DenseNet Convolutional Neural Network for Breast Cancer Diagnosis

Xinkai Yuan[1, *, †], Lanrui Zhang[2, *, †], Shuming Zhao[3, *, †]

[1]Beijing JiaoTong University, Shang Yuan Street, Beijing, CN
[2]School of Mathematics, University of Birmingham, Birmingham B15 2TT, UK
[3]Sierra Canyon School, 20801 Rinaldi Street, Chatsworth, USA
**Corresponding author: [1]20723035@bjtu.edu.cn, [2]lxz984@student.bham.ac.uk, [3]Shuming.zhao@scsstudent.org,*
†These authors contributed equally.

Abstract:
Breast cancer is a fatal disease, among which, its sub-type invasive (or infiltrating) ductal carcinomas (IDC) dominate the death cases of it. Detecting the features of such disease in an X-ray image by human eyes can be challenged, especially in cancer's early stage. Thus, this study is aimed at developing a system to assist doctors' diagnoses and help the patient to have a preliminary understanding of their own health conditions. More specifically, an IDC detection system based on the Convolutional Neural Network (CNN) is developed, where the DenseNet121 is applied here. In fact, DenseNet 169 and DenseNet 201 are also tested but their performances are not as good as DenseNet121 in this study. As is expected, the system can automatically judge whether the region in a breast histology image is IDC positive or not. This method achieves a high precision, 0.9725 validation accuracy, 0.97 test accuracy, 0.96 recall, 0.96 F1-score, and 0.965 AUC in the sub-dataset selected from Kaggle's Breast Histopathology images dataset. The time to predict 200 images is about 54 seconds and so the average prediction time for a single image is 2.7 s, which is fast enough for practical use.

Keywords: *Breast cancer detection, Convolutional neural network, DenseNet*

1 INTRODUCTION

Breast Cancer is one of the most lethal diseases of all. According to research, although the mortality of breast cancer has followed a downward trend thanks to the increasing development of medical technology, it still lingers around 14.4 per 100,000 women in 2017 in Europe [10]. Azam et al. also conducted a related survey and found that the mortality rate increased 0.7 per 100,000 from 1990 to 2015 on average around worldwide [2] Thus, it is believed that it is important to let people keep an eye on their health condition with greater care using a more pragmatic approach, which is the reason why this paper came up with the idea of developing a breast cancer diagnosis program to help those who suspect themselves having breast cancer to be aware of their health condition. In particular, a subtype of breast cancer, invasive (or infiltrating) ductal carcinomas (IDC), was brought to our attention, considering 80% of all breast cancer cases can be diagnosed as IDC [11]. Since pathologists want to assign a so-called "aggressiveness grade", they usually need to know which region of the patient's chest is IDC-positive. Consequently, this study aims at detecting the IDC-positive region in our project using deep learning. Furthermore, this paper would also like to develop an appendant chatbot to communicate with the users to give them results and advice. In the past 20 years, Computer-aided detection (CADe) and diagnosis (CADx) system, the computer-aided detection and diagnosis system, were introduced to the realm of biomedical technology as aid for clinical diagnosis of cancer. However, they do not perform as well as people expected since the analyzed examination images have too many false positive marks and lack the power of sufficiently analyzing certain key characteristics of tumor samples. Thus, CADe and CADx are not strong enough to be applied in the actual clinical situations for the diagnosis of breast cancer yet [3].

In Winching Liu's recent study, a new classification method called DeepBC for classifying breast cancer pathology images based on deep convolutional neural networks was proposed. DeepBC integrates networks such as Inception, ResNet, and AlexNet to detect key characteristics of the cancer examination images and

© The Author(s) 2023
B. Fox et al. (Eds.): IC-ICAIE 2022, AHCS 9, pp. 197-202, 2023.
https://doi.org/10.2991/978-94-6463-040-4_30

classify images into benign and malignant tissues. Liu's study significantly enhanced the accuracy of detecting breast cancer according to the high validation and testing accuracy [6].

