

Pulmonary Nodule Classification in CT Images Using ResNet18-Attention-LSTM Network

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Abstract. Pulmonary nodules serve as a common indicator for lung tumors, and prompt identification is essential in the early phase to prolong survival. Now, Computed Tomography (CT) is often used to check the lungs for lung cancer and determine if there is any. The old way of reading CT images manually is labor-intensive, time-consuming, and relies heavily on the experience of radiologists; therefore, different people may have different diagnoses. Recently, some deep learning methods have shown good results in medical image analysis and are now being used to automatically detect lung nodules. Due to the problem that traditional Convolutional Neural Networks (CNN) cannot use three-dimensional spatial information of pulmonary nodules well, this paper presents a pulmonary nodule CT image recognition model based on ResNet18, Attention Pooling and Long Short-Term Memory (LSTM) networks. Experiments will be carried out on the NoduleMNIST3D dataset, and the results of the model will be compared through CNN ablation studies, Recurrent Neural Network (RNN) ablation studies and attention mechanism comparison experiments. According to the findings, the integrated ResNet-Attention-LSTM framework has achieved a classification precision of 88.06% and an Area Under the Curve (AUC) of 0.9195 on the test set; it exceeds that of the baseline CNN and Convolutional RNN (CRNN) architectures. Based on these outcomes, it has been concluded that the merger of residual learning, attention mechanisms and temporal sequence models is suitable for improving the accuracy of pulmonary nodule classification and building intelligent lung cancer auxiliary diagnosis systems.

Keywords: Pulmonary nodule classification, CT image recognition, Deep learning

1. Introduction

Lung cancer is still one of the top reasons for death due to cancer around the world; therefore, earlier diagnosis can extend people's lives [1]. Pulmonary lesions represent initial indicators of lung tumors; at present, manual Computed Tomography (CT) reading is slow and subject to different opinions among doctors [2]. Despite deep learning exhibiting promising outcomes in the examination of clinical images, most Convolutional Neural Networks (CNN)-driven approaches rely on localized attributes and fail to leverage the trans-slice spatial data.

Recently, numerous deep learning architectures have been employed for the categorization of lung masses. Setio et al. demonstrated that 3D convolutional networks are viable for the

examination of pulmonary nodules [3]. Shi and others put forward convolutional Long Short-Term Memory (LSTM) to model space and time together [4]. Zhang and others have put forward an attention-based CNN to improve the feature representation of lesions [5], and He and others have introduced the ResNet architecture for deep feature extraction [6]. Hatamizadeh and others have recently put forward the Transformer model for the analysis of 3D medical images to solve the problem of long-range dependence in 3D data [7]. There are still problems with the small capacity, high computational cost and overfitting of the sequence model on a small amount of data.

Based on the problems above, a ResNet18-Attention-LSTM framework for pulmonary nodule classification has been put forward. Based on the empirical outcomes from the NoduleMNIST3D collection, the suggested model achieves a validation Accuracy (ACC) of 88.06% alongside a validation Area Under the Curve (AUC) of 0.9195, and it outperforms conventional CNN and Convolutional Recurrent Neural Network (CRNN) techniques.

2. Method

2.1. Dataset

The Experiments in this paper will use the NoduleMNIST3D dataset from MedMNIST v2 [8, 9]. The dataset has been organized to classify pulmonary nodules, and after preprocessing and expert annotation of chest CT images, it has been frequently employed to assess the efficacy of deep learning frameworks within medical image processing. Each sample in the dataset is a 3D volume of size 28x28x28 that contains the whole spatial structure and voxel-level information of pulmonary nodules [8]. Compared with the traditional two-dimensional CT image, a 3D volume can show the size and boundary of a nodule, as well as the structure of internal tissues; therefore, it is more convenient for the network to learn the spatial distribution pattern of lesions [10]. This dataset is partitioned into training, validation, and testing subsets, typically maintaining equal sizes; the former is utilized for parameter optimization and hyperparameter tuning, while the latter two are utilized for assessing its overall generalization capacity.

