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Comparison and analysis of the number of convolutional layers in CNN-based breast cancer detection

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Abstract. Breast cancer is becoming more and more common, and the mortality rate is increasing, which is indeed a serious problem. To alleviate this problem, this study applies a convolutional neural network (CNN) model to analyze breast cancer images formed by mammography. The CNN model has the property of automatically learning hierarchical feature representations from the original image data. The structure of the CNN enables it to capture spatially hierarchical features at multiple scales, including edges, textures, and objects. Specifically, this study explores the performance of CNN models on prediction tasks by varying the number of convolutional layers. This study is conducted on the DDSM mammography dataset. The experimental results demonstrate that CNN models are effective for detecting breast cancer, both in terms of accuracy and loss rate, and that more convolutional layers improve performance. In particular, the model saturates at four convolutional layers to reach the highest performance. Thus, this study helps to accelerate the efficiency of breast cancer detection and paves the way for more efficient methods in the future.

Keywords: breast cancer detection, DDSM Mammography, convolutional neural network.

1. Introduction

Recently, breast cancer is becoming the top of the most common diseases. The current methods for breast cancer detection include X-ray examination, magnetic resonance imaging (MRI) and so on. However, mammography is the most widely used method so far, taking cost and reliability into consideration. It uses X-ray to produce images of breast and certain sections can be observed more closely. Breast cancer primarily affect female population on account of its high morbidity and mortality among women. According to research written by Huang et al., breast cancer is the fifth most prevalent cause of cancer deaths in women, accounting for more than 11.6% of all female cancer cases and 6.6% of all cancer fatalities [1]. Additionally, data provided by Sun et al. also reviewed that over 25% of all women with cancer, to be specific, breast cancer affects 1.5 million women each year [2]. Due to the high morbidity and mortality of breast cancer, it is necessary to classify benign and malignant breast cancer images in order to allow patients to be treated as soon as possible and ultimately decrease mortality.

Many methods have been developed in the field of classification and detection of breast cancer. Before the widespread use of digital imaging, almost all laboratories in the world relied on glass sections for pathologic diagnosis [3]. This approach resulted in patients not being treated in a timely manner because glass sections or specimens being sent to the appropriate pathologist would waste time [3]. Considering the advancement of technology, Venmathi et al. mentioned that computer-assisted systems for mammography usually consist of two modalities; identification of the region of suspicion (ROS) by a computer-assisted diagnostic system (CADe); and determination of the region of suspicion as benign and malignant by a computer-assisted diagnostic system (CAD) [4]. In addition, Ali et al. stated that detection sensitivity with the help of a computer-aided diagnostic system (CAD) will be 10% higher than detection sensitivity without CAD [5]. In addition, CLAHE improves the image quality is an important step in preprocessing because it separates the noise from the photographs [6]. In terms of classification, Chaudhury et al. used fuzzy SVM, Bayesian classifiers and random forests to process preprocessed photos [6]. Deep learning, meanwhile, has significantly enhanced the outcomes of data analysis. In the field of image processing, neural networks are used more and more. Particle Swarm Optimized Wavelet Neural Networks (PSOWNN) were employed by Dheeba and Selvi to detect breast cancer [7]. J.Arevalo et al. explained different Convolutional Neural Network (CNN) used for quality detection tasks and experimented on the BCDR-FM dataset [8]. The CNN framework uses a rectified linear cell activation function to ensure nonlinearity. The signal transformation issue is resolved, and precise feature extraction occurs after passing through the fully connected layer [9].

The major goal of this study is to apply a CNN-based machine learning system to identify breast cancer in DDSM Mammography images. Specifically, first, DDSM Mammography dataset is down sampled and is resized to 75*75 pixels in order to increase effectiveness. Second, instead of extracting the final training data directly from the original dataset, the positive and negative examples will be separated, and the same amount of data will be extracted from them. Finally, CNN is applied to construct evaluation models. CNN model includes convolutional layer, activation layers, pooling layers and so on. Eventually, this study compares the effect of different convolutional layer number on the model performance. The result demonstrates the CNN model's capability to accurately identify breast cancer images, and the final accuracy reaches 86.3%. The research in this paper advances breast cancer detection, which is conducive to the timely treatment of patients and the reduction of breast cancer mortality.

