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Deep Learning Based Efficient Pneumonia Detection in Chest X-Ray Images

Mr. K. Soundararajan[1], J. Jeshmitha[2], N. Kannika[3*] & V. Karthika[4]

[1]*Assistant Professor, Department of Information Technology, Vivekanandha College of Technology for Women, Elayampalayam, Tiruchengode, Namakkal, Tamilnadu, India.* [2-4]*Department of Information Technology, Vivekanandha College of Technology for Women, Elayampalayam, Tiruchengode, Namakkal, Tamilnadu, India.*
*Corresponding Author (N.Kannika) E-mail: kannikan2002it@gmail.com**

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ABSTRACT

Medical motion plays an essential role in clinical treatment. The deep neural network is an emerging machine learning method that has proven its potential for different classification tasks. Notably, the convolutional neural network dominates with the best results on varying image classification tasks. However, medical image datasets are hard to collect because it needs a lot of professional expertise to label them. Although it can be detected and treated with very less sophisticated instruments and medication. Therefore, this paper how to apply the Convolutional Neural Network (CNN) based algorithm on a chest X-ray dataset to classify pneumonia. The objective and automated detection of pneumonia represents a serious challenge in medical imaging because the signs of the illness are not obvious in CT or X-ray scans. Further on, it is also an important task, since millions of people die of pneumonia every year. Deep learning-based methods have shown good generalization traits over various problem domains, which prompts researchers around the globe to work tirelessly and come up with more efficient and effective models than earlier. However, this robust nature comes at the cost of high computational resources and, in general, it requires a huge amount of data to train the model efficiently. The latter requirement sometimes cannot be fulfilled, especially in the biomedical field. The main goal is to propose a solution for the above-mentioned problem, using a novel deep neural network architecture. The proposed novelty consists of the use of dropout in the convolutional part of the network. The proposed method was trained and tested on a set of labeled images. This project aims to introduce a deep learning technology based on the computational neural network, which can realize automatic diagnosis of patients with pneumonia in X-ray images.

Keywords: Pneumonia; Chest X-ray images; Convolutional neural network; Deep transfer learning.

1. Introduction

Pneumonia is an acute respiratory infection that affects the lungs. It is a fatal illness in which the air sacs get filled with pus and other liquid [1]. Treatment of bacterial pneumonia is done using antibiotic therapy, while viral pneumonia will usually get better on its own [2]. It is a prevalent disease all across the globe. Its principal cause includes a high level of pollution. Pneumonia is ranked eighth in the list of the top 10 causes of death in the United States [3]. The problem is even worse for developing and under-developed counties.

The proposed method would help in the early detection of the disease, and consequently, it may benefit many. Convolutional Neural Network (CNN) is used in multiple computer vision tasks, such as image classification, object detection, etc. Computer vision is a relevant application field of Artificial Intelligence (AI), which comes as no surprise, mainly because it offers solutions to a vast amount of problems that humans face in the 21st century. One of the fields of computer vision that has proved to be fruitful again and again is medical image diagnosis with the aid of AI. Further, with significant data growth in healthcare communities, medical data could be analyzed for early disease detection.

Furthermore, reduction of computation complexity has been taken into account here. To this end, preprocessing for the input image data is necessary. On the basis of the evaluation experiments the proposed mechanism not only achieves reduction of computations, but also performs well compared with the conventional machine learning methods and some prevalent convolutional neural networks. This paper proves that the proposed model can provide

accurate classification despite the reduced number of trained parameters and can even benefit from this property in terms of efficiency. Computer-aided diagnosis using artificial intelligence based solutions is becoming increasingly popular these days [5],[6]. The study includes Convolutional Neural Network to detect pneumonia (bacterial or viral) using chest X-ray images databases.

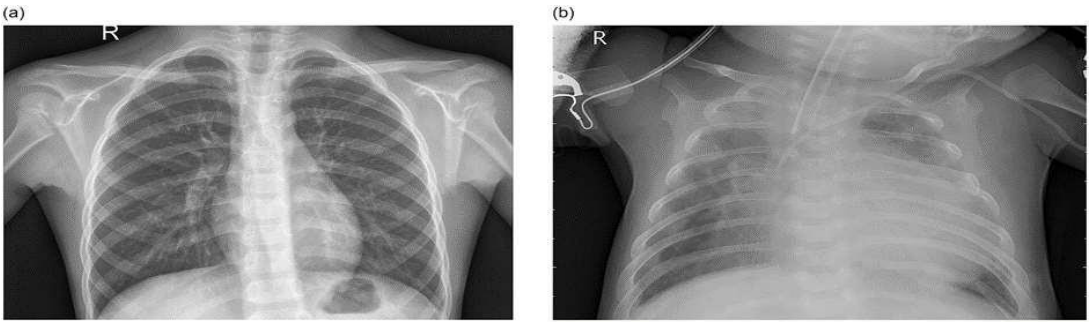

Figure 1. (a) Normal chest X-ray images, (b) Chest X-ray images of patient with pneumonia

The proposed system discusses solving a medical problems, Pneumonia which is a dangerous disease that may occur in one or both lungs usually caused by viruses, fungi, or bacteria. This disease is detected based on X-rays. