Research and Implementation of Breast Cancer Intelligent Recognition Algorithm Based on Deep Convolutional Neural Network

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Abstract. Breast cancer is one of the most dangerous cancers with a particularly high mortality rate for women. In the face of thousands of female pathological pictures, how to use computer related control algorithms to quickly and efficiently intelligently identify female breast cancer images has become an urgent problem in the world. With the development of computer vision and deep convolutional neural networks, this paper applies the convolutional neural network (CNN) algorithm to solve the classification and recognition computer tasks of histological images for breast cancer, aiming to learn from tens of thousands of histological images features for breast cancer, and to assist doctors in diagnosing patients’ disease was found by computer control algorithm. There are many well-known neural network computer algorithms, such as AlexNet, Inception-Net, ResNet. Image recognition for breast is a binary classification problem, and it is not appropriate to use a ResNet network with a large amount of parameters. Therefore, this paper borrowed Alexnet algorithm and redesigned the algorithm, then used it for breast cancer experiments. We compared with the capsule algorithm used by Anupama authors. Our experiment improves the accuracy rate by 2%, and reduces the amount of neural network parameters, which greatly speeds up the training time.

1. Introduction
With the development of deep learning, computer vision technology has also achieved world-renowned achievements, and image classification tasks have received more and more attention in our life. Every year the ImageNet competition proposes many famous algorithms and models, such as Alexnet [1], Googlenet, Vgg16, ResNet, which can achieve a very low error rate. With the difficulty of classification tasks and the expansion of image data sets, the network models have also become more and more complex, and training requires more time and more powerful GPU. In recent years, deep learning technology has also made great progress in medicine. This article draws on the author Anupama's "Breast Cancer Classification using Capsule Network with Preprocessed Histology Images" [2].
Cancer is one of the most common diseases in the whole world [3]. Hundreds of millions of patients die from cancer every year worldwide, and millions of patients die from cancer every year in China. Many patients who die from cancer are dead because they are already at the advanced stage when they discovered, and they miss the best diagnosis. Therefore, early prevention and diagnosis of cancer is particularly important. Breast cancer is one of the most common cancers. Compared to different types of cancer, breast cancer is also a type of cancer with a very high mortality rate. Breast cancer is a malignant tumor that occurs in the epithelial tissue of the breast glands. There are 99% of breast cancer occur in women and only 1% in men. Mammography is the main method of breast cancer screening recommended internationally in recent years. It found that breast cancer detected by clinical examination. The cause of breast cancer is not completely clear. Studies have found that the incidence of breast cancer has a certain regularity. Women with high risk factors for breast cancer are susceptible to breast cancer. Early detection and early diagnosis of breast cancer is the key to improving the efficacy.

In this paper, because we are dealing with a binary classification problem to determine whether a patient has breast cancer, we borrowed AlexNet and rebuilt the neural network to propose a new end-to-end training model. Compared with the vgg16 network, our model parameters reduced and the model complexity reduced. The rest of this article organized as follows: In the second part, we briefly introduced the public data set we used and the preprocessing of experimental data. In the third part, this article introduces our model structure and training model in detail. The fourth section introduces the experimental results and experimental analysis. Finally, Section V presents conclusions.

2.RELATED WORK
The previous breast cancer identification used the BACH 2018 challenge dataset. Due to the small dataset, so we used Breakhis dataset [4] in this article. Tomas used the capsule network structure to deal with the classification of breast cancer with an accuracy rate of 87%. However, they used 400 images to solve the four classifications problem, and first solved the four classification tasks of normal, benign, in situ and invasive. Then Carlos performed the binary classification task using Inception V2 to achieve 76% accuracy. This article draws on Alexnet. The data sets we obtained are 700x460x3. We reshape it to 256x256x1. Through experiments, we achieved 89.5% accuracy.

The Breakhis dataset created in collaboration with the Pathology and Anatomy and Cytopathology of the P & D Laboratory in Parana, Brazil. This dataset consists of 9,109 microscopic images of breast tumor tissue from 82 patients, with each group of maps Images are composed of images with different magnifications (40X, 100X, 200X, and 400X), and each picture has a resolution of 700x460x3. The data set was divided into benign tumors and malignant tumors, of which 2480 were benign and 5429 were malignant. Benign divided into adenopathy (A), fibroadenomas (F), phyllodes tumors (PT), and tubular adenomas (TA). Malignant tumors divided into malignant tumors (breast cancer): cancer (DC), lobular carcinoma (LC), Mucinous carcinoma (MC), and papillary carcinoma A (PC). This article only studies whether the patient is sick and does not perform specific classification tasks. Therefore, the data is re-scrambled and a corresponding label file produced. We choose 80% of all images used as the training set and 20% used as the testing set, and not used validation set.

3.PROPOSED ARCHITECTURE

3.1Alexnet
A GTX 580 GPU has only 3GB of memory, which limits the maximum capacity of one neural network that be trained. Then the author trained the network on two GPUs. AlexNet contains 60 million parameters and 650,000 neurons, including five convolutional layers, several of which followed by a max-pooling layer, and three fully connected layer, because Alexnet does the Imagenet challenge is a classification task for 1000 classes of objects, so the final fully connected layer added to softmax for classification, with 1000 neurons. In order to speed up training, AlexNet uses Relu non-linear activation function and an efficient GPU-based convolution operation method. In order to reduce the overfitting
of the fully connected layer they used Dropout and set 0.5 to Dropout. As shown in Figure 1: The AlexNet structure,

![AlexNet structure](image)

Figure 1. The Alexnet structure.

### 3.2 Improved AlexNet

The difference between this article and Alexnet is mainly in the following three aspects. First, we do not use two GPUs for training; second, in terms of neuron input, we reshape the input image to 256x256x1, not 256x256x3. When performing classification tasks, we can ignore the number of channels, the advantage of this is that by reducing the number of channels, the training parameters of the neural network are reduced, and the model is easier to train. In addition, a BN layer is been used in each convolutional layer, which speeds up the model's forward direction; third, the size of the convolution kernel is changed, similar to VGG16, and only a 3x3 convolution filter is used to extract features.

After analyzing the Breakhis data. Therefore, we abandon large networks such as VGG16 [5] and choose Alexnet to build a network structure suitable for breast cancer. As shown in Figure 2: We use four convolutional layers and three fully connected layers. The convolution layer consists of Batch Normalization [6], convolution, max pooling, and activation function. The proposal of Batch Normalization speeds up model training, the batch normalization also added when designing the model in this paper; the fully connected layer uses 2048, 1000, and 2 neurons respectively. To prevent overfitting, we use the Dropout method. Dropout added after each fully connected layer and set to 0.5.

![Proposed method of using self-built model diagrams for breast cancer classification](image)

Figure 2. Proposed method of using self-built model diagrams for breast cancer classification.
4. EXPERIMENTAL RESULTS

4.1 Experiment Platform
This article has been implemented in the Tensorflow framework, which can print model process diagrams and calculate model parameters. The algorithm was developed in Python 2.7 and TensorFlow 1.4.0. The operating system was Ubuntu 16.04 LTS. All experiments were performed on a Linux OS on a computer with CPU Intel (R) Core (TM) i7-8700K @ 3.70 GHZ, GPU NVIDIA GeForce GTX1080Ti, and 11 GB of RAM. The experimental environment of this paper was shown in Table 1.

We set the epoch to 150 and the batch size to 64 during training. We used Adam as our model optimizer. The initial learning rate was 0.001 and the decay rate was 0.95. The learning rate was automatically adjusted every 20 epochs. Because there are only 7100 training pictures, we set the inner-loop to 10 during training. This parameter represents that all the data would be iterated 10 times during each epoch training, which solved the problem of fewer images in the data set to a certain extent.

Table 1. The experimental environment.

| Operating system | CPU          | Graphics card | Programming language | Framework     |
|------------------|--------------|---------------|----------------------|---------------|
| Ubuntu 16.04     | i7-8700k     | GTX 1080 11GB | Python 2.7           | Tensorflow 1.4.0 |

4.2 Loss Function

4.2.1 Activation function
We use softmax as the activation function. The softmax calculation method is as follows. This experiment belongs to supervised learning. We make labels in the 2.1, and convert them to one-hot encoding using tensorflow. For example, [0:1], the first position indicates benign, the second position indicates malignancy, when the label indicates that the patient is sick, [1:0] indicates that the patient is not sick. Softmax activation performed on the output of the neural network, and the result is converted to a value between 0 and 1.

$$\text{Softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$  \hspace{1cm} (1)

4.2.2 Loss function
This article compares MSE, cross-entropy loss function, focal loss, etc. We decided to use cross-entropy loss function to deal with the binary classification problem. When Softmax used for the activation function, cross-entropy used for the loss function, which will get better results.

$$H(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i)$$  \hspace{1cm} (2)

4.3 Experimental result
As is shown in Figure 3, at the beginning of the iteration, because the parameters of the network training are the initial values, the loss value is relatively large. The model is been continuously iterated and the parameters are been updated, the loss is been continuously reduced, and the model's effect is been continuously optimized. After 12000 iterations, the loss has been approached zero and remained stable, indicating that the model has converged, which is consistent with the characteristics of Lyapunov's stability, and prove that our model is objective.
As is shown in Figure 4, at the beginning of the iteration, the effect of the model is relatively poor, and the accuracy is been closed to zero. During the continuous iteration and parameters updating of the model, the loss is continuously decreasing, and the breast cancer recognition is continuously increasing. Since this task is a two-class classification problem, in the late training period, as the model is been continuously trained, the recognition rate will remain stable and there will be shocks. Therefore, in the future work, we will carry out specific classification tasks for the differentiated malignant breast cancer. In order to solve what kind of lesion malignant breast cancer belongs to in each picture. For the current model, this article tests the effect in the test sets, and the test results shown in Table 2:

| epoch (iter) | Average Accuracy (%) |
|-------------|----------------------|
| 10          | 0.875                |
| 20          | 0.9175               |
| 30          | 0.9175               |
| 40          | 0.8655               |

5. CONCLUSION
In this paper, by drawing on the Alexnet, building its own model and applying it to classification and recognition task of breast cancer histological images, it obtain an accuracy of 89.75%. Through this work, we can conclude that when we use a larger number and better quality data set, we can rely on traditional convolutional neural network models to train the data set. The model is analysed and
optimized, and the corresponding loss function is selected to improve the performance of the complex model. The data set image is used in this article is 700x460x3. We analyse the data set and believe that the grayscale image used for image classification tasks. Therefore, when we build the model, we will reshape the image to 256x256x1 and give up the colour features of the image. In doing so, the parameters for training the model reduced by one third, and the speed of training could be faster. Compared with Anupama's article, we also improve about 2% Identification accuracy. The experimental results show that our model used to assist doctors in automatic disease diagnosis, prevent in advance, and improve cancer survival rate. In future work, we will try to apply it to more complex data, hoping that it not only identify whether it has cancer, but also specifically classify what cancer it has, and further get better under the premise of accelerating the calculation efficiency.

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