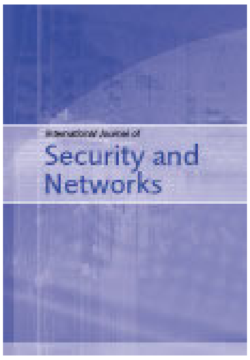


International Journal of Security and Networks

ISSN online: 1747-8413 - ISSN print: 1747-8405
https://www.inderscience.com/ijsn

A neural network for disease recognition of radiological images of pneumonia

Jianlan Ren, Vladimir Mariano

DOI: 10.1504/IJSN.2025.10069626

Article History:

Received:	08 November 2024
Last revised:	19 November 2024
Accepted:	20 November 2024
Published online:	17 March 2025

A neural network for disease recognition of radiological images of pneumonia

Jianlan Ren*

College of Computing and Information Technologies,
National University,
Manila 1008, Philippines
Email: renj@students.national-u.edu.ph
and
School of Information Engineering,
Jiangxi V&T College of Communications Nanchang,
Jiangxi 330013, China
*Corresponding author

Vladimir Mariano

College of Computing and Information Technologies,
National University,
Manila 1008, Philippines
Email: vymariano@national-u.edu.ph

Abstract: Pneumonia ranks among the top causes of significant illnesses and fatalities globally, especially among the elderly and immunocompromised populations. The traditional diagnostic methods for pneumonia include X-ray and computed tomography imaging. Still, these methods have certain limitations, such as low image resolution and reliance on the experience of doctors for diagnosis. The application of artificial intelligence, especially neural network technology, in medical image analysis has provided new solutions for automatically detecting pneumonia. This article aims to explore a pneumonia image classification and recognition method based on neural network technology, analyse and compare the performance of convolutional neural network, visual geometry group, ResNet, and attention mechanism in pneumonia detection, and combine transfer learning to enhance the precision and reliability of detection even further. The experimental results show that the ResNet neural network combined with the attention mechanism performs the best in pneumonia image classification, with significantly improved accuracy and robustness. This study provides an efficient and accurate technical means for automatically detecting pneumonia, which has important clinical application value.

Keywords: pneumonia detection; neural network; computed tomography imaging; attention mechanism.

Reference to this paper should be made as follows: Ren, J. and Mariano, V. (2025) 'A neural network for disease recognition of radiological images of pneumonia', *Int. J. Security and Networks*, Vol. 20, No. 1, pp.23–31.

Biographical notes: Jianlan Ren has obtained her Bachelor's and Master's degree from Tongji University in China and is currently pursuing a doctoral degree at the National University of the Philippines. Her research interests include image recognition and artificial intelligence.

Vladimir Mariano is the Chief Teacher of Technology and Innovation at YSEALI College of Fulbright University in Vietnam and a National University of the Philippines professor. He received his BS in Statistics, an MS in Computer Science from the University of the Philippines Los Banos, and PhD in Computer Science and Engineering from The Pennsylvania State University. His research interests include computer vision, digital image processing, and machine learning.

1 Introduction

Pneumonia, an inflammatory disease of the lungs caused by bacterial, viral, or fungal infections, poses a severe threat to global public health. According to statistics from the World Health Organization, pneumonia is one of the leading causes of death among children, with approximately 800,000 children under five dying from it annually. Pneumonia not only threatens the lives and health of children but also poses a higher risk to the elderly and immunocompromised patients. Rapid and accurate detection and diagnosis are crucial for these populations, facilitating timely treatment and reducing mortality rates. However, traditional pneumonia detection methods, such as X-ray imaging (X-ray) and computed tomography (CT), have certain limitations and are difficult to meet practical needs. In particular, although CT images have high resolution, their high cost and radiation risk to patients hinder widespread adoption.

Furthermore, traditional imaging diagnosis largely relies on doctors' experience and judgment, leading to subjectivity and potential inconsistencies in diagnostic results due to individual differences in judgment. Deep learning (DL), especially convolutional neural networks (CNNs), has shown great potential in automatically detecting pneumonia images. CNNs can automatically extract spatial features from images and handle image classification tasks effectively. However, medical image analysis still faces several challenges in practical applications: Firstly, medical images often have complex backgrounds and high noise levels, making classification and recognition tasks difficult; secondly, pneumonia images may exhibit blurred features and low contrast, leading to errors in feature extraction and classification; thirdly, the amount of medical image data is limited and unevenly distributed, posing higher requirements for model generalisation. This paper introduces a combined approach of residual networks (ResNet) and attention mechanisms based on CNNs to address these issues and improve detection performance. Using the squeeze-and-excitation (SE) attention mechanism, the model's focus on key features can be effectively enhanced. Additionally, this paper incorporates transfer learning technology, enabling the model to fully leverage the feature advantages of pre-trained models and further improve classification accuracy and robustness.

