A Deep Learning Approach Considering Image Background for Pneumonia Identification Using eXplainable AI (XAI)

Yuting Yang, Gang Mei*, Francesco Piccialli*

Abstract—Pneumonia mainly refers to lung infections caused by pathogens, such as bacteria and viruses. Currently, deep learning methods have been applied to identify pneumonia. However, the traditional deep learning methods for pneumonia identification take less account of the influence of the lung X-ray image background on the model's testing effect, which limits the improvement of the model's accuracy. In this paper, we propose a deep learning method that considers image background factors and analyzes the proposed method with explainable deep learning for explainability. The essential idea is to remove the image background, improve the pneumonia recognition accuracy, and apply the Grad-CAM method to obtain an explainable deep learning model for pneumonia identification. In the proposed approach, (1) preliminary deep learning models for pneumonia X-ray image identification without considering the background are built; (2) deep learning models for pneumonia X-ray image identification with background consideration are built to improve the accuracy of pneumonia identification; (3) Grad-CAM method is employed to analyze the explainability. The proposed approach improves the accuracy of pneumonia identification, and the highest accuracy of VGG16 reaches 95.6%. The proposed approach can be applied to real pneumonia identification for early detection and treatment.

Index Terms—Pneumonia; Image Background; Deep Learning; Explainable AI; X-ray

1 Introduction

Pneumonia mainly refers to lung infections caused by pathogens, such as bacteria and viruses, and is one of the common infectious diseases in clinical medicine [1], [2], [3]. It has a short period of onset and a high incidence, often with typical symptoms, such as fever, cough, and sputum. Pneumonia occurs mostly in countries with scarce medical resources. Additionally, it occurs mostly in children and elderly people with low immunity [4], [5]. The lack of medical resources and poor sanitary conditions in underdeveloped areas can easily lead patients to develop pneumonia from the common cold [6]. The children's immune system is not yet fully developed, and the immune system of the elderly is declining; both groups have lower immunity, and thus, the incidence of pneumonia is relatively high. The increased resistance of germs due to the illogical use of antibiotics and the diversity of modern pathogenic factors also contribute to the high incidence of pneumonia [7]. Although the treatment and methods of pneumonia are much improved, the lethality rate is still high, and if left untreated, it may threaten the life of the patient [8], [9]. Both H1N1 [10] and SARS [11] are highly contagious types of pneumonia caused by viral infections, which not only endanger people's lives and health but also cause great losses in the country.

In late 2019, the outbreak of the novel coronavirus pneumonia (COVID-19) led to a dramatic increase in the number of pneumonia cases worldwide [12]. According to data provided by the World Health Organization (WHO) and official notifications from various countries, as of December 8, 2021, there are more than 260 million cumulative confirmed cases and more than 5 million cumulative deaths worldwide, which seriously threatens the lives of people around the world. Novel coronaviruses are new viruses, and it takes time to understand them to develop a vaccine for them. Therefore, timely and effectively identifying pneumonia and isolating patients helps to stop the spread of pneumonia. These are currently the most effective means of preventing and treating COVID-19 [13]. Consequently, the timely recognition and diagnosis of pneumonia, both in the past and at present, is very important.

In the past, the initial diagnosis of general pneumonia was based on clinical symptoms combined with imaging methods, including computer tomography (CT) [14], magnetic resonance imaging (MRI) [15], and X-rays [16], etc. X-ray methods, however, are used more often in clinical practice because of their lower price and good imaging quality. Currently, the most commonly used method for detecting novel coronaviruses is the nucleic acid method, which uses reverse transcription-polymerase chain reaction (RT–PCR) by collecting specimens from nasal mucus, lower respiratory secretions, and perianal secretions [17]. However, the nucleic acid method also struggles with the lack of sensitive reagents, long reaction time, and false-negative test results [18]. Therefore, if the nucleic acid test is positive, further tests are required to confirm the diagnosis of COVID-19 [19]. Using imaging methods is an important part of the diagnosis of COVID-19, and X-ray detection is one of the more commonly used methods [20], [21].

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For pneumonia identification from X-ray images, manual analysis and diagnosis methods are generally used, but this is highly dependent on professional knowledge. Thus, the diagnosis is usually made by physicians with more clinical experience and a higher level of expertise [22]. However, even experienced doctors need to spend a certain amount of time for observation and analysis when diagnosing pneumonia, and after observing a large number of X-ray lung effects every day, they are prone to visual fatigue, subjectivity, and other problems, which can easily lead to large fluctuations in the accuracy of diagnostic results [16]. In remote areas, there is a shortage of professional doctors, which makes it even more difficult to accurately identify and diagnose pneumonia [23]. Therefore, the use of computer-aided diagnostic technology can help physicians make a rapid diagnosis of pneumonia, improve the accuracy of pneumonia identification and diagnostic efficiency, and reduce the problem of the scarcity and uneven distribution of medical resources.

With the rapid development of computer technology, artificial intelligence methods have been applied to the medical field [24], [25]. Among them, deep learning methods are widely used in the field of computer vision because of their good robustness and high recognition accuracy [26], [27]. Using deep learning methods, medical image classification utilizing convolutional neural networks can abstract visual image information into relevant features for end-to-end automatic recognition and diagnosis, improve recognition efficiency, greatly shorten the diagnosis time, improve the accuracy of pneumonia recognition, and to a certain extent, reduce the occurrence of misdiagnosis and missed diagnosis [28], [29], [30]. It is of great importance to achieve early detection and treatment of pneumonia to reduce the mortality rate.

In this paper, we propose a deep learning method that considers image background factors and perform an explainability analysis of the method for application to real-life pneumonia recognition. First, we collect and obtain the pneumonia X-ray image dataset and took appropriate methods to clean and process the data. Second, we use ResNet50 and VGG16 pretrained models to build deep learning models for pneumonia X-ray image classification and conduct training and testing with background conditions. Third, we consider the influence of background factors on the accuracy of the model, remove the background factors of pneumonia images, and use the established deep learning models to conduct training and testing on pneumonia images without background conditions. Finally, by using Grad-CAM, the proposed method is analyzed for explainability, and trustworthy deep learning models are obtained to ensure that highly accurate and trusted pneumonia recognition models can be established to achieve efficient detection and diagnosis, as well as maintain people's health and lives.

The rest of this paper is organized as follows. Section 2 introduces related work. Section 3 describes the proposed method in detail. Sectionn 4 analyzes the results obtained by this method. Section 5 discusses the advantages, applicability, and disadvantages of the proposed method, as well as possible future work. Section 6 concludes the paper.