The CT images of pulmonary nodules have certain problems, such as small lesion size, blurred borders and low contrast; thus, it is difficult to distinguish benign from malignant ones. To enhance the classification accuracy, we need to extract the space and lesion information in nodules efficiently. To solve the above problems, a combination of CNN, Attention mechanisms and LSTM networks is employed to construct a deep learning model for pulmonary nodule classification in this paper.

2.2. CNN

CNNs are one of the many popular deep learning models in the field of medical image analysis [11, 12], and they can learn local features and spatial structure information automatically from images.

The parts of a CNN are as follows: Input layer, Convolutional layer, Activation function, pooling layer and fully connected layer. A small number of local features from the input image are obtained in the convolutional layer by filters. Add a non-linear function, such as ReLU, to the network and use pooling layers for down sampling of the size of feature maps; thus, it will be more stable in the face of fluctuations in space. Lastly, a fully connected layer is added to combine the high-dimensional features, and after applying the SoftMax function, the classification result in the form of class probabilities is outputted. A hierarchy of architecture is employed to gradually extract meaningful information in different levels of detail from the CNN.

Figure 1 is the whole process of a CNN; first, many convolution, activation and pooling layers are used to automatically extract features, then these are flattened and passed to the fully connected layer to get the final classification result.

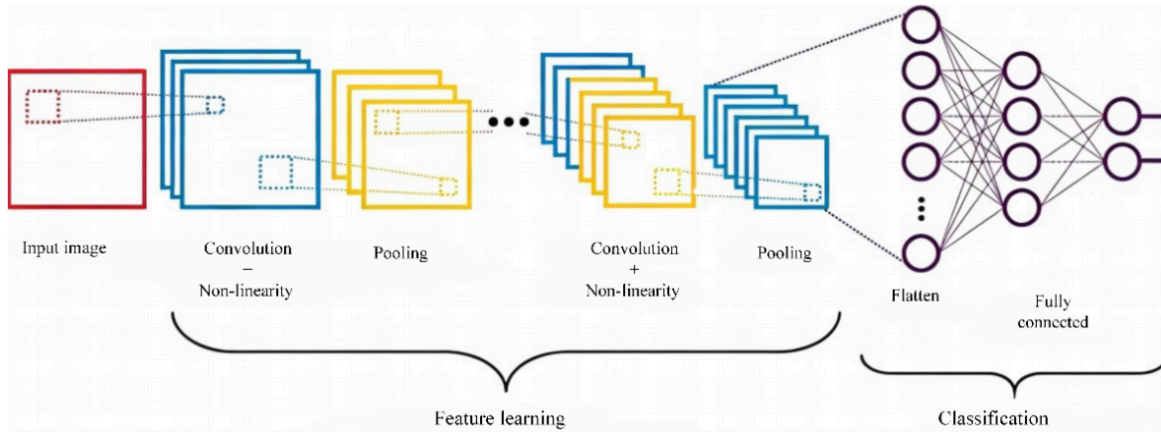


Figure 1. This caption has one line so it is centered

Medium CNN+LSTM model is the base comparison model in this paper. It is a lightweight CNN, and it has the form of a LSTM network. The convolutional network extracts the local spatial features in the image of a lung nodule, such as edge information, texture patterns, etc. Finally, a pooling layer is used to reduce the dimensionality of features and remove some information. LSTM will then model the sequence of convolutional features and learn the time dependency of CT slices.

2.3. LSTM

The schematic in Figure 2 represents an LSTM architecture, featuring the input gate, forget gate, output gate, and cell state pathway. This gating process flexibly regulates which historical elements must be retained and which must be discarded to address the gradient disappearance issue in conventional RNNs during long-term training processes [13].