In recent years, neural network technologies have been widely applied in medical image classification and have achieved remarkable results. CNNs are widely used in image processing tasks due to their automatic feature extraction capabilities. For example, the visual geometry group (VGG) neural network improves image classification accuracy by increasing network depth (Li et al., 2020b); ResNet resolves the gradient vanishing problem in deep network training by introducing residual connections, significantly enhancing classification accuracy and stability (Zhang et al., 2022). Furthermore, attention mechanisms are gradually being applied to medical image analysis to enhance the model's ability to recognise key features. For instance, the SE attention mechanism improves classification accuracy and model generalisation by recalibrating the channel weights of feature maps, enabling the model to focus more on important features (Li et al., 2023). In specific tasks of pneumonia detection, neural networks combined with attention mechanisms exhibit particularly outstanding classification performance. However, different models vary in effectiveness for pneumonia detection. While the VGG network can capture detailed features, it has high computational complexity. While the SE mechanism can improve the recognition of key features, its additional computational cost cannot be ignored. Therefore, combining ResNet's residual connections with the SE attention mechanism is expected to balance accuracy and computational efficiency, providing a more effective solution for pneumonia detection.

This study proposes a hybrid model based on residual neural network and SE attention mechanism for classifying and recognising pneumonia images, aiming to improve the model's performance in complex medical imaging tasks.

The research contributions of this paper mainly include the following aspects: multiple experiments were designed to comprehensively compare the performance of different neural networks such as CNN, VGG, and ResNet in pneumonia detection. After a detailed analysis of the advantages and disadvantages of different network structures, this paper designed a ResNet model (ResNet+SE) that combines transfer learning and SE attention mechanism. The model effectively avoids the gradient elimination problem through residual connected features and focuses on key pneumonia-related features through the SE mechanism. The detection ability of the model is enhanced by weighting key features. Applying transfer learning techniques to improve generalisation ability: By utilising the feature advantages of pre-trained models, the model can adapt to different data distributions, thus better solving the common problems of insufficient samples and feature differences in pneumonia medical images, enhancing the adaptability of pneumonia image features to different geographical regions and populations, and significantly improving classification performance. In the experiment, this study showed that the ResNet+SE model has significant advantages over other methods in pneumonia image classification, especially in terms of accuracy and robustness.

The remainder of this paper is organised as follows: Section 2 provides a detailed review of the relevant research background and the advantages and disadvantages of existing technologies; Section 3 introduces the proposed model structure and experimental design; Section 4 presents and analyses the experimental results of various models; and the final section summarises the main conclusions of this study and proposes possible directions for future research.

2 Related work

In recent years, research on using neural networks for CT image classification has gradually increased, and many scholars have achieved significant results in this field. The following are several relevant research papers and their main contents from 2020 onwards:

Chen et al. (2020) used CNN to classify CT images of pneumonia. Through data augmentation and DL techniques, researchers have improved the accuracy, and the results show that CNN performs better than traditional machine learning methods in pneumonia image classification (Chen et al., 2020). Huang et al. (2021) propose a pneumonia detection method based on the VGG neural network. This method has been trained and tested on large-scale CT image datasets, achieving high accuracy and sensitivity. Research has shown that deep neural network structures can help improve image classification performance (Huang et al., 2021). Zhang et al. (2022) used the ResNet neural network model to classify CT images of pneumonia. The problem of gradient vanishing in deep network training has been solved by introducing residual connections, making the model perform well in complex image classification tasks (Zhang et al., 2022). Li et al. (2023) combines the SE attention mechanism with CNNs to propose an improved pneumonia CT image classification method. The experimental results indicate that the SE attention mechanism can significantly enhance the model's attention to important features and improve classification accuracy (Li et al., 2023). Shao (2023) proposed a new network based on the fusion of neural network and attention mechanism, mainly based on the X-ray tooth image aided diagnosis network, to improve the diagnosis efficiency.

In summary, although different neural network models have shown good performance in pneumonia CT image classification, each has advantages and disadvantages. CNN has a simple structure but may have shortcomings when dealing with complex image features (Sun et al., 2022); VGG can capture more detailed information but has higher computational complexity; ResNet solves the training problem of deep networks, but the model structure is relatively complex; The SE attention mechanism can enhance the model's attention to key features, but it also increases the computational burden. Therefore, the comprehensive utilisation of various neural network technologies combined with transfer learning methods is expected to improve pneumonia detection's accuracy and robustness.