2 Related Work

Much research work has been conducted in the field of pneumonia identification using deep learning. For example, Hua et al. [31] addressed the problem of lung disease diagnosis by combining deep belief networks (DBNs) and convolutional neural networks to improve the accuracy of lung disease diagnosis compared to traditional methods. Shin et al. [32] used a transfer learning strategy to reduce the large amount of training data required for deep learning models, solving the problem of insufficient medical data for deep learning of small samples. Salehinejad et al. [33] used generative adversarial networks (GANs) to generate artificial images due to the lack of image datasets for medical data, which were combined with real images to train deep convolutional neural networks (DCNNs) to improve the performance of DCNNs (deep convolutional neural networks) for the classification of chest pathology images.

Moreover, Wang et al. [34] proposed a two-branch structure for thoracic disease classification. The dual branches are a classification branch that serves as a feature extraction and classification network and an attention branch that explores the correlation between category labels and the location of pathological abnormalities. The recognition performance of the model is poor due to the poor imaging quality of the X-ray image itself, as well as the influence of background factors in feature extraction on the whole chest X-ray image. To overcome the limitations of classical convolutional neural network methods that are insensitive to the location of pathological abnormalities in the images. Liang et al. [28] proposed a deep migratory learning method combining the idea of residuals and null convolution for pediatric pneumonia recognition. This method helps to overcome problems, such as overfitting, degradation, and loss of feature space information due to increasing the model's depth of deep learning models. Harsh Sharma et al. [35] extracted feature architecture from chest X-ray images and used a deep convolutional network model to classify the X-ray images to determine the presence of pneumonia.

In addition, after the outbreak of COVID-19, scholars from various countries have also conducted research related to applying deep learning to the recognition of COVID-19. Keles et al. [36] developed inference engines by deep learning to detect COVID-19. The engines were named COV19-CNNet and COV19-ResNet because they were based on convolutional neural network architecture and residual neural network (ResNet) architecture, respectively. The engines could classify COVID-19 better with other viral types of pneumonia that are similar to its X-ray images. Wang et al. [37] combined UNet+ and ResNet50 to build a deep learning model that can be used to identify pneumonia and achieved a high accuracy rate of 97.4%. Wang et al. [38] proposed a CAD framework to assist radiologists in automatically recognizing and localizing COVID-19. Compared to the radiologists' identification and localization results, the accuracy of COVID-19 was 98.71% discriminatory using the Discrimination-DL and 93.03% localization accuracy using the Localization-DL. This research confirms that the framework based on deep learning has high accuracy when performing COVID recognition, approaching the level of professional radiologists. Zhang et al. [39] proposed an

EfficientNet-based diagnostic model for pneumonia detection, CAAD, which consisted of a shared feature extractor, an anomaly detection module, and a confidence score prediction module. The model is capable of identifying COVID-19 pneumonia and performing abnormality detection, which can achieve a high accuracy rate.

However, the current research on deep learning methods for pneumonia recognition considers less the influence of background factors on pneumonia recognition, which can limit the further improvement of pneumonia recognition accuracy. To address the above problems, in this paper, we propose a deep learning method that considers image background factors. Additionally, this paper analyzes the proposed method with understandable deep learning for explainability to obtain trustworthy deep learning models for real-life applications.

3 Materials and Methods

3.1 Overview

In this paper, we propose a deep learning method that considers image background factors, and explainable deep learning is used to analyze the proposed method.

First, we collect X-ray image datasets of pneumonia patients and normal people from publicly-available websites and then organize and clean these raw images. Second, suitable deep learning models, ResNet50 and the VGG16 pretrained model are selected to build deep learning models for pneumonia X-ray image classification using the idea of transfer learning. The training and testing are first conducted with the background condition included. Third, the background of the image is removed, and the training and testing are performed using ResNet50 and VGG16 pretrained deep learning models for X-ray images without the background condition to obtain a deep learning model for pneumonia X-ray image recognition considering the image background. Finally, a visual explainability analysis of the deep learning model is performed using the Grad-CAM method to further obtain a trustworthy deep learning model for practical application of pneumonia recognition. The workflow of this paper is illustrated in Fig. 1.

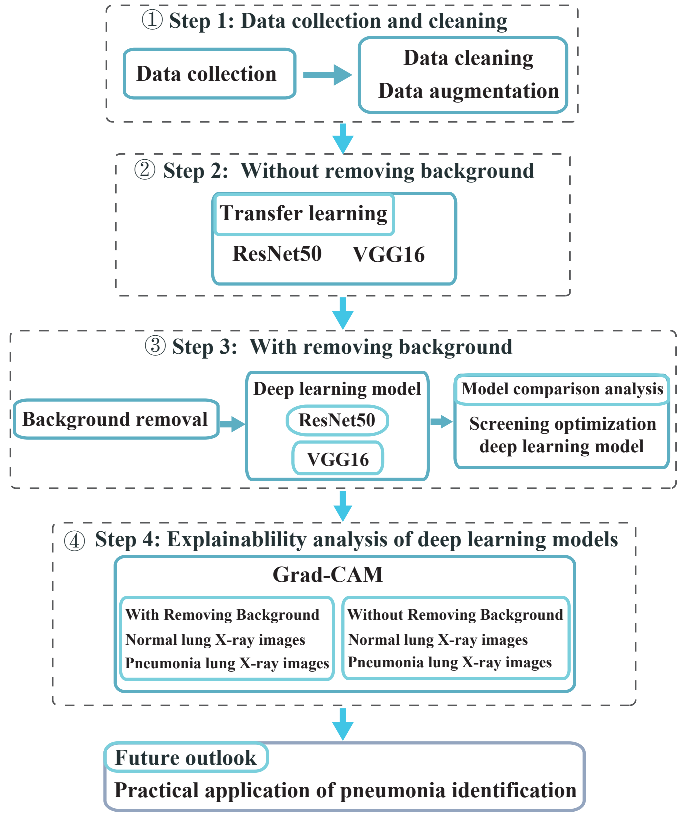


Fig. 1: Workflow of the proposed deep learning approach for the identification of pneumonia

3.2 Step 1: Data Collection and Cleaning

3.2.1 Data Collection and Processing

We acquired the dataset of chest X-ray images of pneumonia patients and normal subjects from Guangzhou Women's and Children's Medical Center in children aged 1 to 5 years [40]. The dataset contains a total of 5840 images, of which 4265 are X-ray images of patients with pneumonia and 1575 are normal X-ray images. To guarantee the accuracy of the model training and testing results, we select the same number of X-ray images of pneumonia patients and healthy people. 80% of them are randomly selected as the training set and 20% as the testing set to obtain the chest X-ray image dataset containing the background. Then, the background of all chest X-ray images is removed, and only the features of the heart and lung parts are retained, which results in a chest X-ray image dataset without a background. Before training and testing, the images are scaled to a uniform size, such as 224×224.

