully connected and pooling layer etc., that stacks to form a deep neural network [7] [17]. CNN algorithms have been proven highly effective in image processing and computer vision [4]. Approaches have been taken by using CNN to tackle breast cancer detection, according to Romano et al., their CNN architecture have achieved around 86% accuracy [12]. Rushabh Patel achieved around 89 % accuracy with a deep CNN with 10 layers [11]. However, their results still have a room to be improved.

In this regard, this paper designed a new CNN algorithm to increase the accuracy of the diagnose of invasive ductal carcinoma by training a deep convolutional neural network similar to VGGNet with

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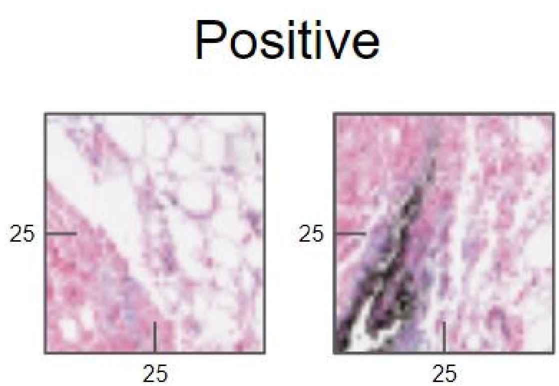
dataset of histopathology images. VGGNet is a CNN architecture introduced by Karen Simonyan & Andrew Zisserman [15], where image pass through a stack of CNN layers with kernel size 3×3 before performing MaxPooling, achieving high accuracy in image detection. An alter structure was created for breast cancer detection where traditional convolutional layers was change to a depth – wise convolution layer in help of reducing matrix multiplication due to large volume of input data. Overall, the model achieved over 90% in testing accuracy and around 22% loss.

2 METHOD

2.1 Dataset

In this paper, Kaggle dataset of Breast Histopathology images of Invasive Ductal Carcinoma (IDC) was used [10]. The original dataset contains 162 while mounted slides of Breast Cancer at 40× magnification. There are 275,524, 50 by 50 images extracted from whole slides. Within the dataset, there are 198,738 negative images and 78,786 positive images. Each image is names in a format of id + x corp + y corp + class (0 or 1), 0 means no IDC, 1 means IDC positive. Examples of images are shown in Figure 1.



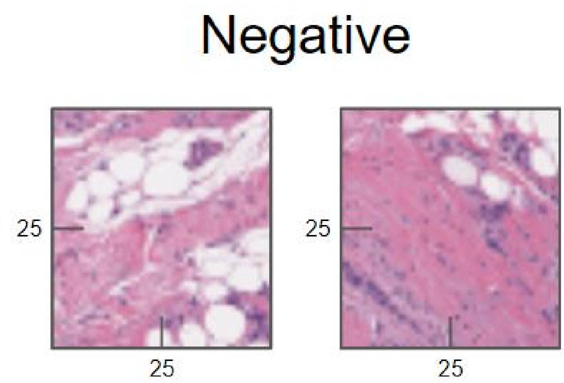


Figure 1: Visualization of Dataset.

To preprocess the image, all images are parsed by classes, with negative and positive classes. However, there existed the problem of an imbalanced dataset, if ignoring this problem, the training process will be biased towards the negative dataset thus making the training invalid. Down sampling was implemented in this paper. Positive image data was down sampled to have the same number of images as the negative data, both containing 78,786 images. Then, the datasets are randomized to prevent overfitting, random seeding and shuffling are applied to the datasets. Next, the dataset is resized in to a 50 × 50 × 3 NumPy array and split into test and training dataset, with 25% test split of the entire data.

2.2 Proposed Model

In this paper, deep convolutional neural network (CNN) is used, VGG16 was utilized for reference [15].

Convolutional Neural Network (CNN) is a deep learning algorithm that is able to extract features from spatial data, i.e., images. CNN is typically consisted of 3 different layers namely Convolution, MaxPooling and Fully Connected layers. Convolution and MaxPooling layers are used for feature extraction and reduction for number of parameters, by a user defined kernel applied to each position in dataset, i.e., each image in dataset, which reduce the dimension and extract features out of dataset. Fully Connected layer performs mapping from extracted features to output [17].