3 The research method

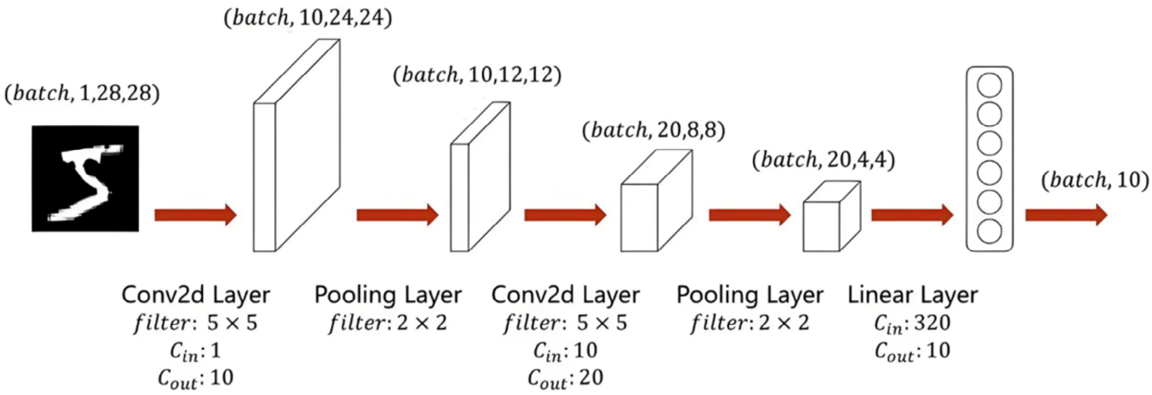
3.1 Selection of machine learning models

Upon investigating the task of classifying and recognising pneumonia images, a decision was reached to employ neural networks augmented with the SE attention mechanism, drawing comparisons with conventional machine learning approaches (namely random forest and support vector machine – SVM) and simpler baseline models. The rationale for this choice is elaborated below:

- Automated feature extraction and pattern recognition: Neural networks can autonomously extract pertinent features from raw images and discern intricate patterns, indispensable for pneumonia image classification. Conversely, traditional machine learning techniques necessitate manual feature engineering. SVM, for instance, demands rigorous feature selection and preprocessing, necessitating manual intervention. Although less reliant on extensive feature engineering, random forest still requires some feature selection and preprocessing for performance enhancement. This process is time-intensive and may lead to omitting crucial information.
- Streamlined end-to-end learning: Neural network architectures facilitate end-to-end learning, eliminating the need for the decoupling of feature extraction and classifier design that is characteristic of traditional methodologies, thereby simplifying the model design and optimisation process.
- Superior generalisation capabilities: Random forest's performance may be constrained in medical images characterised by complex backgrounds and high noise levels. However, through extensive training on vast datasets, neural networks can learn the latent data distribution patterns, exhibiting robust generalisation on novel samples. This is especially pertinent in medical image classification, where encountering new, unseen cases is common in practical applications.

In conclusion, despite the merits of traditional machine learning methods in certain domains (such as interpretability and computational efficiency), neural networks, particularly those integrated with the SE attention mechanism, demonstrate superior efficacy in automated feature extraction, complex pattern recognition, end-to-end learning, and generalisation ability when handling intricate medical image data. Hence, this study selects neural networks as the primary pneumonia image classification and recognition methodology.

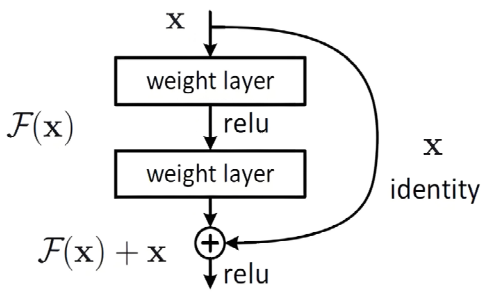
Figure 1 The architecture of CNN (see online version for colours)



3.2 CNN

CNN is a DL model for image processing and computer vision tasks. CNN can effectively extract spatial features of images, reduce model parameters, and improve computational efficiency through local receptive fields and shared weight mechanisms. Its basic structure includes convolutional, pooling, and fully connected layers (Arya and Singh, 2019). The convolutional layer performs convolution operations on the input image through convolutional kernels to extract feature maps (Qiu and Bi, 2022). The pooling layer reduces the size of feature maps and preserves important information through downsampling operations. The fully connected layer classifies the extracted features (Song et al., 2023). CNN performs well in tasks such as image classification, object detection, and image segmentation and is currently one of the mainstream image recognition technologies (Sarwinda et al., 2021). The architecture of CNN is shown in Figure 1.