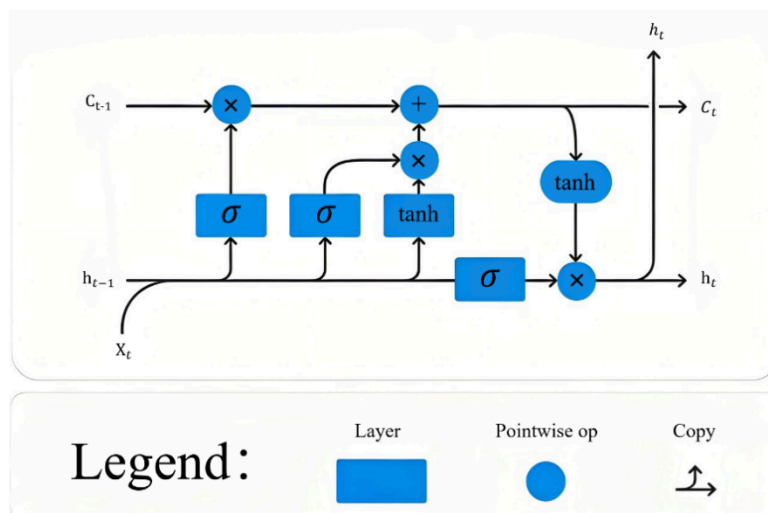


Figure 2. This caption has one line so it is centered

LSTM can be used to take the spatial information of a few consecutive slices as input and learn the 3D structure features of the model. It will be more stable and accurate in the prediction of benign-malignant division for lung nodules. LSTM is also relatively stable on the small-sample medical image dataset, and both the validation set and the test set have high accuracy and AUC. It will lay a good foundation for the next stage of deep models with attention mechanisms [6, 14] and enhance the ability of these models to process time series data.

2.4. Attention Pooling (AP)-ResNet18 model

To improve the feature extraction ability of lung nodules, ResNet18 is also used as the back-bone feature extraction network in this paper.

To solve the problem of vanishing gradient and network deterioration in the training of deep neural networks, ResNet18 has added a residual connection [15]. The residual structure can be expressed by equation(1):

$$H(x)=F(x)+x \quad (1)$$

where $F(x)$ is the residual map and x is the input feature.

ResNet18 has learned richer high-level semantic representations than the previous CNN [16, 17], so it can improve the recognition accuracy of complex lung nodules by the model [18].

ResNet18 is used as the backbone, and then an Attention Pooling module is added to assign different weights to various feature maps and emphasize important parts of lesions. The process of calculation is given as equations (2, 3):

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^n \exp(e_j)} \quad (2)$$

$$z = \sum_{i=1}^n \alpha_i h_i \quad (3)$$

where α_i denotes the attention weight and h_i represents the input feature.

AP can be employed to focus more attention on the region of the lung nodule, reduce background noise, enhance feature representation, etc.

2.5. AP-LSTM-ResNet18 model

To make better use of the strong feature extraction ability of CT images, this paper proposes the AP-LSTM-ResNet18 model to address the problem of lesion-focused attention and the issue of sequential information in lung nodule classification.

The processing pipeline is as follows: First, the CT image is input to the ResNet18 network for feature extraction. A Pooling Layer incorporating attention is utilized to minimize the dimensionality of the acquired feature array. Subsequently, the refined sequential data is forwarded to the LSTM module to capture temporal-based dependencies. Ultimately, a dense layer coupled with a SoftMax activation is employed for the classification task.

In this study, ResNet18 serves for capturing advanced spatial characteristics of pulmonary lesions. AP is utilized to allocate distinct weights across features while concentrating on the

pathological region. LSTM is employed to model the spatial correlation of adjacent CT slices and obtain 3D structure information.

The new model is no longer the original CNN; it can also learn local texture features of lung nodules and use information from adjacent slices to improve the recognition accuracy of all kinds of lesions.

ResNet18 is a deep feature extractor in the above architecture, Attention Pooling is used to improve the feature representation of lesions, and then LSTM is employed to obtain 3D contextual information. The above parts can be used to classify the CT images of lung nodules accurately.

2.6. Evaluation metric

To comprehensively assess the performance of the model, ACC, Precision, Recall, F1-score and the AUC will be used in this study [19].

The ACC is as equation (4):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

A larger value indicates that a higher proportion of the samples have been correctly classified; that is to say, the model has good predictive ability.

The formula for precision as equation (5):

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

High precision means that, of all the samples predicted to be positive, a relatively large proportion are positive; that is, there are few false positives.

Recall is given by equation (6):

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

A higher Recall means that a larger proportion of the true positive samples have been correctly recognized; that is to say, there are fewer false negatives.

