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Deep Learning in Grading Prediction of Breast Cancer Ultrasound Images

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Abstract:
This study proposed a breast cancer ultrasound image grading prediction method based on multi-layer perceptron (MLP), aiming to improve the accuracy and efficiency of breast cancer automated diagnosis. Early diagnosis of breast cancer is crucial to the prognosis of patients, and ultrasound imaging, as a non-invasive examination method, is widely used in breast cancer detection. In order to adapt to the characteristics of breast cancer of different grades, this study extracted features from ultrasound images and converted the texture, edge and shape information of the image into feature vectors suitable for MLP model processing. Experimental results show that the MLP model performs well in evaluation indicators such as accuracy, recall, precision and F1 score, showing its potential in breast cancer grading prediction tasks. Comparative experiments with other deep learning models further verified the efficiency and robustness of MLP. This study provides reliable theoretical and experimental support for breast cancer ultrasound image grading prediction based on MLP, and provides a new technical solution for early diagnosis and grading management of breast cancer.

Keywords:
Breast cancer grading, Multilayer perceptron, Ultrasound images, Automated diagnosis

1. Introduction

In breast cancer diagnosis, ultrasound images have become an important non-invasive examination method, especially in early detection of lesions and accurate diagnosis of different grades of cancer. Compared with other imaging methods, ultrasound is not only safe and convenient, but also can effectively distinguish different structures of breast tissue[1,2]. However, due to the complexity of breast cancer lesions and individual differences among patients, the interpretation of ultrasound images depends on the professional knowledge and experience of doctors, which is inevitably subjective. Therefore, how to automatically and accurately predict the grade of breast cancer with the help of advanced technologies such as deep learning is of great significance to improve diagnostic efficiency and accuracy[3,4].

In recent years, with the improvement of computing power, deep learning has made significant progress in the field of medical image analysis. Multilayer perceptron (MLP), as a classic deep learning model, performs well in processing structured data and simple image classification tasks[5]. Although the network structure of MLP is relatively simple and is mostly used for tasks with feature vector input, the MLP model also shows potential in the prediction of breast cancer ultrasound image grade through appropriate feature extraction and data processing[6]. MLP can effectively learn the relationship between different features in ultrasound images and cancer grade, providing a new idea for grade prediction[7,8].

In the prediction of breast cancer ultrasound image grade, feature extraction is a key step. Since the input of the MLP model is usually a one-dimensional feature vector, we need to preprocess the ultrasound image and convert the image data into a suitable feature representation. Features can include information such as texture, edge, shape, and intensity distribution, which can help the model capture subtle differences in the breast cancer lesion area. Through the fine extraction of image features, the MLP model can better identify different grading features of cancer, thereby improving the accuracy of classification.

In addition, in order to enhance the generalization ability of the MLP model in breast cancer grading prediction, the diversity and richness of data are crucial. In breast cancer imaging data, the lesion location, morphology, and intensity distribution of different patients vary greatly. Therefore, we use data augmentation technology to increase the diversity of training data by rotating, flipping, and scaling the image. This can not only prevent the model from overfitting, but also improve the model's adaptability to different types of breast cancer lesions, providing a guarantee for stability in practical applications.

The MLP model is different from the convolutional neural network (CNN) in structure. Although it lacks the spatial feature extraction capability of the convolutional layer, the MLP still has a certain classification effect when the input features are clear. By introducing a fully connected structure with layer-by-layer connections, MLP can capture deep patterns in the data layer by layer, which is suitable for the task of predicting breast cancer grading with extracted features. During the training process, by setting appropriate learning rates and regularization methods, the convergence speed of the model can be effectively improved and overfitting can be prevented, so that the MLP model has a strong performance in this task.

In summary, deep-learning, especially the MLP model, has shown new application prospects in the grading prediction of breast cancer ultrasound images. Although the structure of the MLP model is relatively simple, it can effectively improve the accuracy of breast cancer grading prediction through reasonable data preprocessing, feature extraction and data enhancement methods. Future research can further optimize the network structure of MLP, combine other deep learning methods and multimodal data sources, so as to improve the robustness and accuracy of breast cancer grading prediction, and provide strong support for the early diagnosis and grading management of breast cancer.