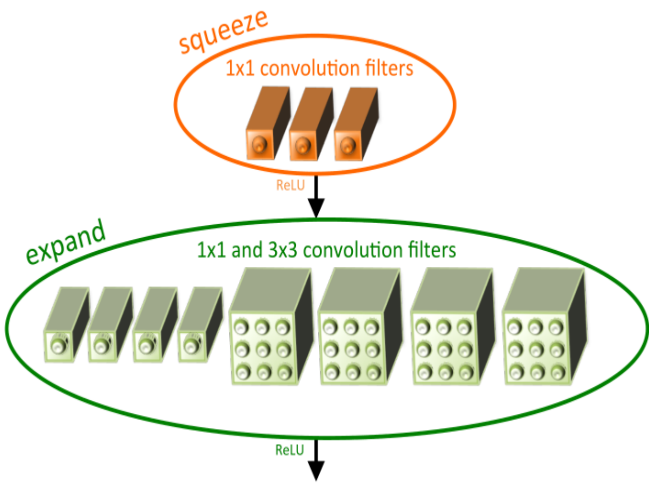
Figure 2 The architecture of ResNet



3.3 ResNet

A ResNet is a deep neural network model proposed by Microsoft Research Institute, which solves the problems of gradient vanishing and exploding in deep network training by introducing residual connections (Zhang et al., 2020). The basic unit of ResNet is a residual block in which input information is retained through cross-layer connections, allowing the network to train deeper layers. Typical ResNet models include ResNet50, ResNet101, and ResNet152, with depths of 50, 101, and 152 layers, respectively (Song et al., 2023). ResNet performs well in tasks such as image classification and object detection and is currently one of the most popular deep-learning models (Sarwinda et al., 2021). The Architecture of ResNet is shown in Figure 2.

Figure 3 The architecture of SqueezeNet (see online version for colours)



3.4 SqueezeNet

SqueezeNet is a neural network designed for high accuracy in image classification with significantly fewer parameters, making it ideal for devices with limited computational resources. Developed by researchers at DeepScale, UC Berkeley, and Stanford, SqueezeNet features Fire modules composed of squeeze and expand layers (Song and Mariano, 2024). The squeeze layer uses 1×1 filters to reduce input channels, while the expand layer uses 1×1 and 3×3 filters to increase output channels, enabling the learning of complex features (Ucar and Korkmaz, 2020). The network also employs global average pooling instead of fully connected layers, reducing spatial dimensions and parameters. The classification process starts with an initial convolutional layer extracting low-level features, which pass through fire modules for complex feature learning (Minu et al., 2022). Pooling layers reduce spatial dimensions, enhancing efficiency and reducing overfitting. Global average pooling averages each feature map, resulting in a final vector, which the softmax layer uses to produce class probabilities. SqueezeNet's advantages include a reduced model size, efficient computations, and maintained accuracy comparable to larger networks like AlexNet. Its design reduces parameters, making it suitable for constrained devices, and ensures efficient computations, speeding up training and inference while retaining high accuracy. The Architecture is shown in Figure 3.

3.5 SE attention mechanism

3.5.1 Operating principle of the SE attention mechanism

The SE attention mechanism is a technique that enhances neural networks' attention to important features by recalibrating the channel weights of feature maps. The SE module contains two main operations: the Squeeze operation and the Exception operation. The Squeeze operation compresses the features of each channel into a single value through global average pooling (Setiawan et al., 2021). The excitation operation generates weights for each channel through fully connected layers and activation functions and then applies these weights to each channel in the feature map (Hassanpour and Malek, 2020). Specifically, the SE attention mechanism achieves feature weighting and selection through the following steps:

- Feature extraction: A CNN is used to extract feature maps from the input image. These feature maps contain spatial and channel information about the image (Zou and Liu, 2024).
- Squeeze operation: the SE module employs a global average pooling layer to aggregate the spatial dimension, compressing each channel's feature map into a scalar value, thereby obtaining a global feature descriptor. This operation helps the network capture global information and embed statistical data of channel features.
- Excitation operation: A fully connected layer (typically a two-layer fully connected layer with a ReLU activation function) maps the global feature descriptor into a weight vector. This weight vector represents the importance of each channel. Subsequently, an activation function (such as the sigmoid function) normalises the weight vector to obtain the attention weight vector.
- Feature weighting: The attention weight vector is multiplied by the original feature maps to obtain weighted features. These weighted feature maps focus more on important channel features, improving network performance.

The SE attention mechanism can be embedded into existing CNNs to improve the model's feature representation and classification performance.

3.5.2 Advantages of the SE mechanism in pneumonia detection

- Improved detection accuracy: The SE attention mechanism enhances the network's focus on pneumonia-related features by weighting important channel features, thereby improving detection accuracy.
- Reduced computational complexity: Although the SE module increases network complexity, its computational overhead is relatively small and does not significantly affect overall performance.
- Enhanced generalisation ability: The SE module can learn channel relationships across different datasets and tasks, enhancing the network's generalisation ability and enabling it to better adapt to various pneumonia detection tasks.

3.6 Hyperparameter tuning

Hyperparameter tuning plays a core role in machine-learning experiments for pneumonia image classification and recognition. In this experiment, we pay special attention to the setting of key hyperparameters, such as learning rate and sample batch, to balance computational efficiency and model performance.

Firstly, the learning rate is carefully set to 0.001. This choice aims to prevent the parameter update amplitude from being too large, thereby preventing the model from getting stuck in the local optima or oscillating near the optima during the training process. A smaller learning rate helps the model converge more stably, ensuring a smooth training process.