3.2.2 Data Augmentation

When the dataset is small, data augmentation operations are used to expand the dataset and prevent the phenomenon of overfitting. Data augmentation refers to the use of transformation operations on the original dataset to produce a series of transformations in the size, orientation, and color of the original image to generate new data and achieve expansion of the dataset and create a more valuable dataset with limited data [41]. Data augmentation is a widely used data processing method in deep learning applications for image classification.

The methods of data augmentation include: flipping (mirroring the image by horizontal or vertical axis to flip the image), rotation (rotating the image left and right by a certain angle, either by freely setting the angle or by random angle transformation), scaling (enlarging or reducing the image by a certain proportion without changing the image content), cropping (cropping the image by a certain size, either centrally or randomly), brightness transformation (changing the brightness of the image), contrast transformation (changing the saturation and brightness components while keeping the hue unchanged) and hue transformation (random perturbation on the image channel) [41], as illustrated in Fig. 2.

The data augmentation operation can improve the model's generalization, reduce the overfitting phenomenon in the deep learning process, and improve the robustness of the model [42]. In medical image analysis, the available datasets are generally small, and since the dataset used in this paper is small, data augmentation is used to expand the amount of data.

3.3 Step 2: Identification of Pneumonia without Removing the Background of the X-ray Images

3.3.1 Transfer Learning

Transfer learning is a method that can be used to train other similar or related problems. The obtained relations are transferred to the task to be processed when the amount of data for a task is small and there is not enough data available for model training. The transfer learning approach can reduce the large amount of training data required for deep learning, reduce the data dependency, and solve the corresponding problems with a small amount of data. The basic principle of transfer learning is illustrated in Fig. 3. Because of the small amount of data in this paper, the transfer learning method is used to build the deep learning model using pretrained models, thus reducing the dependence on the amount of data and improving the accuracy.

3.3.2 Deep Learning Model Construction

In this paper, a transfer learning approach is used to construct deep learning models for pneumonia recognition using the pretrained ResNet50 [43] and VGG16 [44] models in the ImageNet dataset, and two deep learning models are finally constructed: the ResNet50 model and the VGG16 model, each of which is described in detail as follows.

(1) ResNet50 model: the deep residual network (ResNet), proposed by Kaiming He et al. [43] in 2015. ResNet introduced the residual block, which reduces the problem of gradient disappearance caused by increasing the depth of the deep neural network, while also accelerating the training of the neural network, and improving the accuracy of the model. In this paper, we use the ResNet50 model with a residual blockage, which reduces the number of input channels by a 1×1 convolution, thus reducing the number of parameters of the overall model and speeding up the model computation.

(2) VGG16 model: the model structure is simple and employs small convolutional kernels (3×3) instead of large convolutional kernels to increase the network depth and reduce the parameters, thus improving the network's fitting ability. The use of the VGG16 network [44] structure is deeper and wider than the use of the AlexNet model architecture, and the scale of an increase in computation is controlled.

3.4 Step 3: Identification of Pneumonia with Removing the Background of the X-ray Images

3.4.1 Background Removal

The heart-lung images extracted by image segmentation and target extraction methods still have certain deviations, which are prone to problems, such as inaccurate image extraction and insufficient image extraction accuracy. Therefore, in this paper, we employ the manual processing method to manually extract the heart-lung images one by one to remove the background factors to obtain the heart-lung images with a better extraction effect when removing the background.

3.4.2 Deep Learning Model Construction

Two deep learning models for pneumonia recognition without considering the background, the ResNet50 pretraining model and the VGG16 pretraining model, are still used for training and testing with the pneumonia X-ray image dataset removed from the background to obtain a deep learning model for recognizing pneumonia in X-ray images.

3.5 Step 4: Explainable Analysis by the Grad-CAM Method

In this paper, the Grad-CAM method [45] is used to explain the deep learning model and understand the results by visualization, which leads to a trustworthy deep learning model for pneumonia recognition. Before developing Grad-CAM, the CAM method is usually used for visualization calculation, but the CAM method requires a global average pooling operation to obtain the weights of each channel of the feature map, and then the heat map of the network region of interest is obtained by linear weighted summation. For models with multiple fully connected layers, it is difficult for the CAM method to calculate the importance of the weights of each channel of the feature map. Therefore, the CAM method is not applicable for many CNN models, and if CAM method needs to be used, the structures of the CNN models should to be changed by replacing the fully connected layer behind the network model with global average pooling.

The Grad-CAM method uses the weighted gradient class activation map to calculate the weights of each channel of the feature map with the network back propagation gradient according to the output vector. The weights corresponding to the obtained feature map are then weighted and summed, and the class activation map is obtained after the ReLU activation function. The attention of the neural network is then visualized in the form of a heat map showing the regions in the image that are important for target prediction and classification.

Compared with the CAM method, the Grad-CAM can be applied to various CNN network models without changing the structure of the network model, avoiding the tradeoff between explainability and model accuracy, and not requiring retraining, which can show more fine-grained details and achieve better visualization. The heatmap for the identification of pneumonia using the Grad-CAM method is illustrated in Fig. 4, where areas of high concern are indicated in red. From the heatmap, it can be seen that the lung has a high degree of attention, enabling the pneumonia to be identified.

4 Results

4.1 Experimental Environment

The software and hardware environment configurations used in this paper are listed in Table 1.