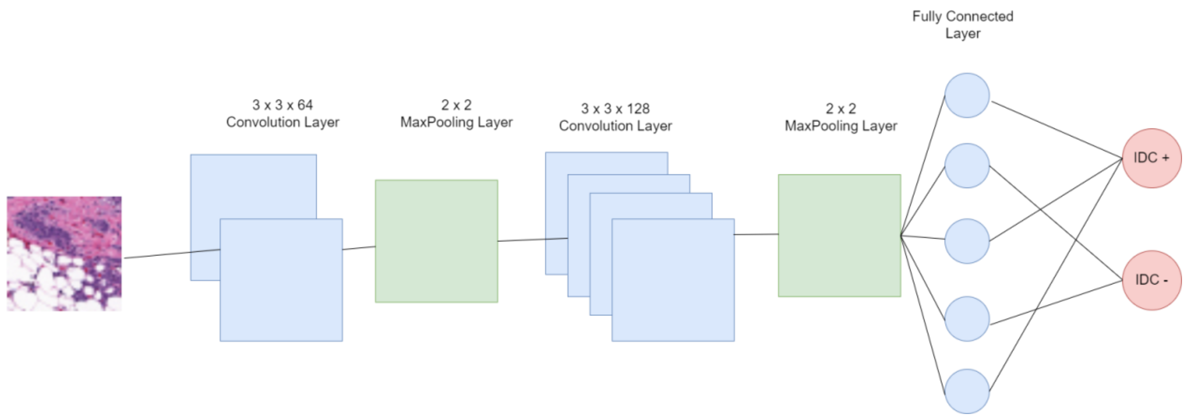


Figure 2: Structure of proposed CNN.

The network in this paper contained 6 3×3 Convolutional Layers, 3 MaxPooling Layers, 2 fully connected layers. Instead of traditional Convolutional Layers, Depth-Wise Convolutional Layer is used in place of it. Depth-Wise Convolutional Layer differ from the traditional layers by separating the convolution step into two steps to reduce multiplication required. The first step is channel – wise spatial convolution, a kernel of 3×3 is applied independently to each channel of input. The second step is point-wise convolution, which combine the output of each channel, and project the output into a new channel space [2]. MaxPooling Layers down samples the input data by preserving the maximum value in a specified non- overlapping region. Fully Connected layer performs linear multiplication by a weighted matrix to the input array [8]. Table 1 and Figure 2 show basic structure of proposed CNN.

Table 1: Model Summary.

Layer Number	Type	Size
1	SeparableConv	3×3×64
2	SeparableConv	3×3×64
3	MaxPooling	2×2
4	SeparableConv	3×3×128
5	SeparableConv	3×3×128
6	SeparableConv	3×3×128
7	SeparableConv	3×3×128
8	MaxPooling	2×2
9	Fully Connected	128×128×2

The network takes 50 × 50 RGB image, performing a group of depth-wise convolution before MaxPooling, the network outputs a binary probability, of both the probability of being IDC positive and IDC negative. The result of the prediction will be based on the probability of outputs, with probability greater than 0.5 being in dominance.

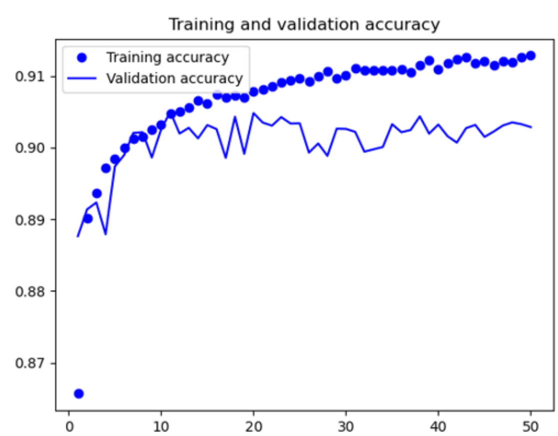
2.3 *Implementation Detail*

In this paper, the training process is controlled by 50 epochs and 250 batch size. Adagrad optimizer was used, with learning rate of 1×10-2, decay equal to learning rate divided by number of epochs. For the loss function, Binary Crossentropy was considered in this study since it can reduce the probability error between target and predicted label which can greatly improve the result [13].