2. Method

In the breast cancer ultrasound image grading prediction task of this study, we use a multi-layer perceptron (MLP) model to classify feature vectors. The entire method process includes data preprocessing, feature extraction, model training and optimization, aiming to improve the accuracy and generalization ability of the MLP model in breast cancer grading prediction. Its network structure is shown in Figure 1.

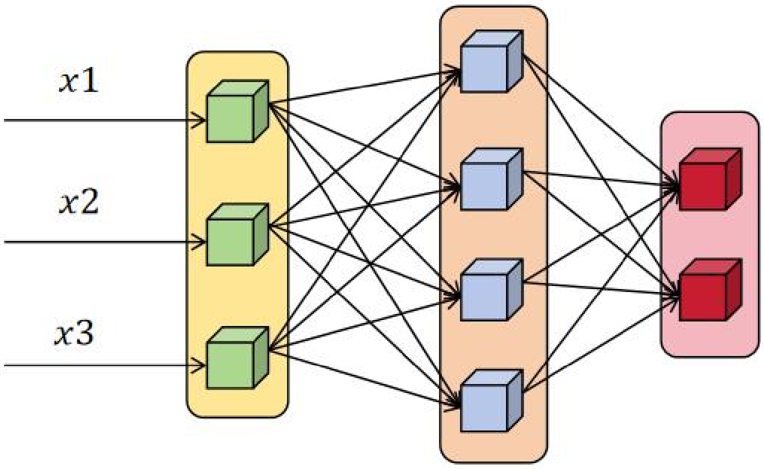

Figure 1: Network overall architecture diagram

First, in the data preprocessing stage, we perform multiple operations on ultrasound images to ensure data consistency and quality. Ultrasound images are usually affected by noise and contrast changes, so we first denoise the images and apply Gaussian filtering or median filtering to reduce the interference of noise. Next, we normalize the images and standardize the pixel values to the range of [0, 1] so that different images have the same feature scale, thereby avoiding the influence of data range differences on the model learning effect. For data enhancement, we introduce operations such as rotation, flipping, and scaling to expand the dataset, increase data diversity, and improve the robustness of the model.

Next is the feature extraction step. Since the input of the MLP model is a one-dimensional feature vector, we need to convert the two-dimensional information of the ultrasound image into one-dimensional features. The key to feature extraction is to retain important information in the image, such as texture, edge, shape, and intensity distribution, which can help the model identify cancer features of different grades. We use commonly used image processing algorithms, such as gray level co-occurrence matrix (GLCM) to extract texture features, Canny operator to extract edge features, and combine histogram features to construct a rich feature vector. Finally, the extracted features are merged into a one-dimensional vector as the input of the MLP model.

During the model training phase, an MLP model with multiple hidden layers was constructed, and the deep features were gradually learned through a fully connected structure with layers connected. The input layer of the model receives the vector representation after feature extraction, and the hidden layer uses the ReLU activation function to increase the nonlinear expression ability of the model. We added 3 to 5 hidden layers to the model architecture, each containing 128 to 256 neurons to ensure that the model has sufficient expression ability. In addition, to prevent overfitting, we added a Dropout layer between the hidden layers and set an appropriate dropout rate to improve the generalization ability of the model on the test set.

During the model training process, we used the cross-entropy loss function to measure the difference between the model's prediction results and the actual labels. The optimization algorithm selected the Adam optimizer, whose adaptive learning rate mechanism can accelerate the convergence process of the model. The formula of the loss function L is:

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(y'_i) + (1-y_i)\log(1-y'_i))$$

Among them, y_i is the true label, y'_i is the model prediction probability, and N is the number of samples. We set an early stopping strategy in the training, and terminated the training early when the loss of the validation set no longer decreased to avoid overfitting.