The definition of F1-score as equation (7):

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

A higher F1-score is a good indication of a better trade-off between Precision and Recall, and its range is from 0 to 1.

The x-axis of the Receiver Operating Characteristic Curve (ROC) is the false positive rate (FPR) and the y-axis is the true positive rate (TPR), as equation (8):

$$TPR = \frac{TP}{TP + FN} \quad (8)$$

It indicates how well the model can recognize positive samples correctly, and a larger value is better, as equation (9):

$$FPR = \frac{FP}{FP + TN} \quad (9)$$

It is the probability that a negative sample is misclassified as a positive one; a smaller value is better.

AUC is the area under the ROC curve, and its value is between 0 and 1. A relatively large AUC is a good indicator.

Due to the class imbalance of lung nodule datasets, ACC and F1-score may be influenced by the data distribution. AUC is more general; that is, it considers all possible thresholds of a classifier. Therefore, AUC will be used as the main evaluation index in this paper, and Accuracy, Precision, Recall and F1-score will be used to assess all models.

3. Preparation

3.1. Image preprocessing

To help the model better learn the features of lung nodules and improve its generalization ability, the following preprocessing will be carried out on the CT images from the NoduleMNIST3D dataset.

Grayscale normalization: All CT images are normalized to the range [0, 1] to eliminate variations caused by different scanning devices and image intensity differences, as shown in equation (10):

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (10)$$

Data expansion: To enhance the variety of the training dataset and prevent overfitting, stochastic rotation, flipping, shifting and cropping are applied. Such modifications can more effectively address the issue of diverse lesion forms and scanning orientations for the framework.

Sequence construction: As CT slices are naturally in a sequence, the order of the slices is preserved to form a 3D sequence for the LSTM module and extract context information of lung nodules in three dimensions.

Preprocessing has been conducted to normalize the intensity distribution of image data and increase the diversity of samples, so the deep learning model can learn the characteristics of lung nodules more reliably and stably.

3.2. Devices and parameter

To ensure that all the models are tested fairly, they were all conducted at the same hardware and software level. Table 1 is the layout of the experimental equipment, and Table 2 shows the settings of the training parameters.

Table 1. Experimental hardware configuration

Item	Configuration
Operating system	Windows 11 64-bit
CPU	AMD Ryzen 9 9955HX
CPU base frequency	2.5
GPU	NVIDIA GeForce RTX 5070 Ti Laptop GPU
GPU memory	12 GB GDDR7
RAM	32 GB DDR5
Deep learning framework	PyTorch 2.0
Programming language	Python 3.10
CUDA version	CUDA 12.0

Table 2. Model training parameter settings

Item	Configuration
Batch Size	32
Epoch	30
Optimizer	Adam
Learning Rate	0.001
Weight Decay	1×10^{-4}
Loss Function	Cross Entropy Loss
CNN Base Channel	48
LSTM Hidden Size	128
Dropout	0.5
Number of classes	2
Input size	$28 \times 28 \times 28$

4. Results

4.1. CNN backbone parameter analysis

To find an excellent CNN feature extraction structure for classifying lung nodules, a few basic configurations of CNN base channels were tried out in this paper, and the results are shown in Figure 3(a). Based on the experimental results, cnn_base16, cnn_base32 and cnn_base48 all show relatively good performance in the early stages of training; however, they are also fluctuating significantly in the first 10 epochs. The drop in AUC for cnn_base32 is relatively small at epoch 8, at 0.66.

In the later stage of training, cnn_base16 is around 0.79-0.81; at the same time, cnn_base32 and cnn_base48 are relatively stable at about 0.84-0.85 and 0.84-0.86. Based on the above results, increasing the number of convolutional channels can expand the feature representation ability of the network and extract more edge, texture and lesion structure information effectively. Therefore, cnn_base48 will be chosen as the backbone CNN configuration in the following experiments.

To get a better sense of the spatial relationships among CT slices, this paper compares the sequence modelling abilities of Gated Recurrent Unit (GRU), LSTM and various types of deep LSTM in Figure 3(b). Based on the above results, lstm_h128 has performed the best and shown a stable validation AUC of around 0.84-0.85; gru_h128 is only about 0.81-0.82.

