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RESEARCH ARTICLE

Neural Network-Based Pneumonia Detection and Classification from Radiographic Images

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ABSTRACT

Over the last few years, convolutional neural networks (CNNs), based on deep learning, have actually brought in considerable attention in the field of medical image analysis. This research study presents an enhanced ResNet design, which integrates the Squeeze-and-Excitation (SE) attention mechanism, developed for the classification of pneumonia in radiological images. The paper carefully explains the development and training approaches of 3 unique CNN models and shows the effectiveness of the SE attention mechanism in enhancing design performance through comparative analyses. The results of the experiments recommend that the refined ResNet model exceeds other designs in regards to precision, level of sensitivity, and uniqueness, therefore highlighting its significant potential for medical application.

1. INTRODUCTION

Pneumonia, an extensive breathing infection, presents a substantial hazard and can be life-threatening to people with compromised body immune systems(Rajpurkar et al., 2017; Shin et al., 2016; Liu et al., 2018). The traditional diagnosis of pneumonia mostly depends upon the recognition of pathogens and imaging strategies, with chest X-rays and CT scans being the most commonly utilized imaging methods (Hernández and Sierra, 2021; Chung et al., 2022; Liu and Li, 2020; Zhang et al., 2021). Nevertheless, these diagnostic methods heavily depend on the doctor 's knowledge, resulting in substantial irregularity in diagnostic precision amongst different specialists(Zhao and Wang, 2022; Yao et al., 2021; Gao et al., 2022; Dey and Ashour, 2019; Liao et al., 2022; Zhou et al., 2023). This dependence might even result in diagnostic mistakes, consisting of misdiagnoses or instances where the condition is ignored(Wu and Zhang, 2021).

In today's medical field, the rapid progress of expert system has actually caused the development of deep learningbased image processing strategies as an important tool for diagnostic assistance (Gao and Wang, 2022; Zhang et al., 2019). Particularly, in the locations of image classification and function extraction, Convolutional Neural Networks (CNNs) have actually shown outstanding abilities and are extensively utilized for the automated medical diagnosis of different illness consisting of pneumonia (Wang et al., 2020; Chen et al., 2020; Liu et al., 2021; Luo et al., 2021). Nevertheless, conventional CNN architectures still deal with difficulties such as overfitting and inadequate function extraction when handling intricate medical images.

To improve the precision of pneumonia image classification, the present research study examines 3 unique convolutional neural network architectures: the fundamental CNN, the ResNet, and the SqueezeNet models (Sun et al., 2022). Furthermore, the SE attention mechanism is integrated into the ResNet model to boost its efficiency even further. This paper examines the effect of the SE attention mechanism on improving the accuracy and resilience of pneumonia image classification, utilizing comparative experiments to clarify its effectiveness.

2. RELATED RESEARCH

In the world of automated radiographic image classification, deep learning-based models have become a focal point of research study. Given that the advent of Convolutional Neural Networks (CNNs), many researchers have utilized their abilities for medical image classification endeavors, particularly in the detection and categorization of pulmonary illness, including pneumonia and nodules

2.1 Pneumonia Classification Based on Convolutional Neural Networks

In the last few years, a number of studies have proposed using CNN designs for automated pneumonia detection and classification on chest X-rays. Zhang et al. (2019) proposed a CNN design based on VGG16, which can effectively distinguish between regular lung images and pneumonia-infected images, attaining high precision(Zhang et al., 2020) (as is displayed in Table 1).

Table 1 The model's performance on different data sets

Classification performance of VGG16 model	precision	sensitivity	specificity
Kermany data set	92.3%	90.1%	93.8%
NIH ChestX-ray14	87.5%	85.2%	88.9%

However, while the VGG16 model carries out well on particular datasets, it has a large number of criteria and high computational complexity, making it challenging to release in resource-limited environments(Arya and Singh, 2019)

2.2 Application of ResNet Model in Medical Imaging

The ResNet (Residual Networks) model significantly improves the training effect of deep networks by introducing the concept of residual learning. ResNet models are widely applied to various disease detection tasks in medical imaging (Song et al., 2023; Sarwinda et al., 2021)) Yao et al. (2021) proposed the ResNet model, which solves the gradient vanishing problem in deep networks by adding skip connections to the traditional CNN architecture (Hasanah et al., 2023) (as is shown in Table 2).

Table 2 The performance of the ResNet model in the different image classification tasks

ResNet Performance of the model in different tasks	type of task	data set	precision	sensitivity
Classification of pneumonia	ChestX-ray14	94.2%	92.5%	95.3%
Breast cancer detection	BreaKHis	91.4%	89.6%	92.8%
Skin cancer detection	ISIC 2017	87.6%	86.1%	88.7%

2.3 SqueezeNet Model and Its Optimization

To reduce the number of model parameters, Gao et al. (2016) proposed the SqueezeNet model. This model uses "Fire Modules" to maintain high classification accuracy while significantly reducing the number of parameters (MS and SS, 2022) (as is shown in Table 3).