Considering not only the relatively faulty and insufficient diagnosis validity of the previous detection methods using computer aids without the application of neural networks, but also the evidence that applying deep neural networks is able to provide a significantly higher diagnosis accuracy, convolutional neural network (CNN) was considered in this study, to create a state-of-the-art breast cancer diagnosis mobile application to help the potential breast cancer patients in the pre-clinic self-diagnosing process and contribute in clinical situations where medical professionals make actual diagnosis in real life. It is also worthy to mention that the CNN model not only showcases computational efficiency but passes on the important features of a certain tumor sample image to the next layer so that the classification efficiency is only increasing over time as well. It is believed that the limitations of the conventional diagnosis methods are that they do not capture all the necessary characteristics or features in the examination images. This is why this study implemented a deep learning model of convolutional neural networks.

In addition, complex tests were conducted on an existing benchmark dataset to evaluate the performance of DeepBC. Evaluating the performance of DeepBC. The evaluation results showed that DeepBC achieved 0.92 and 0.9643 accuracy in classifying patients and images, respectively, and 0.9643 accuracy with an F1 score of 0.9738. 0.9738, which is better than the state-of-the-art methods. This paper improved on this by using a convolutional neural network approach to analyze each pixel point of the image, achieving 0.97 accuracy. A natural language processing approach was also used to provide a better interactive experience for patients.

2 METHOD

2.1 *Data and Preprocessing*

In our study, we acquired the "'Breast Histopathology Images"' dataset from Kaggle, in which 198,738 IDC-positive (benign) and 78,786 IDC-negative (malignant) image patches are collected [7]. Since small-scale medical institutions cannot normally acquire a large amount of sample data, we only took 1,000 benign images and 1,000 malignant images (total 2000) to set up the training dataset and validation dataset, each accounting for 80% and 20%, respectively. We then extracted 100 benign and 100 malignant images (total 200) from the original dataset as the testing dataset. After that, we processed all images to the size of 224×224 (height×width) pixels with an RGB level of three channels to feed the whole system for the sake of reducing complexity and higher training efficiency.

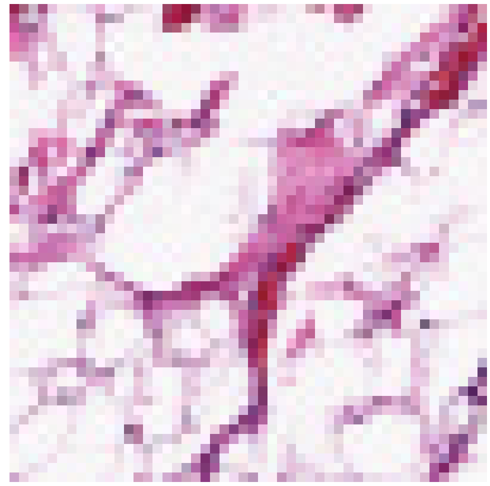

Figure 1: Benign Sample image.

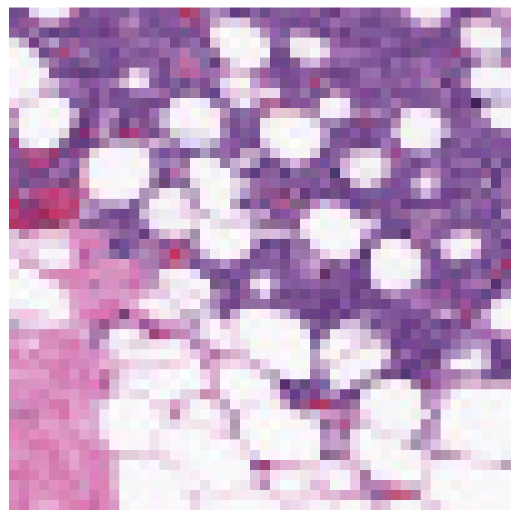

Figure 2: Malignant Sample image.

2.2 *Proposed model (CNN)*

Among all deep learning algorithms, CNN is the most popular one and has been used in a wide range of applications, including machine vision [9], speech processing [8], and human face identification [5]. The advantage of CNN is that it is able to extract subtle features which could not be recognized by human beings [1].