The gate function in LSTM is used to keep the essential information about time and disregard other parts, so it can model dependencies among nearby slices of CT images. GRU has fewer parameters and thus cannot solve the problem of long-term dependencies well. Deep LSTM is not suitable for a small dataset, etc. Therefore, the sequence model that will be employed is a single-layer LSTM with 128 hidden units.

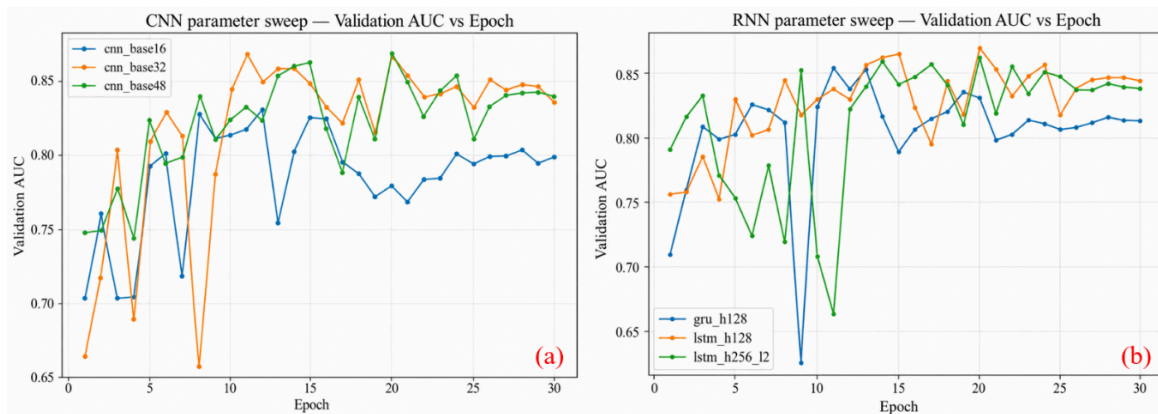


Figure 3. Parameter sweep results of CNN and RNN components. (a) validation AUC vs. epoch under different CNN base filter settings; (b) validation AUC vs. epoch under different RNN unit configurations

Figure 4 illustrates the training process of the optimal configuration (cnn_base = 48 + LSTM h128). From the training loss curve, it can be observed that the loss steadily decreases from approximately 0.67 to 0.48, showing a stable downward trend. This indicates that the model is continuously learning effective features and gradually converging.

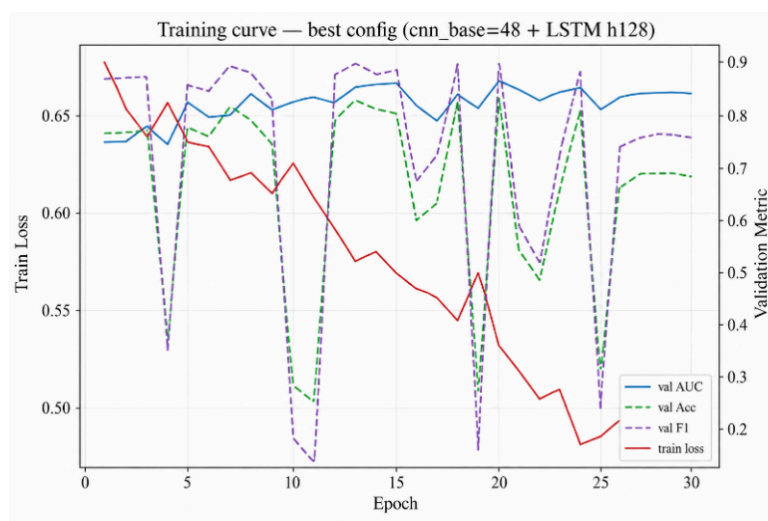


Figure 4. Training curves of the optimal model configuration

At the same time, the validation AUC is also in the range of 0.80 to 0.86. Despite minor variations, the general effectiveness stays at a quite elevated standard, indicating that the framework possesses robust categorization capacity.

On the other hand, validation ACC and F1-score show relatively large fluctuations and have a considerable drop at some epochs. The range and the number of sharp changes in the F1-score are relatively large. Given the limited scale and class disparity of the lung nodule dataset, both Accuracy and F1-score are susceptible to such oscillations.