4.2 Experimental Data

The obtained dataset is filtered and cleaned, because the pneumonia dataset in this paper contains bacterial pneumonia and viral pneumonia, there are more pneumonia X-ray

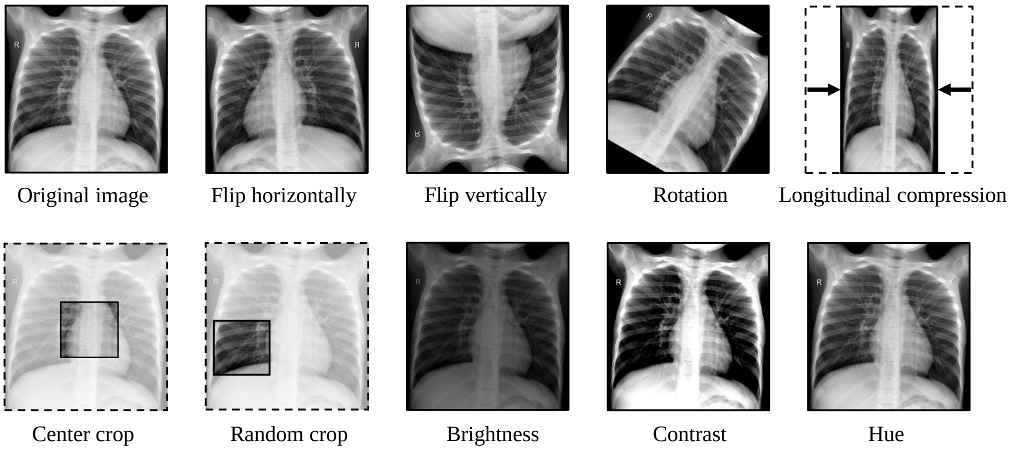


Fig. 2: The outcome of different data augmentation methods

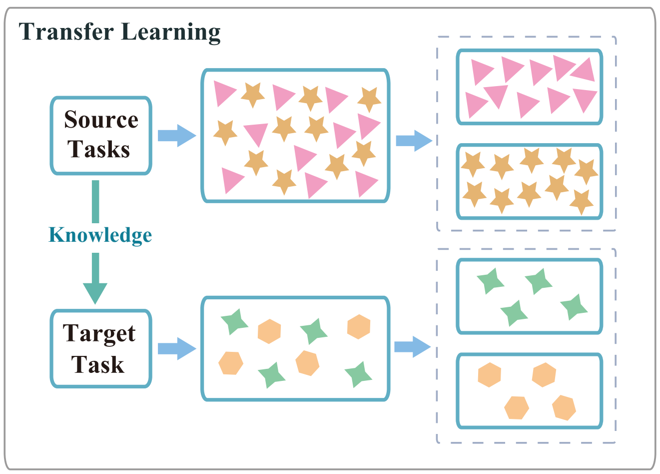
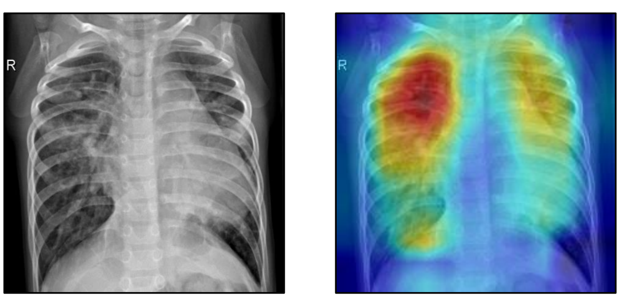


Fig. 3: Principle of transfer learning method



(a) Original Image **(b)** Grad-CAM 'Chest'

Fig. 4: X-ray image of the chest before and after Grad-CAM

TABLE 1
ENVIRONMENT CONFIGURATIONS

Environment configurations	Details
OS	Windows 10 Professional
Programming language	Python
Deep learning framework	PyTorch
Dependent library	Torch,Numpy,CUDA etc.
CPU	Intel Xeon Gold 5118 CPU
CPU Frequency (GHz)	2.30
CPU core	48
CPU RAM (GB)	128
GPU	Quadro P6000
GPU memory (GB)	24
CUDA cores	3840
CUDA version	v9.0

images. However, only the binary classification of pneumonia and normal X-ray image recognition is performed. To guarantee the accuracy of the pneumonia recognition, we remove some of the pneumonia images to ensure that the numbers of pneumonia and normal images are the same.

The dataset for training and testing the deep learning models for pneumonia recognition in X-ray images are obtained, containing a total of 2500 images, with 1250 images of pneumonia patients and 1250 images of healthy people. 80% of the images with and without pneumonia are randomly selected as the training set, and the remaining 20% are selected as the testing set. Therefore, the training set contains a total of 2000 images, 1000 normal images, and 1000 images with pneumonia. The testing set contains a total of 500 images, 250 normal images, and 250 images with pneumonia. Among them, normal human chest X-ray images have fewer impurities in the lungs, as illustrated in Fig. 5 (a). In contrast, the lung pictures of chest X-ray images of patients with pneumonia are less clear, with blurred and thickened lung textures, as illustrated in Fig. 5 (b).

Then, 2500 images that are divided into training and testing sets are processed utilizing manual methods to remove the image background to obtain 2500 X-ray images of the heart and lung parts without a background to train and test the deep learning model for pneumonia recognition in X-ray images considering the image background. The background-removed X-ray images of pneumonia patients and healthy subjects are illustrated in Fig. 5 (c)∼(d).

4.3 Analysis of the Results of Pneumonia Identification without Removing the X-ray Image Background

The deep learning pretraining models used to construct the deep learning models are the ResNet50 pretraining model and the VGG16 pretraining model. In this paper, the constructed deep learning models are referred to as the ResNet50 model and the VGG16 model. The loss function

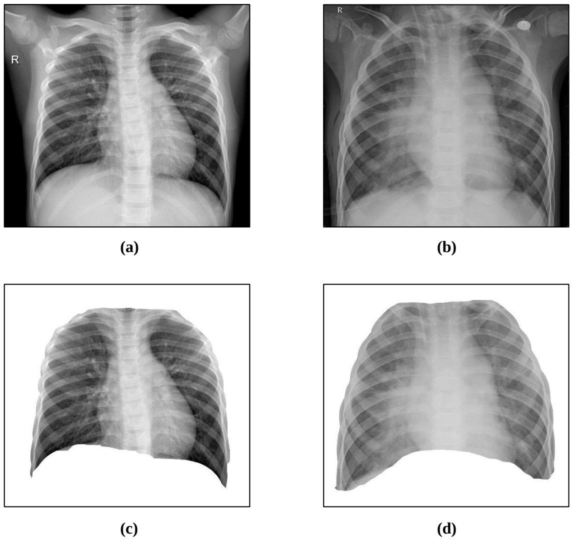


Fig. 5: Comparison with and without pneumonia, (a) is a chest X-ray image of healthy people before removing background, (b) is a chest X-ray image of pneumonia patient before removing background, (c) is a chest X-ray image of healthy people after removing background, (d) is a chest X-ray image of pneumonia patient after removing background

used for the models is $torch.nn.CrossEntropyLoss()$ and the optimizer is $torch.optim.SGD()$. The accuracy of the two models is compared and analyzed as follows.