2. Methodology

2.1. Dataset description and processing

This study uses DDSM Mammography dataset, sourced from Kaggle [10]. This dataset consists of breast tissue images formed by mammography, which have been pre-processed and converted to 299*299 images and the data is finally stored as tf-records files. The main features of this dataset are the pixel values of images and pathological properties of breast tissue. The goal here is to classify the images of breast tissue by detecting abnormalities, broadly divided into positive and negative categories. The dataset has been separated into test files, which are evenly divided into test and validation data, and training files, which consists of 5 files in the form of tf-records, with a total of 55890 training examples. Figure 1 shows some examples from the dataset in grayscale.

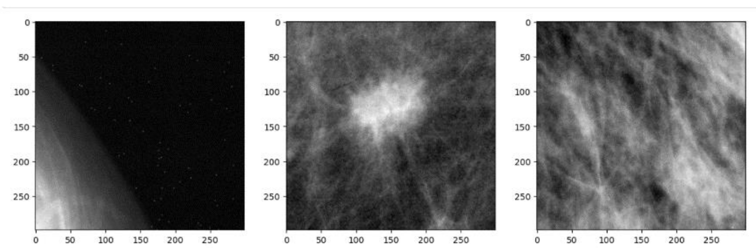

Figure 1. Images from DDSM Mammography dataset.

2.2. Proposed approach

The classification method of breast cancer proposed in this paper is mainly realized by CNN model. The initial size of images is 299*299 pixels, while the input shape of data in this research is set to be 75*75 pixels, which means that the images are resized first. The following step is to separate the dataset according to the positive and negative cases and the purpose is to equally select part of the data from the dataset as experimental objects, avoiding the situation of uneven distribution. After confirming the final data to be used for training, a CNN model is applied in the experiment. By adding different numbers of convolutional layers, the accuracy of the model is compared. Finally, loss curves were created to further analyze the effects of different number of convolutional layers on the study results. Figure 2 below illustrates how this study was conducted.

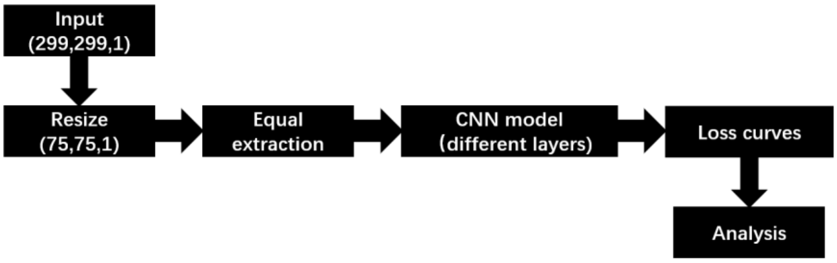

Figure 2. Process of the research.

2.2.1. CNN. CNN, primarily for image recognition and computer vision tasks, is a class of artificial neural networks that can automatically and adaptively learn spatial feature hierarchies. Convolutional layers, pooling layers, fully linked layers, and several other components make up the various building blocks that make up CNN. The fundamental concept of CNN is based on convolutional layers, which use small filters or kernels to convolve over the input image and perform element-wise multiplication and summation to produce feature maps that highlight specific patterns or features present in the image. To extract hierarchical features from input images, convolutional layers are stacked with filters, activation functions are added to introduce non-linearity, and pooling layers are used to reduce spatial dimensions and increase computational efficiency. After the convolutional layers, fully connected layers are utilized to classify the data using the recovered features. The CNN model also has an output layer designed for the particular job, such as object or picture detection. Using backpropagation and gradients from a specified loss function that assesses the discrepancy between predicted outputs and ground-truth labels, an optimization algorithm modifies the model's parameters during training. Over the dataset, the training procedure is iterated until the model performs satisfactorily. The general CNN model method is shown in Figure 3.

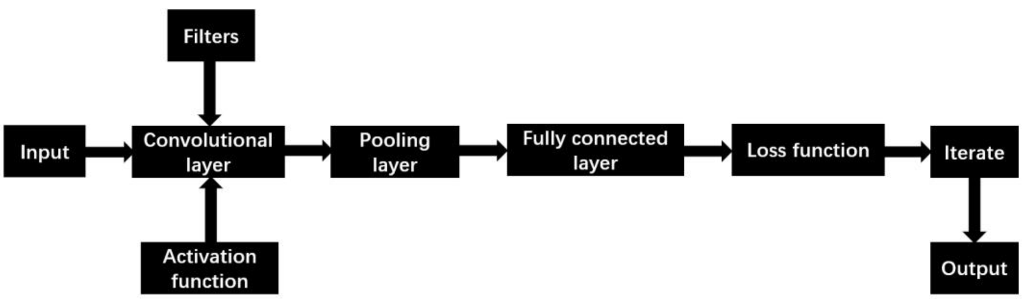

Figure 3. Process of CNN model.