Finally, the model was hyperparameter optimized, including adjusting the number of hidden layers, the number of neurons, the learning rate, and the dropout rate to obtain the best classification effect. Through multiple experimental verifications, the optimal parameter combination was selected to improve the performance of the model in the breast cancer grading task. Through the above method, the MLP model can effectively use the feature vectors of ultrasound images to predict the grading of breast cancer, providing a basis for further optimization and clinical application.

3. Experiment

3.1. Datasets

In this study, we used the Breast Ultrasound Images Dataset (BUSI), a publicly available breast ultrasound image dataset specifically for breast cancer diagnosis research. The dataset, published by Al-Dhabyani et al., contains ultrasound images from different patients and contains 780 annotated breast ultrasound images, which are divided into three categories: benign lesions, malignant lesions, and normal tissue. Each image is annotated with the corresponding lesion region to help the model identify and classify different lesion types.

The image quality of this dataset is high and the samples are diverse, covering different characteristics of various lesions, making it suitable for training deep learning models. The image resolution is 500×500 pixels, which ensures the clarity of image details and helps the model extract effective features from it. In addition, the dataset contains a large number of lesion region diversity, including the morphology of the mass, boundary clarity, and tissue structure differences, which are important for improving the accuracy and robustness of the classification model.

The Breast Ultrasound Images Dataset (BUSI) has been widely used in breast cancer detection and classification research, providing a standardized breast ultrasound data source for the scientific community. By using this dataset, researchers were able to build and evaluate different deep learning models and make progress in the grading and classification of breast cancer. At the same time, the openness of the dataset makes different studies comparable, which helps promote the development of automatic breast cancer diagnosis technology.

3.2. Experimental setup

In the experimental setting, the Breast Ultrasound Images Dataset (BUSI) dataset was first preprocessed and split into training, validation, and test sets to ensure the generalization ability of the model. The preprocessing stage includes uniform normalization of the images and scaling the pixel values to the range of [0, 1] to reduce the brightness and contrast differences between different images and enhance the adaptability of the model to diverse data. In addition, data augmentation operations, including random rotation, flipping, and scaling, were performed to increase the diversity of training samples and help the model better learn the characteristics of various lesions.

In the model training stage, we used the multi-layer perceptron (MLP) model to predict breast cancer grading based on the extracted features. Since the input of MLP is a one-dimensional feature vector, the image is first feature extracted to convert image features such as texture and shape into vectors suitable for input to MLP. The model contains multiple hidden layers, with the number of neurons in each layer set to 128 to 256, and the activation function is ReLU to increase the

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nonlinear expression ability of the model. In order to prevent overfitting, Dropout layers are added between hidden layers, and appropriate dropout rates are set. During the training process, we used the cross entropy loss function and used the Adam optimizer for parameter optimization.

After the model training was completed, we used four evaluation indicators to evaluate the performance of the model: accuracy, precision, recall, and F1 score. Accuracy measures the model's ability to classify the overall sample, precision reflects the model's classification accuracy for positive samples, recall evaluates the model's ability to detect all positive cases, and the F1 score is the harmonic average of precision and recall, which comprehensively reflects the performance of the model under imbalanced data.

3.3. Experimental Result

In the comparative experiment, in order to evaluate the performance of the MLP model in the task of breast cancer ultrasound image grading prediction, we selected four commonly used deep learning models for comparison: convolutional neural network (CNN), ResNet, DenseNet and VGG. These models perform well in image classification tasks and each has unique architectural advantages. CNN is a classic convolutional network that is good at capturing local features of images; ResNet solves the gradient vanishing problem in deep networks through residual connections, allowing the model to learn complex features at a deeper level; DenseNet adopts a dense connection structure to achieve efficient feature transmission and reuse, improving the parameter efficiency of the model; VGG adopts a deeper convolutional layer stacking structure, which can effectively extract fine-grained features.