A comparison of the 10 epochs before and after data augmentation for the ResNet50 model and the VGG16 model is illustrated in Fig. 6, and the table is plotted as illustrated in Table 2. From the analysis, it can be seen that the highest accuracy of both the ResNet50 model and the VGG16 models after data augmentation is higher than that before data augmentation. From the graphical analysis, it can be seen that the highest accuracy of both the ResNet50 and VGG16 models after data augmentation is higher than that before data augmentation. This is because the model dataset has fewer images, which tends to lead to overfitting of the model's training. Thus, data augmentation is used to improve the accuracy of the model.

Among them, the accuracy of the ResNet50 model gradually improves with the increase of epoch number, and the accuracy improves insignificantly after the data augmentation. However, the highest accuracy is higher compared with that before the data augmentation. The accuracy of the VGG16 model improves considerably after data augmentation compared with that before data augmentation. This may be because the ResNet50 model is too powerful for the dataset in this paper, and even with data augmentation, it is still too small for the ResNet50 model.

The overall accuracy of the VGG16 model is higher than that of the ResNet50 model, both before and after data augmentation. Before data augmentation, the highest accuracy of the VGG16 model is 92.200%, while the highest accuracy of the ResNet50 model is 90.400%. This is because the classification problem faced is a simpler, binary classification problem, and the dataset is smaller. Therefore, the VGG16 model can achieve better training results.

After data augmentation, the dataset is expanded to a certain extent, which can lead to better model training, and the highest accuracy of both models is improved after data augmentation. The highest accuracy of the ResNet50 model after data augmentation is up to 91.000%, and the highest accuracy of the VGG16 data after data augmentation is up to 94.600%. Among them, the VGG16 model's accuracy is improved more and has a higher accuracy rate. It is more suitable for pneumonia identification in small-scale datasets.

4.4 Analysis of the Results of Pneumonia Identification Considering the X-ray Image Background

4.4.1 Analysis of the Results when Removing the X-ray Image Background

The X-ray images are removed from the background, and only the heart and lung parts are kept. The ResNet50 and VGG16 models are used again for deep learning pneumonia recognition, and the accuracy comparison analysis of the two models is obtained as follows.

The comparison of the ResNet50 and VGG16 models before and after data augmentation with 10 epochs is illustrated in Fig. 7, and the table is plotted in Table 3. From the graphical analysis, it can be seen that the accuracy of the ResNet50 model after removing the background still increases with epoch after data augmentation and then tends to be stable. The highest accuracy rate after data augmentation is improved compared with that before data augmentation, but the model accuracy improvement effect is not obvious. The model accuracy after VGG16 data augmentation improves considerably compared with that before data augmentation.

When data augmentation is not performed, the accuracy of the ResNet50 model increases with the epoch and then stabilizes, while the accuracy of the VGG16 model remains high and does not increase with the epoch. The accuracy of the VGG16 model is more accurate than that of the ResNet50 model.

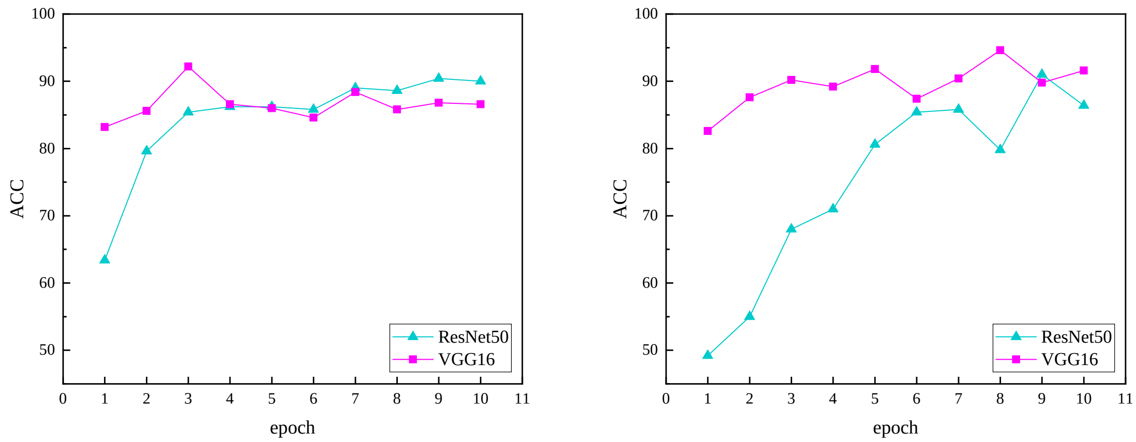
After the data enhancement operation, the VGG16 model still has better results and higher accuracy than the ResNet50 model. The accuracy of the VGG16 model after data augmentation also exhibits certain fluctuations, but the overall accuracy is still high, which could achieve better pneumonia recognition and has strong prospects for development in pneumonia recognition diagnosis.

4.4.2 Comparison of the Results Before and After Removing the Background

The training and testing results of the ResNet50 and VGG16 models before and after the background removal are compared, the accuracy rates before and after the background removal of the ResNet50 model and before data augmentation are illustrated in Table 4 and Fig. 8 (a), and the accuracy rates before and after the background removal of the ResNet50 model after data augmentation are illustrated in Table 4 and Fig. 8 (b). The comparison of accuracy rates before and after the background removal for the VGG16 model before data augmentation is illustrated in Table 5, Fig. 8 (c), and the comparison of accuracy rates before and after the background removal for the VGG16 model after data augmentation is illustrated as Table 5, Fig. 8 (d).

TABLE 2
ACCURACY OF PNEUMONIA IDENTIFICATION WITHOUT REMOVING BACKGROUND

Epoch		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Before data augmentation	**ResNet50**	63.400	79.600	85.400	86.200	86.200	85.800	89.000	88.600	90.400	90.000
	VGG16	83.200	85.600	92.200	86.600	86.000	84.600	88.400	85.800	86.800	86.600
After data augmentation	**ResNet50**	49.200	55.000	68.000	71.000	80.600	85.400	85.800	79.800	91.000	86.400
	VGG16	82.600	87.600	90.200	89.200	91.800	87.400	90.400	94.600	89.800	91.600