In this study, the DenseNet169 is referred to and added to the whole network [4]. Figure 3 and Figure 4 represents the architecture of this series of DenseNet. To be specific, the model consists of the backbone of the DenseNet169, a 2D global average pooling layer, a 50% dropout layer, a normalization layer, and finally a 2-neural dense layer. First, a 224×224×3 RGB image is inputted into the whole system. Then, it went through DenseNet169 and was transformed into a 7×7×1664 size three-dimensional tensor, which will be directly fed into a 2D global average pooling layer and output as a 1664 length vector in order to deal with the overfitted issue and reduce the number of parameters so as to decrease the amount of calculation. Then, the vector will be filtered by a 50% dropout layer and a normalization layer. Finally, the network end with a 2-neuron dense layer since the task is to give the probability of IDC positive and IDC negative in a particular region in the image.

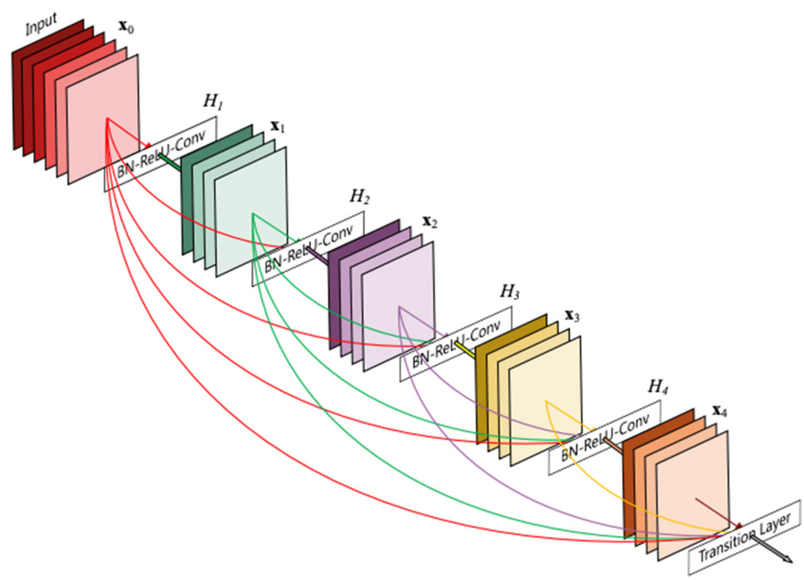

Figure 3: The architecture of DenseNet [4].

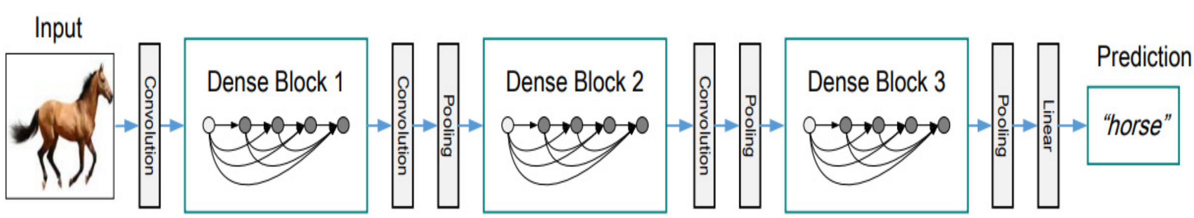

Figure 4: Workflow for DenseNet [4].

2.3 *Implementation details*

Binary cross-entropy is a loss function that is widely used in binary classification problems. The learning rate and batch are set to be 0.0001 and 16 after being fine-tuned. Adam is chosen to be the optimizer in this study and accuracy is the metric since it can give a direct intuition whether an image tends to be IDC positive or not.

2.4 *Application (NLP, Chatbot)*

In this study, further applications regarding CNN are developed to communicate with the user. More specifically, a chatbot based on NLP is able to guide the user to upload the X-ray images to the App, and then provide a diagnosis, which is the probability of the IDC positive, and some professional advice.