Secondly, the sample batch is set to 32. The selection of this value aims to increase the stability of model training while considering the effective utilisation of computing resources. Smaller batches can introduce more randomness, which helps the model jump out of local optima, but larger batches may increase memory consumption and reduce training efficiency. Therefore, setting 32 achieves a good balance between stability and computational efficiency.

In addition, this experiment also used stochastic gradient descent (SGD) as the optimiser. SGD, as a classic and efficient optimisation algorithm, can significantly improve the speed and performance of model training. SGD helps the model quickly converge to the global optimum by continuously updating model parameters to minimise the loss function.

3.7 Transfer learning

Transfer learning is a commonly used auxiliary method in machine learning experiments. It refers to a learning process where models learned in old domains are applied to new domains by leveraging similarities between data, tasks, or models. In utilising the combination of neural networks and the SE attention mechanism to achieve classification and recognition of pneumonia images, transfer learning and using pre-trained models have significantly impacted the experiment. The following is a discussion on the practical impact of transfer learning in this experiment:

3.7.1 Impact of transfer learning on model performance on small localised datasets

Training a complex neural network model from scratch may lead to overfitting when the localised dataset is small. Transfer learning significantly reduces the dependence on new data by utilising a pre-trained model on a large dataset as a starting point, thereby avoiding overfitting. The pre-trained model has already learned many general image features, which are also useful for classifying pneumonia images.

3.7.2 Impact of transfer learning on model performance on data from different geographical regions

When the model is applied to data from different geographical regions with varying pneumonia incidence rates, the adaptability of transfer learning becomes particularly important. Due to potential differences in pneumonia images from different geographical regions (such as lesion morphology, image quality, etc.), the model needs to possess a certain level of generalisation ability to adapt to these changes. The model can learn some general image features also present in pneumonia images from different geographical regions through transfer learning. Therefore, the model can better adapt to new datasets and perform well in pneumonia classification tasks across different geographical regions.

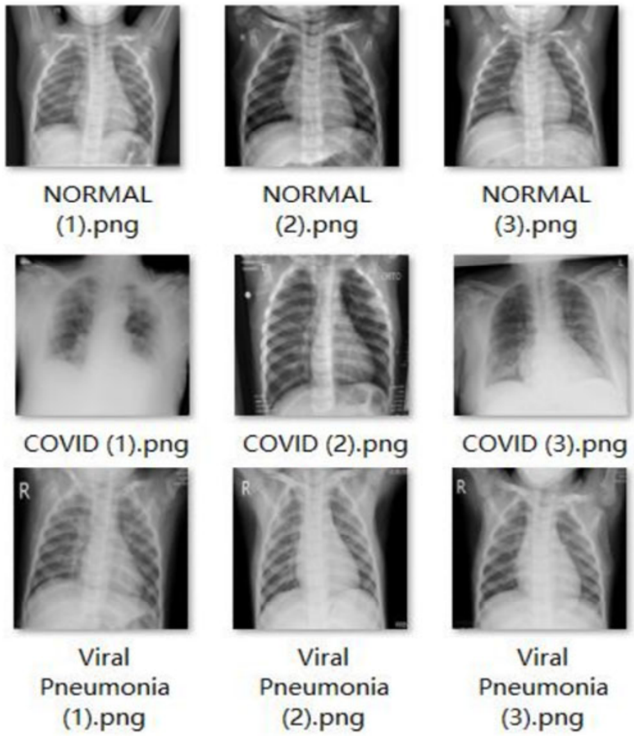
In summary, transfer learning has played a crucial role in this experiment. It improves the model's performance on small localised datasets and enhances its adaptability and generalisation ability on data from different geographical regions. By reasonably utilising pre-trained models and fine-tuning strategies, we can build more efficient and robust models to classify and recognise pneumonia images.

4 Dataset

The data used in this experiment is divided into three types: normal lung pictures, ordinary pneumonia, and COVID-19 pneumonia. There are 2,658 pictures of normal (healthy) lungs, 1,224 pictures of viral pneumonia, and 2,753 pictures of COVID-19 pneumonia. The dataset is shown in Figure 4.

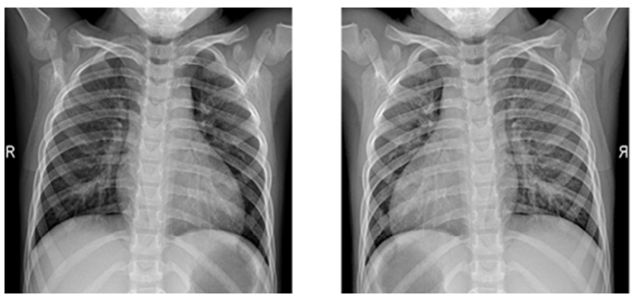
Before conducting model training, it is necessary to preprocess the original CT image data. Data preprocessing includes image normalisation, image enhancement, and noise removal. The normalisation operation scales the image's pixel values between 0 and 1, unifies the data range, and facilitates model training. Image enhancement generates more samples, increases data diversity, and reduces overfitting risks through rotation, scaling, translation, and mirroring operations. Noise removal reduces the impact of image noise on model training through filtering and other techniques.