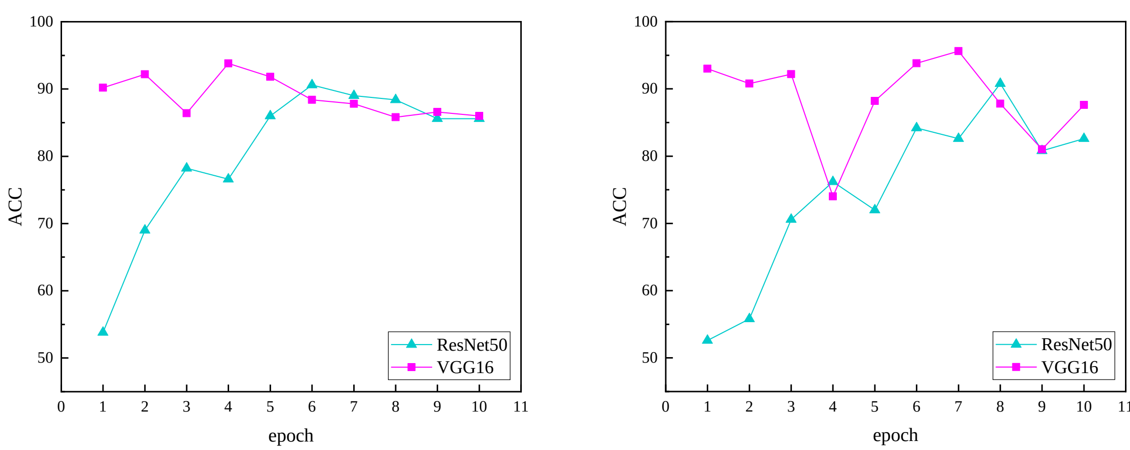


(a) **(b)**

Fig. 6: Accuracy comparison for ResNet50 and VGG16 model before removing background, (a) is before data augmentation, (b) is after data augmentation

TABLE 3
ACCURACY OF PNEUMONIA IDENTIFICATION WITH REMOVING BACKGROUND

Epoch		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Before data augmentation	**ResNet50**	53.800	69.000	78.200	76.600	86.000	90.600	89.000	88.400	85.600	85.600
	VGG16	90.200	92.200	86.400	93.800	91.800	88.400	87.800	85.800	86.600	86.000
After data augmentation	**ResNet50**	52.600	55.800	70.600	76.200	72.000	84.200	82.600	90.800	80.800	82.600
	VGG16	93.000	90.800	92.200	74.000	88.200	93.800	95.600	87.800	81.000	87.600



(a) **(b)**

Fig. 7: Accuracy comparison for ResNet50 and VGG16 model after removing background, (a) is before data augmentation, (b) is after data augmentation

TABLE 4
ACCURACY OF PNEUMONIA IDENTIFICATION BEFORE AND AFTER BACKGROUND REMOVAL BY RESNET50

Epoch		1	2	3	4	5	6	7	8	9	10
Before data augmentation	**Before removing background**	63.400	79.600	85.400	86.200	86.200	85.800	89.000	88.600	90.400	90.000
	After removing background	53.800	69.000	78.200	76.600	86.000	90.600	89.000	88.400	85.600	85.600
After data augmentation	**Before removing background**	49.200	55.000	68.000	71.000	80.600	85.400	85.800	79.800	91.000	86.400
	After removing background	52.600	55.800	70.600	76.200	72.000	84.200	82.600	90.800	80.800	82.600

TABLE 5
ACCURACY OF PNEUMONIA IDENTIFICATION BEFORE AND AFTER BACKGROUND REMOVAL BY RESNET50

Epoch		1	2	3	4	5	6	7	8	9	10
Before data augmentation	**Before removing background**	83.200	85.600	92.200	86.600	86.000	84.600	88.400	85.800	86.800	86.600
	After removing background	90.200	92.200	86.400	93.800	91.800	88.400	87.800	85.800	86.600	86.000
After data augmentation	**Before removing background**	82.600	87.600	90.200	89.200	91.800	87.400	90.400	94.600	89.800	91.600
	After removing background	93.000	90.800	92.200	74.000	88.200	93.800	95.600	87.800	81.000	87.600

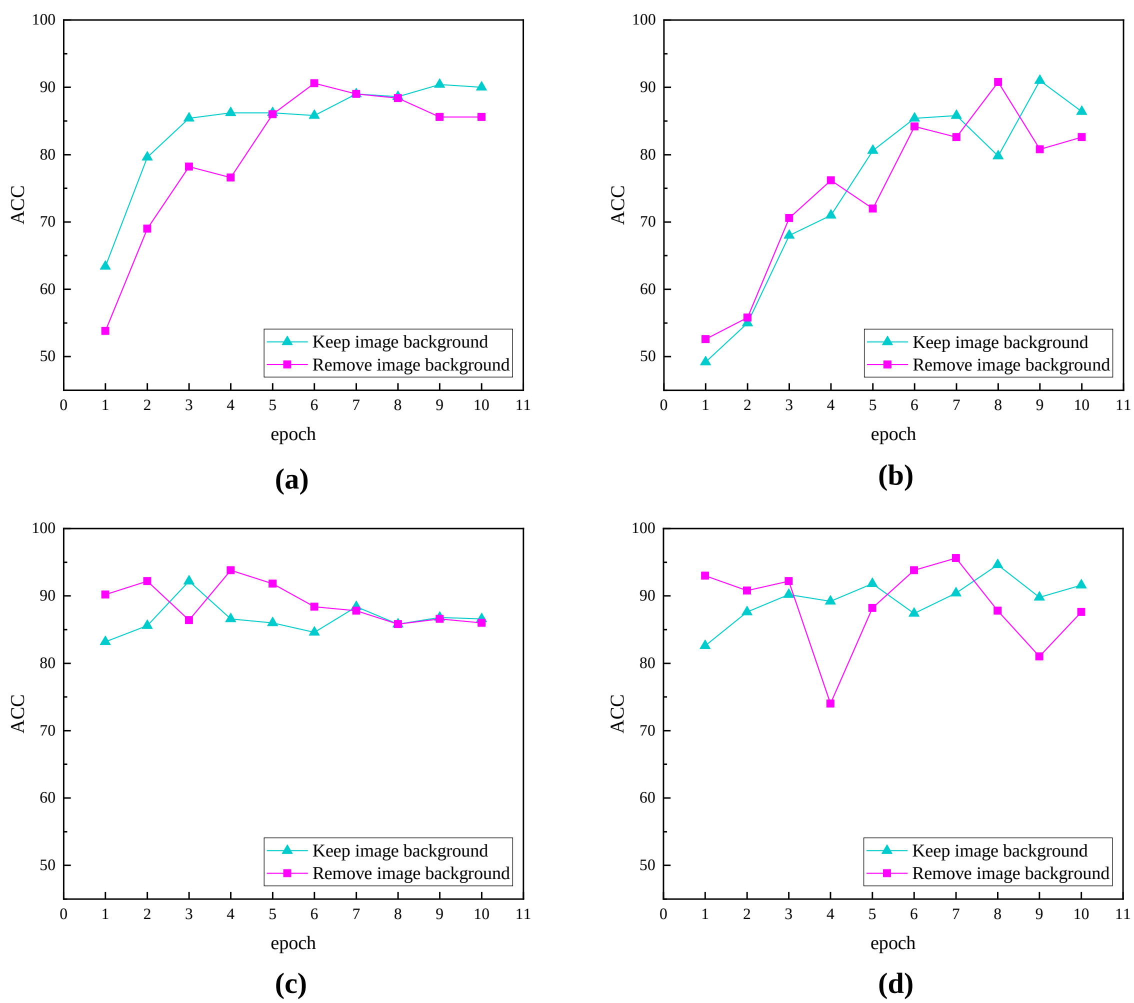


Fig. 8: Accuracy comparison of image background keeping and removing, (a) is accuracy comparison of ResNet50 before data augmentation, (b) is accuracy comparison of ResNet50 after data augmentation, (c) is accuracy comparison of VGG16 before data augmentation, (d) is accuracy comparison of VGG16 after data augmentation