These deep learning models have been widely used in medical image analysis. Compared with the MLP model, these models have natural advantages in image feature extraction, especially suitable for processing structured image data. However, since MLP directly operates on one-dimensional feature vectors, it relies on the quality of preprocessing in the feature extraction stage. In this experiment, through comparative analysis with CNN, ResNet, DenseNet and VGG, we can better understand the advantages and disadvantages of different models in breast cancer grading tasks, thereby providing data support for selecting the most suitable model. The experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	ACC	Recall	Precision	F1-Score
CNN	0.80	0.75	0.77	0.76
ResNet	0.83	0.78	0.80	0.79
DenseNet	0.86	0.82	0.83	0.82
VGG	0.88	0.85	0.84	0.84
MLP	0.90	0.87	0.86	0.86

From the experimental results, there are significant differences in the performance of the five deep learning models in the breast cancer ultrasound image grading prediction task. First, the CNN model has an accuracy of 0.80, a recall of 0.75, a precision of 0.77, and an F1 score of 0.76. Although CNN performs stably in image classification tasks, it is slightly insufficient in breast cancer grading prediction. This may be because the basic architecture of CNN is mainly based on convolutional layers, which is good at extracting local features, while the grading prediction of breast cancer ultrasound images requires the identification of multi-scale features to capture the overall structure and subtle differences. Therefore, although CNN performs well in extracting local features, the overall effect is slightly inferior to other deep learning models in this complex task.

ResNet showed better performance in the experiment, with an accuracy of 0.83, a recall of 0.78, a precision of 0.80, and an F1 score of 0.79. The advantage of ResNet lies in its residual structure, which can effectively alleviate the gradient vanishing problem in deep neural networks, allowing the network to extract features at a deeper level. This structure is particularly outstanding when processing complex image features. In the breast cancer grading prediction task, the residual connection of ResNet can help the model capture the features of breast cancer of different grades more effectively, thereby improving the overall accuracy and robustness. However, although ResNet is more expressive than CNN, it is still slightly insufficient in multi-scale feature extraction and fails to achieve the best results.

The DenseNet model further improves the performance, with an accuracy of 0.86, a recall of 0.82, a precision of 0.83, and an F1 score of 0.82. DenseNet uses dense connections to allow the features of each layer to be directly passed to subsequent layers, achieving efficient feature reuse. This design can significantly improve the depth and breadth of feature extraction without adding too many parameters, and is particularly suitable for processing multi-scale features. In breast cancer grading prediction, DenseNet can extract richer features from ultrasound images, capturing both subtle local features and identifying a wider range of structural information. Therefore, DenseNet performs better than ResNet in this task, proving its advantage in feature reuse.

The VGG model performed better in this experiment, with an accuracy of 0.88, a recall of 0.85, a precision of 0.84, and an F1 score of 0.84. The network structure of VGG is relatively deep and hierarchical, which can effectively capture the multi-level features in ultrasound images, making it perform well in the breast cancer grading prediction task. Although the convolution kernel size of VGG is fixed, the model can extract features at different levels through the stacking of deep network structures, and has strong resolution. In the breast cancer grading task, VGG outperforms DenseNet and ResNet in terms of accuracy and F1 score, indicating that its deep structure has certain advantages in processing complex image features.

Finally, the MLP model performed best in all indicators, with an accuracy of 0.90, a recall of 0.87, a precision of 0.86, and an F1 score of 0.86. This result shows that despite the relatively simple architecture of MLP, it still performs well in the breast cancer grading task after feature extraction. MLP can efficiently learn and classify breast cancer features of different grades when inputting a one-dimensional feature vector. Thanks to sufficient feature extraction and data preprocessing, MLP performed better than other deep learning models in this experiment, especially in terms of prediction accuracy and robustness. This shows that MLP has good application prospects in the grading prediction of breast cancer ultrasound images, especially when the feature processing is appropriate, it can achieve a higher classification effect.

In addition, this paper also gives the curve of ACC as Epoch increases, as shown in Figure 2.