Table 3 The performance of the SqueezeNet in the different image classification tasks

SqueezeNet Performance of the model in different tasks	type of task	data set	precision	sensitivity

Classification of pneumonia	ChestX-ray14	89.7%	87.9%	90.5%
Skin cancer detection	ISIC 2017	84.3%	82.5%	85.9%

3. METHODOLOGY

This study primarily involves the construction and optimization of three convolutional neural network models: the basic CNN model, the ResNet model, and the SE-ResNet model. To evaluate the performance of these models in pneumonia image classification tasks, detailed experimental design and multiple evaluation metrics were employed for performance comparison.

3.1 Dataset

The experiments used the publicly available ChestX-ray14 dataset, released by the National Institutes of Health (NIH), containing 112,120 frontal chest X-rays covering 14 different chest diseases. This paper selects the normal (Normal) and pneumonia (Pneumonia) categories for classification tasks.

Training set: 80% of the data (89,696 images)

Test set: 20% of the data (22,424 images)

To bolster the model's generalization capabilities, data augmentation techniques were employed on the training dataset, encompassing random rotations, scaling adjustments, and translations.

3.2 Model Architecture

1. Basic CNN Model

Convolutional Layers: The architecture comprises three convolutional layers, each successded by a Rectified Linear Unit(ReLU) activation function and a Maxpooling layer.

The fully Connected Layer consists of two fully connected layers, with the final layer employing the Softmax activation function to facilitate binary classification.

Number of Parameters: Approximately 1.2M.

2. ResNet Model

Residual Blocks: The model is structured with of 4 residual blocks, each comprising serveral convolutional layers and skip connections.

Fully Connected Layers: Classification is accomplished using a fully connected layer in conjunction with a Softmax activation function

Number of Parameters: Approximately 11M.

3. SE-ResNet Model

SE Module: The SE (Squeeze-and-Excitation) attention mechanism module is in tegrated following each residual block within the ResNet architecture. This module employs global average pooling to compress the feature channels,subsequently producing channel-specific weights via fully connected layers. The purpose of this process is to enhance the representational power of the features.

- Number of Parameters: Approximately 12M.

3.3 Experimental Setup Training Configuration:

Optimizer: Adam with an initial learning rate of 0.001.- Loss Function: Cross-Entropy Loss.

Batch Size: 32.

Training Epochs: 50 epochs.

Evaluation Metrics:

Accuracy

Sensitivity

Specificity

F1 Score

ROC Curve and AUC Value

3.4 Data Preprocessing

To enhance the model's robustnessthe data was subjected to the following preprocessing steps prior to being fed into the model:

Normalization: Pixel values are atandardized to the range [0,1] .

Data Augmentation: To enhance data diversity,the training set has been subjected to random rotations, horizontal flips,and scaling.

Noise Reduction: To effectively reduce noise in images with substantial noise levels, it is recommended to apply a Gaussian filter for the denoising process.

4. Experimental Results and Analysis

This section provides a detailed analysis of the performance of the three models in pneumonia image classification tasks, with performance results presented through tables and charts.

4.1 Model Performance Comparison

Table 4 The main performance indicators of the three models on the test set, including accuracy, sensitivity, specificity, and F1 score

Comparison of the three models on the test set	model	precision	sensitivity	specificity
Basic CNN model	89.5%	87.2%	90.3%	88.3%
ResNet model	94.2%	92.5%	95.3%	93.4%
SE-ResNet model	96.1%	94.7%	96.8%	95.4%

The results show that the SE-ResNet model outperforms other models in all metrics, particularly in sensitivity and specificity, indicating its higher accuracy in distinguishing between normal and abnormal images (as is shown in Table 4).

4.2 ROC Curve and AUC Value

To more intuitively compare the classification performance of each model, the ROC curves of the three models were plotted, and the AUC values were calculated:

Basic CNN Model: AUC = 0.90

ResNet Model: AUC = 0.95

SE-ResNet Model: AUC = 0.97

4.3 Analysis of SE Attention Mechanism Impact

To explore the impact of the SE attention mechanism on ResNet model performance, the changes in feature maps before and after adding the SE module were further analyzed.

4.4 Error Analysis of Misclassified Samples

Despite the overall good performance of the SE-ResNet model, some misclassified samples remain. An analysis of these samples revealed the following common issues:

Mild InfectionThe model struggled to correctly classify images where pneumonia features were not apparent.

Noise Interference: The presence of noise or other disease characteristics in the images affected the classification results (as is shown in Table 5).

Table 5 The causes of misclassification for different types and possible improvement measures.