2.2.2. Loss curves. Loss curves are graphical depictions of the behavior of the loss function throughout a machine learning model's training phase. In the context of supervised learning, the loss function calculates the difference between a given set of training data's actual labels and the model's expected output. Minimizing this loss during training is the main objective because doing so enhances the model's

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performance on unobserved data. Typically, the loss curve is shown versus the quantity of training epochs or iterations. A complete traverse through the entire training dataset is represented by one epoch. A batch of training data is used to update the model's parameters on each cycle. The loss curve shows how effectively the model is learning and whether it is convergent toward a better answer as training goes on. The loss often reduces as the model is trained, showing that the model is improving at making predictions and fitting the training data. A key determinant of the model's learning rate and convergence speed is the slope of the loss curve.

2.2.3. Loss function. In order to successfully train deep learning models, selecting the appropriate loss function is essential. For the breast cancer classification problems in this experiment, the Binary Cross Entropy loss function is a well-suited choice on account of its good performance in dealing with two-class problems. The uncertain aspect of binary categorization is taken advantage of by binary cross entropy loss. The model produces probabilities, which show the likelihood of an occurrence belonging to the positive class (class 1), rather than simply predicting binary labels (0 or 1), as follows,

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log\big(p(y_i)\big) + (1 - y_i) \cdot \log\big(1 - p(y_i)\big), \tag{1}$$

where y_i signifies the actual class for the data point, $p(y_i)$ is the probability of one, and $1 - p(y_i)$ is the probability of zero.

2.3. Implementation details

A few key points are emphasized in the application of the suggested paradigm. In regard to hyperparameters, a batch size of 32 is used and the model runs for a total of 30 epochs. The Adaptive Moment Estimation (Adam) optimizer is chosen because each parameter is kept at a distinct learning rate, allowing it to automatically alter the learning rate depending on previous gradients and make sure that each parameter is updated with the proper step size. The number of filters in every convolutional layer is chosen to be 128 and the activation function used after performing the convolution is the Rectified Linear Unit (ReLU) activation. Downsampling and resize are applied to data processing to ensure experimental efficiency as much as possible. The images are resized to 75*75 and a total of 3000 examples are selected, equally drawn from the positive and negative examples. In this way, the training data is balanced, which is more conducive to accuracy analysis.

3. Results and discussion

The purpose of this chapter is to analyze and compare experimental results. First of all, the detection accuracy of a CNN model using various convolutional layer counts on the same batch of data is examined and compared. Then, for further analysis, the model loss curves under different number of convolution layers are examined and contrasted.

3.1. Performance evaluation based on accuracy

The detection accuracy improves with more iterations and becomes more stable. Table 1 compares the accuracy of the most recent CNN model iterations with various numbers of convolutional layers.

Table 1. The final accuracy of CNN model with various numbers of layers.

Number of convolutional layers	Accuracy
1	0.8200
2	0.8413
3	0.8507
4	0.8630

Table 1 shows that, the accuracy of the CNN model with four convolutional layers may reach 86.3% by the end of iterations, compared to the accuracy of the CNN model with only one convolutional layer, which is only about 82%. Even though the current gain is just 4%, the benefits of more convolutional

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layers will gradually become apparent with the expansion of training data and the number of iterations. An essential architectural element that affects a CNN's capacity to learn and represent complicated features from the input data is the CNN's depth, which is defined as the number of layers it has. Additionally, more hierarchical information from the input photos can be captured by a deeper network, which enables the model to learn complex patterns and changes in the data. However, a network that is too deep might overfit, memorizing the training data and performing poorly on untrained data, while a network that is too shallow might underfit and fail to learn critical features. Consequently, it is crucial to choose the right number of convolution layers based on the task's complexity, the available computational resources, and the size of the training dataset.

3.2. Performance evaluation based on loss curves

Figure 4 provide loss curves under a CNN model of one convolutional layer and a CNN model of four convolutional layers.