AUC is a different measure of model performance that does not change with the change in classification threshold; therefore, it is more general and stable. Therefore, it will be more stable in this study.

In short, it should have good convergence characteristics in training and maintain a relatively high AUC on the validation set. Based on the above observations, AUC will be used as the main evaluation indicator in the following experiments, and Accuracy and F1-score will also be added for reference.

4.2. CRNN model training

Figure 5 demonstrates the learning and testing progression of the CRNN architecture during the lung nodule categorization assignment. The training error diminishes consistently from 0.54 toward 0.32, whereas the validation error falls sharply within the initial period and subsequently remains around 0.36. The small and stable gap between the two curves indicates that no significant overfitting occurs.

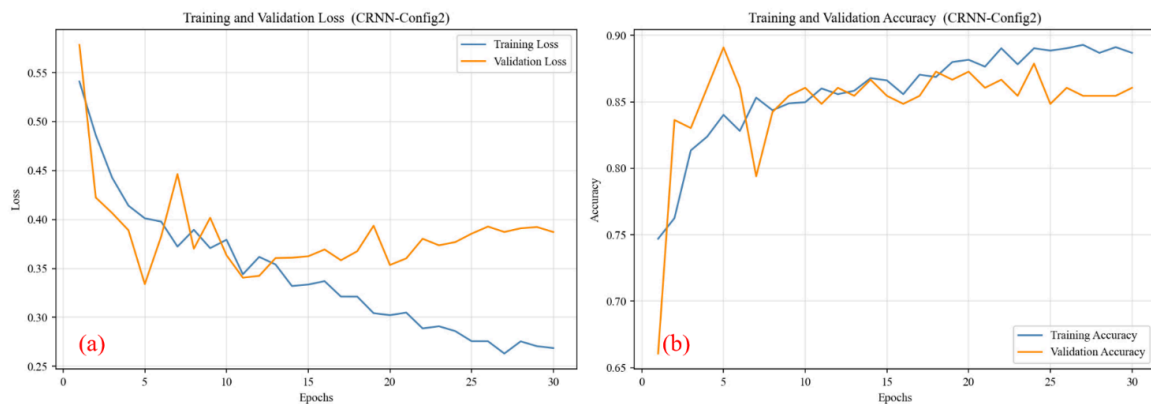


Figure 5. Training process curves of the CRNN_CRNN2 model (a) loss variation curves; (b) accuracy variation curves

During training, the performance accuracy reached 0.75, whereas the validation precision stabilized at roughly 0.85-0.86 across multiple epochs. The training and validation metrics are in line, so the model generalizes well.

The reasons for the improvement in performance are that CNN and LSTM work together well. CNN serves to identify localized spatial characteristics, whereas LSTM is utilized for capturing the contextual data within CT slices. Combining 2D texture information and 3D structure relations to enhance the classification ACC of lung nodules in CRNN.

Figure 6 shows the training process of the ResNet18-Attention model after adding the attention mechanism. The learning loss reaches 0.44, whereas the validation loss initially drops to a low level before slowly rising to 0.45; thus, it can be determined that the model has overfit.