According to the above analysis, for the ResNet50 model, the effect of pneumonia recognition accuracy after removing the background is the same as that before removing the background. This is due to the deeper depth of the ResNet50 model, which can achieve higher accuracy for small datasets, but ResNet50 cannot better utilize its advantages and is not sensitive to data changes. For the VGG16 model, the accuracy of pneumonia recognition is considerably improved after removing the background both before and after data augmentation. The highest accuracy of the VGG16 model test results with the background removed after data augmentation can reach 95.600%, which is due to the simpler structure of the VGG16 model compared with the ResNet50 model and is suitable for training tests on small-scale datasets.

We have also briefly compared the proposed method with some related work. The deep transfer learning method proposed by Liang et al. [28] for pneumonia X-ray image recognition can achieve the accuracy of 90.500%. Harsh Sharma et al. [35] performed recognition of pneumonia X-ray images through different CNN structures with a maximum accuracy of 90.680%. The confidence-aware anomaly detection (CAAD) model proposed by Zhang et al. [39] for screening for viral pneumonia had the accuracy of 83.610%. Yusuf Brima et al. [46] proposed a recognition method for COVID-19 based on deep transfer learning with the accuracy of 94.000%. Compared to the previous methods, the maximum accuracy of the proposed method is 95.600%. Therefore, for the pneumonia recognition, a better test result can be achieved, which also better illustrates the effectiveness of the pneumonia recognition method considering the image background proposed in this paper. However, the dataset used in this paper differs from those employed in related research work. Further rigorous comparative analysis of the various methods is needed in future investigations to propose more efficient pneumonia recognition models.

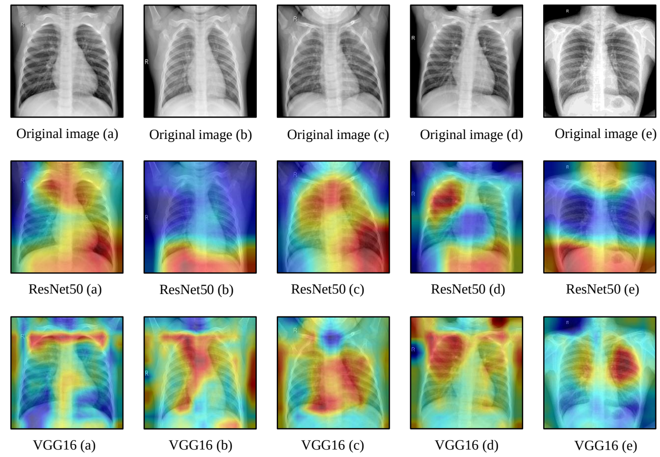


Fig. 9: Normal lung X-ray image of Grad-CAM before removing background

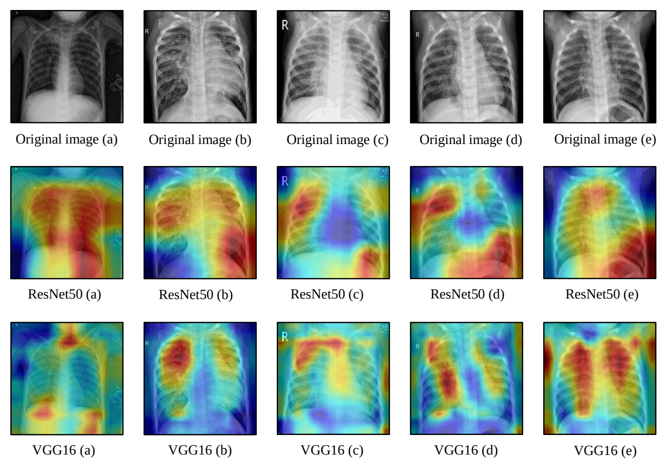


Fig. 10: Pneumonia lung X-ray image of Grad-CAM before removing background

4.5 Explainability Analysis of Deep Learning Model

Employing the Grad-CAM method, five images of normal lung X-ray images and pneumonia lung X-ray images before and after the background removal are randomly selected. The heatmaps of the ResNet50 and VGG16 models before and after the removal of the background to identify the pneumonia X-ray images are illustrated in Fig. 9∼12. Fig. 9 is the heatmap of normal lung X-ray images before the background removal identified by the ResNet50 and the VGG16 models, and Fig. 10 is the heatmap of pneumonia X-ray images after the background removal identified by the ResNet50 and VGG16 models. Fig. 11 is the heatmap of healthy lung X-ray images after the background removal identified by the ResNet50 and VGG16 models, and Fig. 12 is the heatmap of pneumonia X-ray images after the background removal identified by the ResNet50 and VGG16 models. The red part indicates the region of high attention, the blue part indicates the region of low attention, and the yellow part indicates the attention between the two.

From the analysis of Fig. 9∼12, it can be seen that both the ResNet50 and the VGG16 models can identify the key lung locations, in which the recognition of the ResNet50 model is coarser, the focus range is larger, and there are problems, such as inaccurate recognition locations of some images. In contrast, VGG16 identifies more finely compared with the ResNet50 model, with a smaller and more accurate range of attention, and can focus more accurately on the lung texture at key locations, thus realizing the classification of pneumonia X-ray images, which can better explain the higher accuracy of the VGG16 model compared with the ResNet50 model.

Before removing the background, the ResNet50 and the VGG16 models, although able to identify the key lung locations, also generate unnecessary attention in the abdomen, mandible, etc., which may affect the results of the final model test. Therefore, we remove other background factors, such as mandible, abdomen, and arm, that are not relevant to pneumonia identification and keep only the heart and lung parts for pneumonia identification. It can be seen that the attention to irrelevant locations is considerably reduced, and the model focuses more on the key locations of the lungs, thus improving the accuracy of pneumonia recognition and enhancing the performance of the model.