Figure 4 Dataset of pneumonia



Conducting machine learning research on pneumonia necessitates high-quality and diverse datasets. The primary sources for acquiring these datasets are the medical imaging departments of hospitals, publicly available medical datasets, and collaborative projects with scientific research institutions. We have forged partnerships with prominent hospitals, including Sichuan Provincial People's Hospital, to access authentic CT scan data via their imaging departments. Additionally, we leveraged public lung CT image datasets and sourced labelled medical images from open data platforms like Kaggle, enhancing our dataset's comprehensiveness. Notably, our dataset incorporates data from various age groups, with a significant proportion derived from adults (45%), followed by elderly patients (35%), and a substantial minority from paediatric cases (20%). This balance ensures the robustness and applicability of our research across different demographic segments.

Figure 5 Dataset of pneumonia



In the machine learning experiment of pneumonia image classification and recognition, to solve the problem of data imbalance, this experiment first uses data augmentation to generate more samples, including flipping, rotating, and other operations on the original image. Then, it combines class weighting to adjust the weights of different categories of samples during training, giving more attention to minority categories. Through these methods, it is possible to effectively balance the category distribution in the dataset and improve the performance and accuracy of the pneumonia image classification and recognition model. The data augmentation effect is shown in Figure 5.

The dataset is split into 80% for training and 20% for validation. The training portion is utilised for model training and tuning parameters, whereas the validation portion assesses the model's performance and generalisation capability.

5 Experiments

5.1 The workflow of experimental

This study aims to use neural network technology to classify medical images of pneumonia. The experimental process is described as follows:

a Data collection and preprocessing: Collect datasets containing lung CT images, including normal lung and pneumonia infection images. Preprocess the image, such as resizing, cropping, and normalising.

b Model construction: Four model structures were established in this experiment: CNN, SqueezeNet, ResNet, and ResNet, with an added SE attention mechanism. To better achieve multi-class classification, this experiment used softmax as the activation function in the final layer of the model.

c Parameter adjustment: In the experiment, we set parameters such as initial learning rate, batch size, and number of training rounds for different models and adjusted the parameters based on the performance of the validation set. The specific parameter settings are as follows. The initial learning rate is set to 0.001, with a batch size of 16 and a total of 50 training epochs.

d Model training: During the model training process, we use cross-entropy loss function and Adam optimiser to iteratively optimise the model of training and validation errors to ensure model convergence.

5.2 Evaluation indicators

In the experimental evaluation stage, we compared the classification accuracy, precision, and recall of different models on the validation set. We analysed the performance of different models in pneumonia CT image classification.

5.3 The result of experimental

Through this experiment, all three neural network models achieved good recognition results. The ResNet model achieved a recognition accuracy of 92.50% and precision of 93.27% with the best performance among all models. The specific results are shown in Table 1.

Table 1 The result of the experimental

Model	*Accuracy*	*Precision*	*F1*
CNN	0.8650	0.8834	0.8026
SqueezeNet	0.9099	0.9184	0.9038
GoogleNet	0.9250	0.9327	0.9117
ResNet+SE	0.9250	0.9327	0.9218

The loss functions of each model during training are shown in Figures 6–8.

Figure 6 Loss function of CNN (see online version for colours)

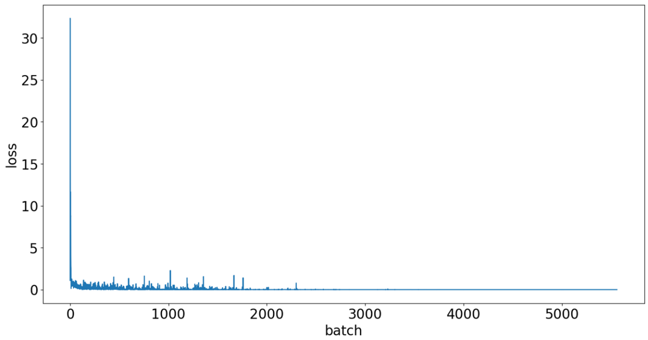


Figure 7 Loss function of ResNet (see online version for colours)