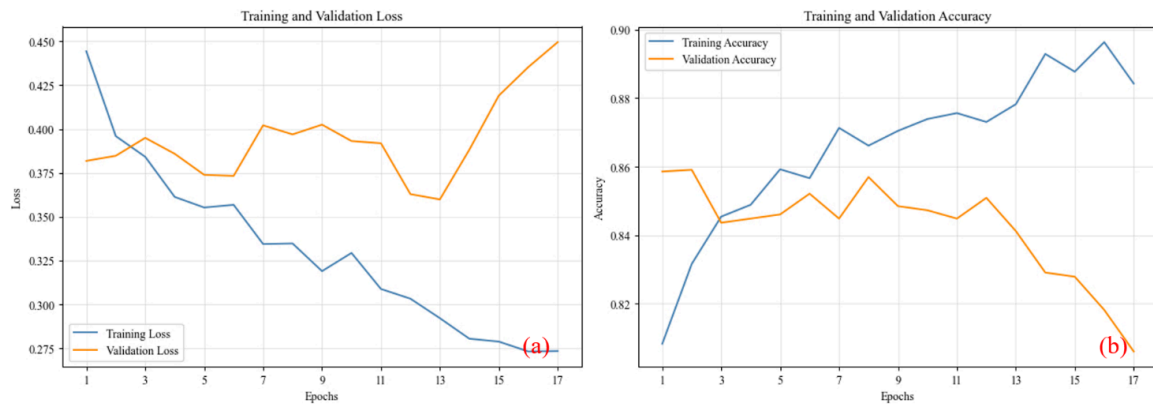


Figure 6. Training process curves of the CRNN model (a) loss variation curves; (b) accuracy variation curves

Meanwhile, the training accuracy reaches 0.89; however, both the validation accuracy has decreased from 0.87 to 0.81, and it also failed to generalize well.

The attention mechanism is responsible for this, so it gives more weight to the local characteristics of the lesion and thus concentrates on distinguishing regional information. There is no time model, and thus the spatial relationships among CT slices cannot be used in the model. Therefore, it tends to be overly fitted to the local patterns in the training data and loses some generality when used on new data.

4.3. ResNet18-Attention-LSTM model analysis

Based on the ResNet18-Attention model, this study further introduces an LSTM module to construct the final proposed model (ResNet-Attn-Config1). The relevant training outcomes are illustrated within Figure 7.

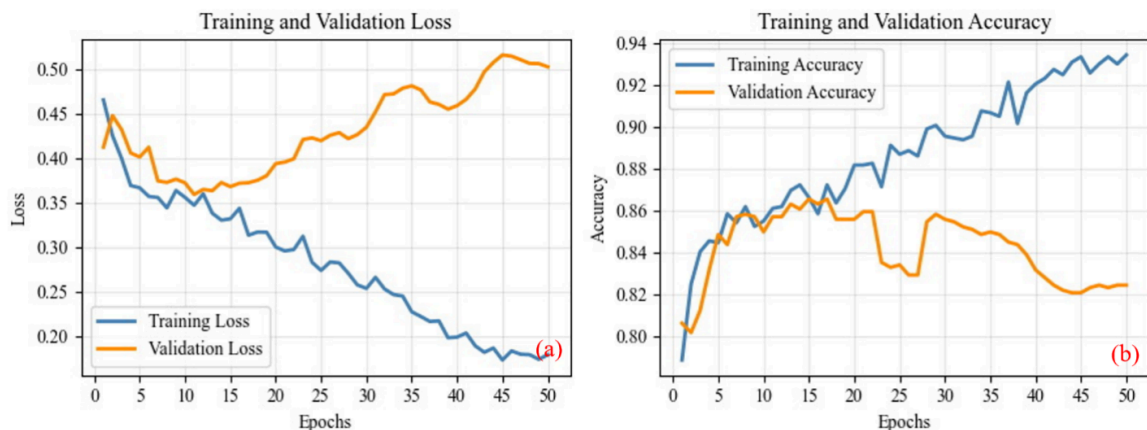


Figure 7. Training process curves of the model (a) loss variation curves; (b) accuracy variation curves

According to the loss curves, the training loss is continuously decreasing from 0.55 to 0.22; thus, it is expected that the model will gradually learn and converge stably. The validation loss has relatively large fluctuations in the beginning but gradually approaches about 0.41; thus, the model can eventually fit the validation data stably.

The final training accuracy is 0.92, and the validation accuracy has been stable at about 0.85-0.86; thus, the model has both strong fit to the training data and good generalization to new data.

The new LSTM module has increased the validation results of the ResNet18-Attention model from the previous one. Specifically, the validation loss no longer keeps rising steadily, and the range of fluctuation in validation accuracy has been reduced to some extent; therefore, it is expected that it will have better generalization ability.

This enhancement occurs because LSTMs can learn the spatial correlations of CT slices and thus solve the problem of the attention mechanism in modelling three-dimensional structure information. Consequently, the framework is equipped to identify local lesion characteristics and the comprehensive slice-to-slice associations. In addition, the training loss has been decreasing gradually and the validation performance is relatively stable; therefore, it is likely that the model has not overfitted to the complex patterns of lung nodules and can learn better features.