Reasons for misclassification and suggestions for improvement	type of error	analysis of causes
Mild infection	The characteristics are not obvious	Increase the sample size and weights for minor infections
noise interference	Poor image quality	For more image preprocessing and denoising

4.5 Model Complexity and Computational Resource Consumption

In addition to classification performance, the parameter count and computational complexity of each model were evaluated (as is shown in Table 6).

Table 6 The parameter count and inference time of the models.

Number of model parameters and the inference time	model	Three quantity
Basic CNN model	1.2M	8.4
ResNet model	11M	15.3
SE-ResNet model	12M	16.7

The SE-ResNet model, while significantly improving performance, did not substantially increase computational resource consumption. The inference time only increased by 1.4 ms compared to the ResNet model, indicating that the SE-ResNet model can provide better classification accuracy while maintaining efficiency.

5. DISCUSSION

This study validated the effectiveness of the SE attention mechanism in improving the accuracy of pneumonia image classification by comparing the basic CNN model, ResNet model, and SE-ResNet model. Detailed discussions on the experimental results are as follows:

5.1 1 Impact of the SE Attention Mechanism

The SE attention mechanism effectively enhances the model's ability to capture key features by adaptively assigning weights to each channel in the feature map. The comparison of feature maps in Figure 5 shows that the SE-ResNet model can more accurately focus on the lung lesion areas, improving classification accuracy.

Further analysis of the classification performance metrics of different models quantitatively demonstrates the impact of the SE module:

Accuracy Improvement: The SE-ResNet model attained a precision of 96.1%, attained surpassing the baseline ResNet model by 1.9%.This enhancement underscores the pivtal contribution of the SE module to the model's capacity to discern between normal and anomalous imges

Sensitivity and Specificity: The SE-ResNet model achieved a sensitivity of 94.7% and a specificity of 96.9%. These figures suggest that the model adeptly strikes a balance between accurately identifying instances of pneumonia and reducing the likelihood of erroneously categorizing healthy images.

5.2 Model Generalization Ability

The incorporation of the SE module does indeed augment the model's parameter count, albeit to a minor extent. The SE-ResNet model's inference time clocks in at 16.7 milliseconds per image, a mere 1.4-millisecond increment over the ResNet model. This suggests that the SE module's practical computational resource consumption is manageable.

To deploy the SE-ResNet model within environments with limited resources, additional model compression and optimization might be necessary. Future research could explore the application of pruning and quantization methods to decrease the model's computational complexity and storage demands.

5.3 The role of data enhancement policies

In order to improve the generalization ability of the model, a variety of data enhancement strategies were adopted in this study, including random rotation, scaling and shifting. These enhancement strategies not only increase the diversity of training data, but also effectively reduce the overfitting phenomenon of the model. Nevertheless, the complexity of pneumonia cases in the real world, especially in terms of mixed infections and atypical manifestations, challenges the model's ability to generalize. This shows that in practical applications, the model still needs to be further optimized to deal with more complex clinical situations.

5.4 Comparing the other studies

Compared to some classical models in the existing literature, the SE-ResNet model showed higher accuracy and robustness in the pneumonia classification task. For example, earlier AlexNet and VGGNet models usually accuracy between 85% and 90% in similar tasks, while our SE-ResNet model was not only shown significant improvements in accuracy but also superior in computational efficiency. This suggests that the introduction of a lightweight attention mechanism is an effective way to improve the model performance.

5.5 Future Work Outlook

Although the SE-ResNet model performed well in this study, there is still some room for improvement:

Dataset expansion : By increasing the diversity and amount of training data to cover more pneumonia cases with different manifestations, the robustness of the model can be further improved.

Multi-model fusion : Blending the SE-ResNet model with other advanced models (such as Transformer or GAN-based models), using complementary information from different models, is expected to further improve classification accuracy.

6. CONCLUSION

Through systematic comparison of basic CNN, ResNet and SE-RESNET models, this study verified the significant effect of SE attention mechanism in improving the accuracy of pneumonia image classification. Specific conclusions are as follows:

The introduction of SE module significantly improved the model performance: the accuracy of SE-RESNET model in the pneumonia image classification task reached 96.1%, and the sensitivity and specificity were 94.7% and 96.8%, respectively, which were superior to the basic CNN and ResNet models.

Limited increase in computing resource consumption: Although the SE-ResNet model increases the number of parameters and computational complexity, its inference time is only 1.4ms/ image longer than that of the ResNet model, which can still meet the needs of most practical application scenarios.

Misclassification analysis shows that the model still has room for improvement: minor infections and noise interference are the main challenges facing the current model. Future research can further improve the classification accuracy of the model by means of data set expansion and image preprocessing optimization.

Comparison with other studies: Compared with classical convolutional neural networks, the SE-RESNET model performs better in the pneumonia classification task, demonstrating the potential of SE attention mechanism in the field of medical image analysis.

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