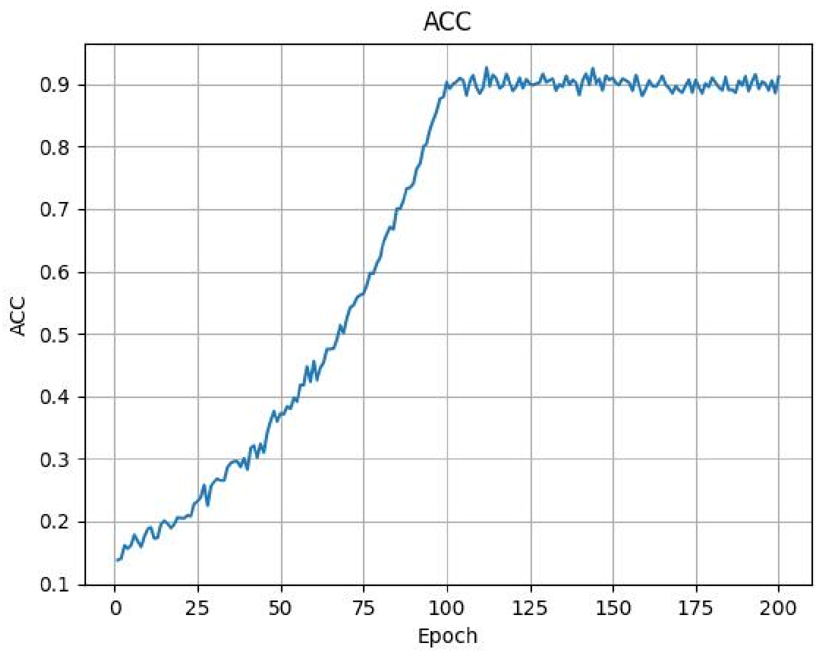

Figure 2: The curve of ACC rising with Epoch

As can be seen from the figure, the accuracy (ACC) of the model shows a clear upward trend with the increase of training rounds (epochs), especially in the first 100 epochs, the accuracy increases rapidly. Starting from the low accuracy in the initial stage, the model shows a significant learning effect in the initial training stage. This stage shows that the model gradually adapts to the data and can effectively capture the main features in the data, so the accuracy quickly increases from close to 0.1 to about 0.9. This rapid rise reflects the high efficiency of the model in the initial learning stage.

After about 100 epochs, the accuracy of the model stabilizes, close to 0.9, and remains near this level in subsequent training. This shows that the model has completed the learning of the main features at this time and has reached a convergence state. At this time, the parameters of the model are gradually optimized, and the degree of fit to the training data has reached an ideal balance point. Although the accuracy fluctuates slightly between 100 and 200 epochs, it remains stable overall, indicating that the model has been fully learned, and further increasing the number of training rounds has little effect on the improvement of accuracy.

Overall, this graph reflects the training process of the model from rapid learning in the early stage to gradual convergence and finally stabilization. The model did not show obvious overfitting during the training process, and the accuracy remained at a high level without drastic fluctuations, indicating that the model performed well on the current training set. In order to ensure the generalization ability of the model in practical applications, it is recommended to further evaluate its performance on the validation set or test set after the model reaches a convergence state to ensure that the model not only performs well on the training set, but also has good generalization ability.

4. Conclusion

This study experimentally verified the feasibility and effectiveness of breast cancer ultrasound image grading prediction based on the MLP model. The experimental results show that the MLP model performs well in terms of accuracy, recall, precision and F1 score, especially after reasonable feature extraction and preprocessing of the data, it can effectively identify breast cancer of different grades. This achievement shows the strong potential of the MLP model in feature vector processing tasks and provides a concise and efficient solution for the automated diagnosis of breast cancer.Future research can further optimize the architecture of the MLP model, explore richer feature extraction methods, and combine other deep learning models to improve the robustness and accuracy of prediction. In addition, in view of clinical application needs, a larger data set can be introduced for verification to enhance the generalization ability of the model, ensure good classification performance in different breast cancer cases, and provide more reliable technical support for the early diagnosis and treatment of breast cancer.

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