According to the findings, it is established that the suggested approach functions effectively and is applicable for small-sample and intricate clinical image challenges.

4.4. Comparative performance evaluation

Table 3. Presents the performance comparison of different models on the validation and test sets

Model	Val ACC	Val AUC	Test ACC	Test AUC
Benchmark (auto-sklearn)	—	0.8775	0.8740	—
CNN backbone		0.8649		—
SmallCNN (CNN-only)	0.8727		—	
MediumCNN (CNN-only)	0.8727	0.8827	—	—
DeepCNN (CNN-only)	0.8727	0.9224	—	—
RNN ablation		0.8897		—
LSTM-S (1-layer 128)	0.8727		—	
LSTM-L (2-layer 256)	0.8667	0.8335	—	—
BiLSTM-L (2-layer 256)	0.8727	0.9071	—	0.8944
CRNN		0.9030		—
CRNN-Config1	0.8424		—	
CRNN-Config2	0.8909	0.8984	0.8452	0.9186
CRNN-Config3	0.8848		—	
+Attention		0.8968		0.9104
CRNN-Attn-Config2	0.8667	—	0.8677	0.9284
SE-CNN+Attn				
SE-CRNN-Config2	0.8848	0.8535	0.8677	0.9195
ResNet+Attn (No LSTM)	—	0.8775	0.8710	—
ResNet+LSTM+Attn		0.8649		—
ResNet-Attn-Config1	0.8788		0.8806	

Based on the Table 3, neither the pure CNN model nor the pure RNN model is better for classification; that is to say, the test set results of both are relatively low compared with those of the hybrid architecture. Incorporating LSTM to construct the CRNN structure yields a test AUC of

0.8944. With the addition of an attention mechanism, the test AUC is 0.9186; therefore, it can be concluded that the attention mechanism has improved the representation of lesion-related features.

The evaluation precision for the introduced ResNet-Attn-Config1 architecture reaches 0.8806 while its assessment AUC equals 0.9195, and both are higher than those of the Auto-Sklearn baseline model. Simultaneously, based on the ablation findings, eliminating the LSTM component causes the test accuracy to fall to 0.8710 and the test AUC to rise to 0.9284. Thus, LSTM will help to improve the stability and balance of the whole classification.

ResNet18, Attention Pooling and LSTM are not usually used together. ResNet18 is used to extract deep features, attention is paid to areas with more information about the lesion, and finally, LSTM models are used to learn the spatial correlations among adjacent slices. The integration of these components can effectively yield superior performance within the lung nodule CT image categorization framework.

5. Conclusion

This study introduces a deep learning framework for categorizing pulmonary lesions, specifically ResNet18-Attention-LSTM, and performs comprehensive evaluations using the NoduleMNIST3D database.

ResNet18 is employed as the feature extractor of the model, an Attention Pooling module is used to focus on the region of interest of a lesion, an LSTM module is employed to model the sequential dependency of CT slices, and finally, benign-malignant classification of lung nodules is carried out.

According to the empirical findings, the developed framework achieves a testing precision of 88.06% and a validation AUC of 91.95%; it outperforms the reference Auto-Sklearn approach (87.40% / 91.40%) and traditional CNN plus CRNN architectures. The training loss is decreasing gradually and the validation set loss has not increased; thus, it is generalizing well.

By altering the parameters and carrying out ablation studies on CNN backbones, RNN variants and attention mechanisms, it has also been determined that each part of the feature extraction, sequence model and region-of-interest enhancement process functions normally.

ResNet18-Attention-LSTM model that is proposed above is a relatively good auxiliary diagnostic method for lung nodule classification, and it combines deep feature extraction, an attention mechanism, and a sequence model. According to the above experiment, the model can classify more accurately and reliably; it will be applied to patients.

Due to the small size of the dataset and weak computing power, there are still performance fluctuations in the case of small samples and complex lesions, and the training cost is relatively high. Moving forward, incorporating Data Augmentation, Transfer Learning, and lightweight Network Design can broaden the applicability scope and enhance the deployment efficiency of the framework.

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