3 RESULTS AND DISCUSSION

3.1 *Performance for DenseNet*

After training 10 epochs for DenseNet 121, we were able to obtain a 0.9394 accuracy in the training dataset and a 0.97 accuracy in the validation dataset. As we trained more epochs, the training accuracy continued to increase and the validation accuracy fluctuated around 0.95 while following an overall upward trend, reaching the peak at the 5th epoch with a validation accuracy of 0.97, which can be found in Figure 5.

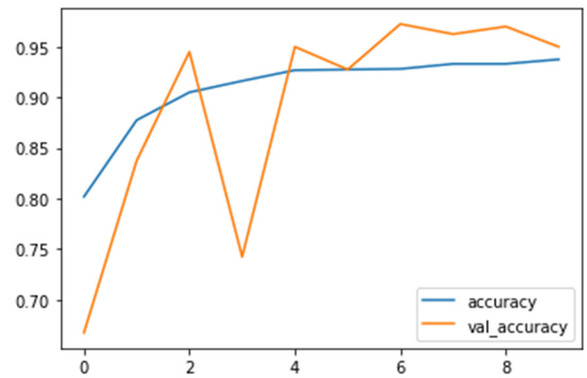

Figure 5: Training Accuracy and Validation Accuracy using DenseNet 121.

Considering the relatively small size of the training dataset input to the model during model training due to the limited computational power and efficiency of the GPU, the results obtained by the model using the DenseNet 121 architecture are quite accurate and efficient. For the same reason, during the model implementation, the model was trained for 10 epochs, which is why the model-based computational results are satisfactory. It is worth mentioning that the model was also implemented using the same dataset during training with the DenseNet 169 and DenseNet 201 architectures, both of which produced a very good validation accuracy but a dramatically less convincing result of both about only 0.90 test accuracy, which can be observed in Figure 6 and Figure 7.

Table 1: Classification metrics of the three neural networks implemented.

	DenseNet 121	DenseNet 169	DenseNet 201
Validation Accuracy	0.9725	0.9800	0.9725
Test Accuracy	0.97	0.90	0.88
Recall	0.96	0.88	0.84
F1 Score	0.96	0.88	0.84
AUC	0.965	0.882	0.840

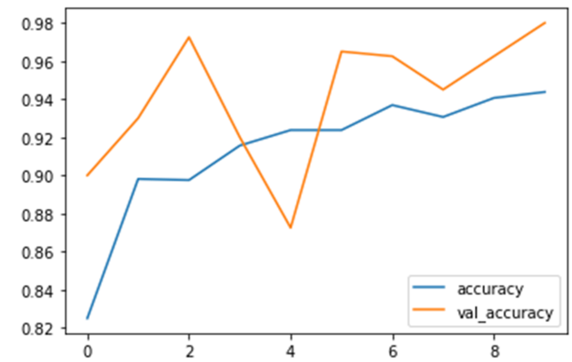

Figure 6: Training Accuracy and Validation Accuracy using DenseNet 169.

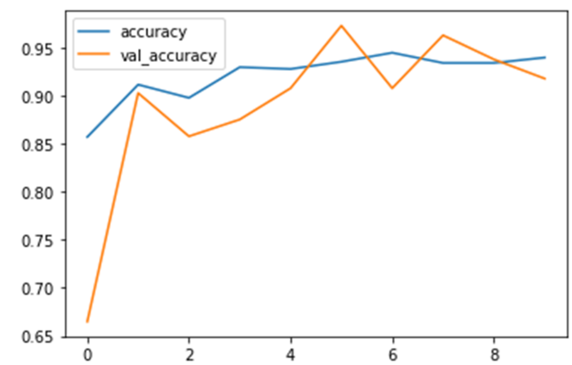

Figure 7: Training Accuracy and Validation Accuracy using DenseNet 201.

3.2 *Application*

We implemented our web app using Next JS as front end and Flask as backend server, which can be observed in Figure 8. In addition, Firebase was chosen as our database.