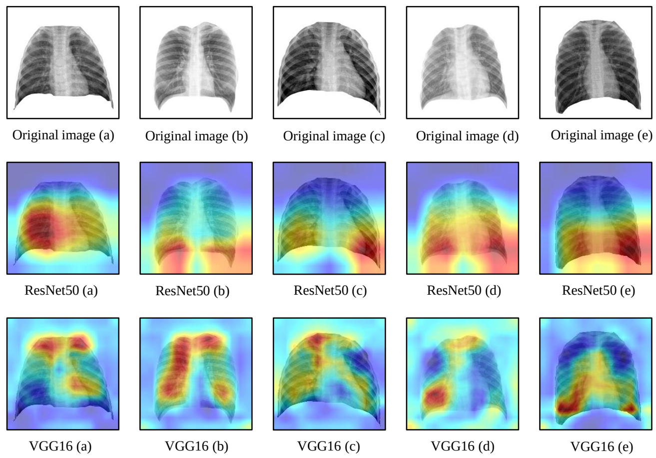


Fig. 11: Normal lung X-ray image of Grad-CAM after removing background

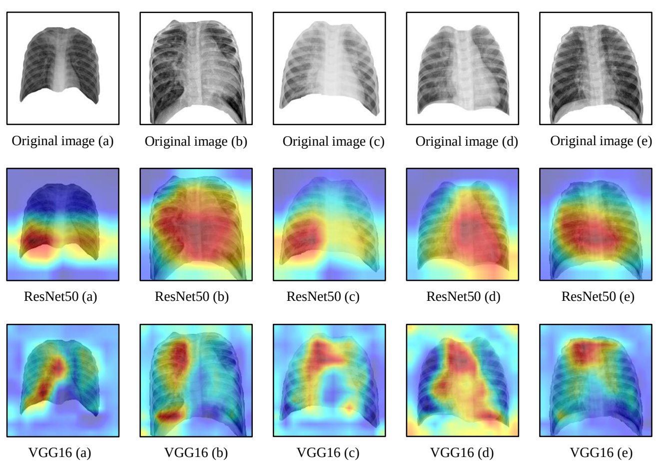


Fig. 12: Pneumonia lung X-ray image of Grad-CAM after removing background

5 Discussion

In this paper, we propose a deep learning method that considers image background factors and an interpretable analysis of the proposed method using explainable deep learning. The transfer learning idea is employed to apply the ResNet50 and the VGG16 pretrained deep learning models for pneumonia X-ray image classification, which reduces the problem of deep learning models requiring massive training data. In addition, data augmentation is applied to the ResNet50 and VGG16 models to expand the dataset and further resolve the problem of using a small dataset, thus improving the accuracy of pneumonia X-ray image recognition. Finally, deep learning models for pneumonia X-ray image classification are constructed, and the corresponding explainability analysis is carried out to visualize the test results of the models, which solves the ”black box” problem of deep learning models to obtain a trustworthy deep learning model for pneumonia recognition, which can be applied in real life to protect people’s health.

However, only the existing pretrained ResNet50 and VGG16 models are employed in this paper, which still has some limitations for pneumonia X-ray image classification. Additionally, there are still some shortcomings for the interpretation of the two types of deep learning models, such as the perspective of the internal structure of the models. The dataset in this paper is small, and better test results cannot be obtained for some models that apply to large sample datasets, and it is impossible to judge the case of pneumonia recognition using deep learning models for large datasets. In addition, since lung X-ray images with high accuracy after background removal cannot be obtained by image segmentation and graph extraction, the manual processing method is used to obtain them in this paper, which is accurate but less efficient and has some difficulties when processing large sample datasets

In this paper, only two deep learning models are employed for pneumonia recognition. In the future, we will compare and analyze more models to filter out the deep learning models with higher accuracy and efficiency. In addition, the deep learning models will be further modified, reconstructed, and selected to create a deep learning model that is more suitable for the classification of lung X-ray images, which can then be employed in the efficient computer-aided diagnosis of pneumonia.

For pneumonia X-ray images, the dataset used in this paper is small, which is caused by the difficulty of obtaining datasets in the field of medical image recognition. In the future, we consider acquiring more pneumonia X-ray image data, conducting corresponding deep learning pneumonia recognition effect comparison analysis for large datasets, and selecting a deep learning model for pneumonia recognition that is more suitable for practical applications. In addition, we can also classify the types of pneumonia, such as bacterial pneumonia, viral pneumonia, to achieve a refined diagnosis of pneumonia and the effect of ”symptomatic treatment”.

At present, the whole world is plagued by COVID-19, and COVID-19 brings a great threat to the world economic construction and people’s life safety [47], [48]. COVID-19, as a kind of viral pneumonia, has several differences from the X-ray pictures of common pneumonia [49], [50]. Therefore, we hope to achieve a rapid diagnosis of X-ray pictures of COVID-19 using deep learning methods in the future and thus to improve the efficiency and accuracy of COVID-19 identification to accelerate the victory over the epidemic.

For background consideration, in the future, we will propose a more accurate image segmentation and extraction method to achieve efficient extraction of lung X-ray images with the background removed to obtain a deep learning model of pneumonia X-ray images with higher accuracy.

6 Conclusion

In this paper, we propose a deep learning method that considers the image background factors, and explainable deep learning is employed to analyze the proposed method understandably. The essential idea is to employ the existing pretrained deep learning model, remove the image background, improve the pneumonia recognition accuracy, and apply the Grad-CAM method to obtain an explainable deep learning model for pneumonia identification of X-ray images with high accuracy and considering the image background.

The results show that (1) after removing the image background, the highest accuracy of the VGG16 model with 10 epochs can reach 95.600%. Therefore, the deep learning method considering the image background can improve the accuracy of the deep learning model for pneumonia X-ray image identification. (2) According to the Grad-CAM heatmap results, after removing the image background factors, the attention of both the ResNet50 and VGG16 models to irrelevant background factors is considerably reduced, and the attention to the key locations of the lungs is increased.

Future work is planned to establish a high-precision and people-trusted pneumonia recognition model. Therefore, we further improve the efficiency and accuracy of pneumonia identification and obtain deep learning models that can be employed for the identification of practical pneumonia X-ray images.

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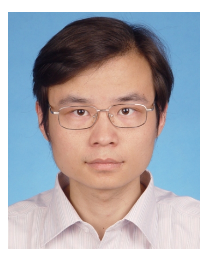

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