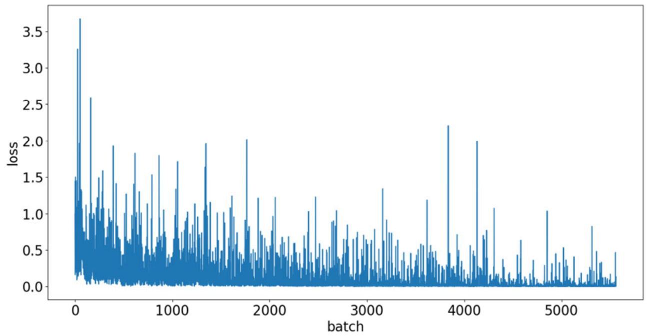
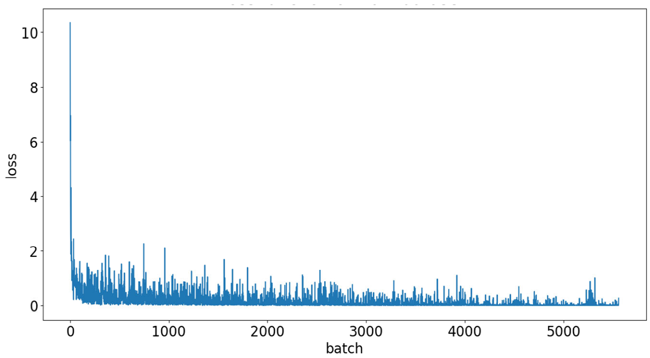


Figure 8 Loss function of SqueezeNet (see online version for colours)



The accuracy of train set of each model during training is shown in Figures 9–11.

Based on the experimental data and illustrations, it is evident that ResNet outperforms the other two network models with lower loss and higher classification accuracy. The reasons for this superior performance are as follows: ResNet reduces the training difficulty of multi-layer networks by using residual connections. This structural design helps ResNet avoid the common problem of gradient vanishing in deep networks, improving its ability to learn and extract key features from images. The residual connections allow the model to directly learn the differences between input and output, accelerating training and enhancing feature extraction precision. In medical image classification, accurately capturing the details of pathological areas is crucial for diagnostic accuracy. Additionally, the attention mechanism enables the model to concentrate on the crucial areas of the image automatically. This enables ResNet to identify subtle differences in pneumonia images more accurately, improving classification accuracy.

Figure 9 Accuracy of CNN (see online version for colours)

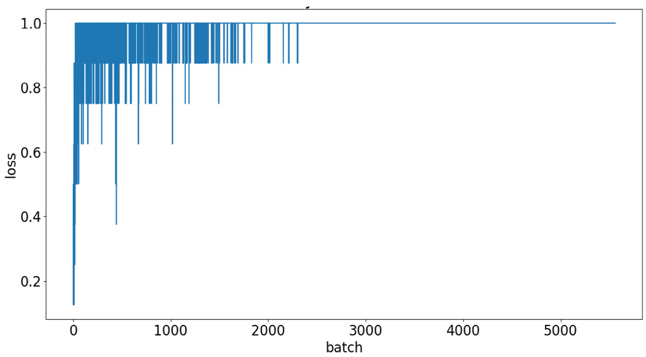


Figure 10 Accuracy of ResNet (see online version for colours)

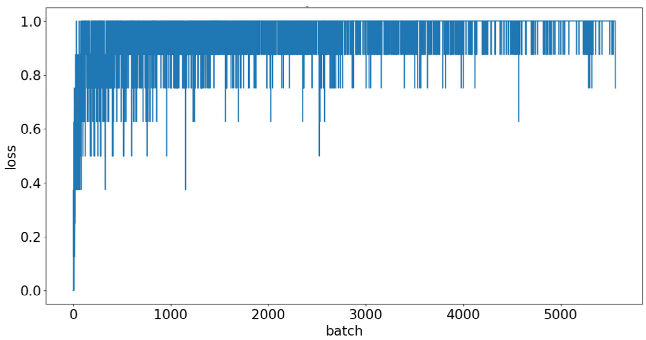
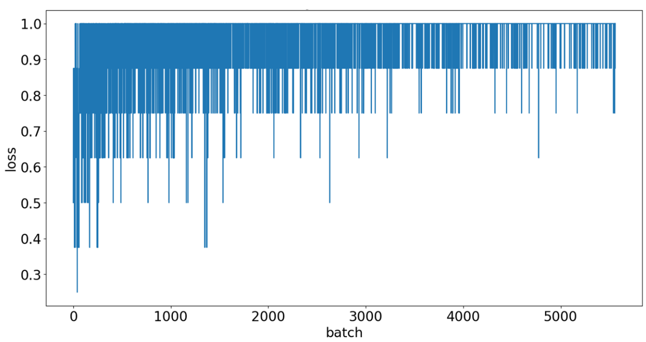


Figure 11 Accuracy of SqueezeNet (see online version for colours)



6 Conclusions

To better identify conditions from pneumonia CT images, this experiment explored using machine learning methods for classification detection. The models tested included CNN, SqueezeNet, GoogleNet, and ResNet, all of which performed well. ResNet, combined with the attention mechanism, notably excelled in image classification tasks. This can be attributed to its efficient training capabilities, parameter efficiency, generalisation ability, enhanced performance due to the attention mechanism, and outstanding feature representation. These factors collectively enable ResNet to handle complex image classification tasks successfully. The experiment demonstrates that machine learning methods can effectively assist doctors in efficiently and quickly classifying and identifying CT images, thereby enhancing the ability to detect pneumonia.