3 Result and discussion

3.1 *Performance for models*

The proposed model was trained with the previous introduced setup, a training accuracy of 91.28% with a loss of 0.22 was obtained. The model achieved its highest accuracy at precisely 50 epochs, as shown in Figure 3.



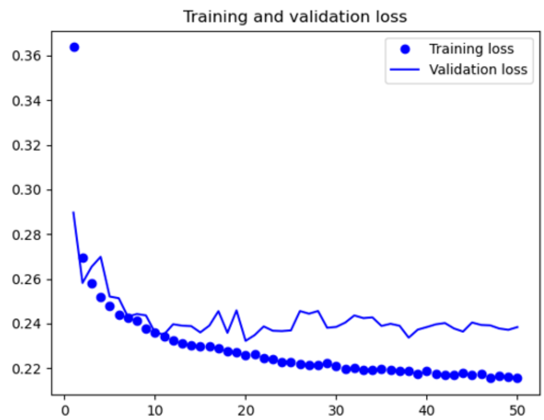


Figure 3: Train/validation accuracy and loss for the proposed model.

Classification report with more details is given in Table 2. IDC Negative has the highest precision and Recall, while Positive prediction remain unstable.

Table 2: Classification Report.

	Precision	Recall	F1-score
Negative	0.95	0.93	0.94
Positive	0.66	0.74	0.70
Average	0.91	0.90	0.90

Precision defines accurately predicting the true case of tumour, positive or negative. Recall measures if a case is correctly predicted to its own class. F1-score is calculated as the mean of precision and recall. From Figure 4, it can be concluded that the precision for Negative cases have the highest accuracy while prediction for Positive cases is lower, with 95% and 66% respectively.

Figure 4 is the Confusion matrix obtained for this model; it visualized the result obtained in Figure 3.

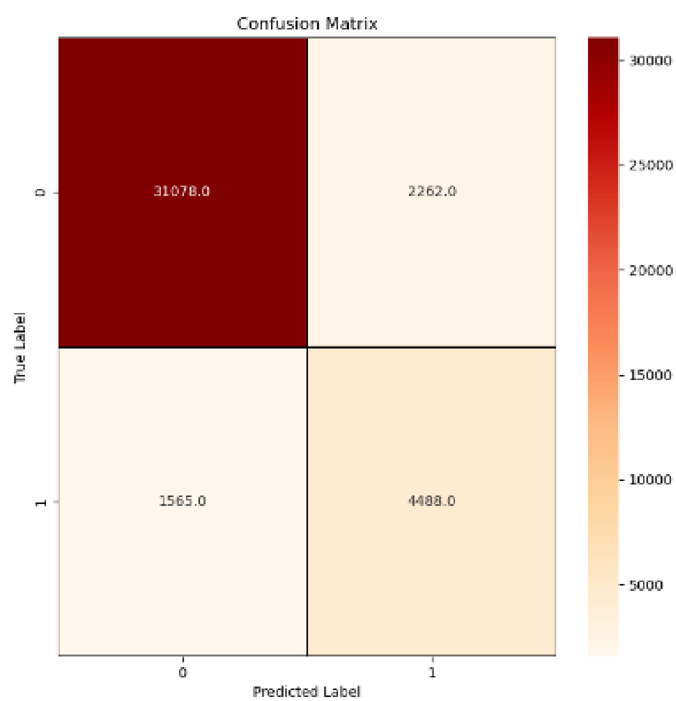


Figure 4: Confusion Matrix for the performance of the model.

3.2 *Discussion*

As shown by the experiments, the model can be used to aid diagnostics in Invasive Ductal Carcinoma since it can achieve satisfactory result regarding accuracy, Precision, Recall and F1-score. However, it still can be observed that there is an overfitting when training model. The results may be further improved by adopting some technology to avoid or mitigate its occurrence so that the proposed model can be more robust.

4 CONCLUSIONS

In this paper, predicting Invasive Ductal Carcinoma (IDC) through deep learning algorithm was achieved on breast histopathology images. This study developed a 10 – layered Deep CNN for the purpose of predicting IDC, with depth-wise Convolutional layer instead of traditional Convolutional layer. a new model with higher accuracy about 91.28% was obtained. The model has a low accuracy on Positive data than Negative data, a revision in dataset preparation maybe needed to increase the accuracy furthermore. And a possible revision to the deep CNN model that can train on more information regarding the patient may result in a higher accuracy.

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