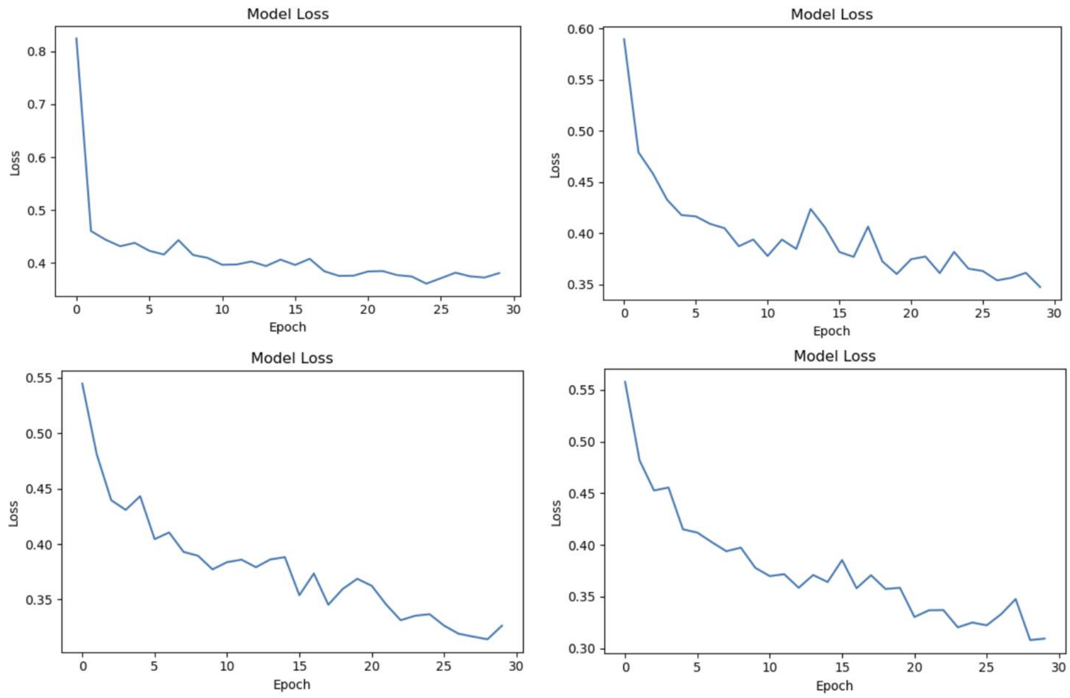

Figure 4. Loss curves of two models. The left top is the loss curve of CNN model with one convolutional layer, the right top is the loss curve of CNN model with two convolutional layers, the left bottom is the loss curve of CNN model with three convolutional layers, while the right bottom is the loss curve of CNN model with four convolutional layers.

As shown in Figure 4, beginning with a loss rate of more than 0.8, the single convolutional layer CNN model eventually drops and essentially stabilizes at 0.4. However, with an initial loss rate of about 0.55, the four convolutional layers CNN model is subsequently decreased to slightly more than 0.3. It is evident that appropriately increasing the number of convolutional layers can almost reduce the loss rate of this experiment by nearly 10%. On the other hand, because the deeper network has more parameters to update, the loss curve of the CNN model with more convolutional layers exhibits a slower convergence rate. Similarly, overfitting may be more likely to occur in extremely deep networks, particularly when the data sets are tiny or noisy. In conclusion, correctly increasing the number of convolutional layers can improve accuracy and, to a certain extent, decrease loss rate. However, in order to prevent overfitting, the number of convolutional layers cannot be increased blindly, instead, it should be selected correctly according to the task's difficulty and the amount of the training dataset. When the number of convolution layers is selected appropriately, the model's performance can be improved, and data can be detected more accurately.

4. Conclusion

This study proposes CNN model for breast cancer prediction through mammography. Different layers are used to analyze the benign and malignant nature of breast cancer. Convolution consists of applying filters to the input image to recognize regional patterns and features. The pooling layer then decreases the features' spatial dimension while keeping the most crucial information. After the convolution and pooling layers, the collected features are fed into fully linked layers for classification and inference. According to experimental findings, when the number of convolutional layers increases from one to four, the model's accuracy rises from 82% to 86.3%. In addition, the convergence of the loss curve tends to slow down and eventually reaches a lower point. This suggests that the four-layer model is saturated and able to effectively perform the prediction task. In the future, the research will consider refining the categories and dividing the images into multiple levels for detection. The focus of the research will be on assigning risk to different breast cancer images, with higher grades being more risky, rather than just predicting benign or malignant. This will hopefully improve the accuracy of breast cancer diagnosis, which will further reduce mortality rates.

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