References

Amyar, A., Modzelewski, R., Li, H. et al. (2020) 'Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: classification and segmentation', *Computers in Biology and Medicine*, Vol. 126, p.104037.

Arya, S. and Singh, R. (2019) 'A comparative study of CNN and AlexNet for detection of disease in potato and mango leaf', *2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*, IEEE, Vol. 1, pp.1–6.

Chen, J. et al. (2020) 'Deep learning-based classification of lung nodules in CT images using convolutional neural networks', *Journal of Thoracic Disease*, Vol. 12, No. 3, pp.1234–1241.

Hassanpour, M. and Malek, H. (2020) 'Learning document image features with SqueezeNet convolutional neural network', *International Journal of Engineering*, Vol. 33, No. 7, pp.1201–1207.

Huang, L. et al. (2021) 'A deep learning approach for automatic detection of COVID-19 using chest CT', *Medical Image Analysis*, Vol. 68, p.101779.

Li, X. et al. (2023) 'SE-ResNet: a squeeze-and-excitation residual network for pneumonia detection', Computer Methods and Programs in Biomedicine, Vol. 213, p.106501.

Li, Y., Zhang, Z., Dai, C., Dong, Q. and Badrigilan, S. (2020a) 'Accuracy of deep learning for automated detection of pneumonia using chest X-ray images: a systematic review and meta-analysis', *Computers in Biology and Medicine*, Vol. 123, p.103898.

Li, Z., Zhong, Z., Li, Y. et al. (2020b) 'From community-acquired pneumonia to COVID-19: a deep learning-based method for quantitative analysis of COVID-19 on thick-section CT scans', *European Radiology*, Vol. 30, pp.6828–6837.

Minu, M.S., Aroul Canessane, R. and Subashka Ramesh, S.S. (2022) 'Optimal SqueezeNet with deep neural network-based aerial image classification model in unmanned aerial vehicles', *Traitement du Signal*, Vol. 39, No. 1, pp.152–157.

Qiu, M. and Bi, Z. (2022) 'Police alarm address recognition and classification based on convolutional neural networks'. *International Journal of Security and Networks*, Vol. 17, No. 1, pp.56–62.

Sarwinda, D., Paradisa, R.H., Bustamam, A. et al. (2021) 'Deep learning in image classification using residual network (ResNet) variants for detection of colorectal cancer', *Procedia Computer Science*, Vol. 179, pp.423–431.

Setiawan, W., Ghofur, A., Rachman, F.H. et al. (2021) 'Deep convolutional neural network AlexNet and SqueezeNet for maize leaf diseases image classification', *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*.

Shao, X. (2023) 'Research on X-ray dental imaging assisted diagnosis method based on fusion neural network and attention mechanism', *Tianjin University of Technology*, Vol. 32, No. 2, pp.33–38.

Song, X. and Mariano, V.Y. (2024) 'Fruit tree disease recognition based on residual neural network and attention mechanism', *Journal of Artificial Intelligence and Technology*, Vol. 4, No. 2, pp.145–152.

Song, X., Baghoolizadeh, M., Alizadeh, A.A., Jasim, D.J., Basem, A., Sultan, A.J. and Piromradian, M. (2024) 'Utilizing machine learning algorithms for prediction of the rheological behavior of ZnO (50%)-MWCNTs (50%)/Ethylene glycol (20%)-water (80%) nano-refrigerant', *International Communications in Heat and Mass Transfer*, Vol. 156, p.107634.

Song, X., Mariano, V.Y. and Shi, X. (2023) 'Apple disease recognition based on comprehensive application of residual neural network', *Machine Learning and Artificial Intelligence*, pp.33–42, IOS Press.

Sun, H. et al. (2022) 'A deep learning method for pneumonia detection and diagnosis from chest X-ray images', *Computers in Biology and Medicine*, Vol. 143, p.105308.

Ucar, F. and Korkmaz, D. (2020) 'COVIDiagnosis-Net: deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images', *Medical Hypotheses*, Vol. 140, p.109761.

Zhang, J., Gao, Y., Liu, J. and Lu, J. (2020) 'Convolutional neural network-based chest X-ray image classification for COVID-19 pneumonia detection', *IEEE Access*, Vol. 8, pp.179074–179082.

Zhang, Y. et al. (2022) 'Residual learning for image recognition', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 44, No. 1, pp.36–48.

Zou, B. and Liu, T. (2024) 'A network traffic classification and anomaly detection method based on parallel cross-convolutional neural networks', *International Journal of Security and Networks*, Vol. 19, No. 2, pp.92–100.