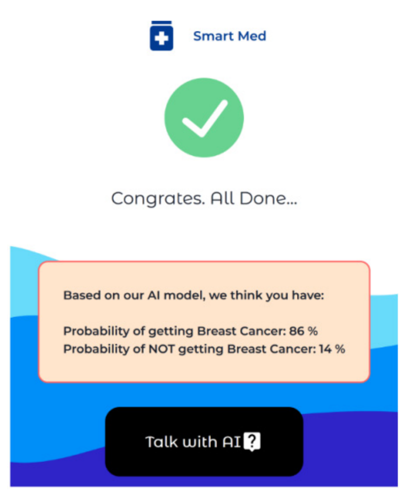

Figure 8: Interface for designed application.

Image can be uploaded in this application. Once the image is uploaded successfully the user can click the button to start the app for prediction. And then the deployed model in the backend will provide proper prediction result. After the result is received successfully from the backend, the user will be navigated to a result page, and we will show the result predicted using the DenseNet 121 model we introduced in the previous section in the backend server. The user shall click the Talk with AI button to go to another page that allows them to talk to our AI chatbot. Since we do not have a login/register system for now. We will store the result in the local storage for different pages to get them. In order for our chatbot to know the result, we will make a POST request again to our server once the user clicks the button.

4 CONCLUSIONS

The use of convolutional neural networks can improve the accuracy of determining cancer risk by identifying early breast images that can be interacted with patients through FF neural networks. This study aims to help users identify if they have breast cancer at an early stage through a feature that is entirely AI driven. It consists of two parts, image classification and a chatbot that communicates with the user. This study used convolutional neural networks to classify images. Natural language processing is used for the human-computer interaction part.

Currently, the algorithm for convolutional neural networks needs to be improved and processing images will take a lot of time based on the GPU not running fast enough. In the future, this study will implement a login/registration system with improvements that will allow users to see a history of prediction results and deploying the application to a public server hosted by Heroku, as well as working with a number of hospitals to allow users to speak directly to cancer specialists for advice on the data and results of this project. This may be a premium feature for which some fees are charged to users.

REFERENCES

[1] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of big Data, 8(1), 1-74.

[2] Azamjah, N., Soltan-Zadeh, Y., & Zayeri, F. (2019). Global Trend of Breast Cancer Mortality Rate: A 25-Year Study. Asian Pacific journal of cancer prevention: APJCP, 20(7),2015–2020. https://doi.org/10.31557/APJCP.2019.20.7.2015

[3] Firmino, M., Angelo, G., Morais, H., Dantas, M. R., & Valentim, R. (2016). Computer-aided detection (CADe) and diagnosis (CADx) system for lung cancer with likelihood of malignancy. Biomedical engineering online, 15(1), 1-17.

[4] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

[5] Jiang, H., & Learned-Miller, E. (2017). Face detection with the faster R-CNN. In 2017 12th IEEE international conference on automatic face & gesture recognition (FG 2017) (pp. 650-657). IEEE.

[6] Liu, Wenzhong, et al (2020). Classifications of Breast Cancer Images by Deep Learning, 10.1101/2020.06.13.20130633.

[7] Mooney, Paul (2017). Breast Histopathology Images. Kaggle, 19 Dec., https://www.kaggle.com/paultimothymooney/breast-histopathology-images.)

[8] Palaz, D., & Collobert, R. (2015). Analysis of cnn-based speech recognition system using raw speech as input (No. REP_WORK). Idiap.

[9] Qiu, Y., Yang, Y., Lin, Z., Chen, P., Luo, Y., & Huang, W. (2020). Improved denoising autoencoder for maritime image denoising and semantic segmentation of USV. China Communications, 17(3), 46-57.

[10] Wojtyla, C, Bertuccio, P, Wojtyla, A, & Vecchia, C. L. . (2021). European trends in breast cancer mortality, 1980–2017 and predictions to 2025. European Journal of Cancer, 152(9935), 4-17.

[11] Breastcancer (2022), Invasive Ductal Carcinoma (IDC), https://www.breastcancer.org/types/invasive-ductal-carcinoma?gclid=EAIaIQobChMIiZbOotze9gIV0NaWCh2jwQg3EAAYASAAEgI60PD_BwE.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.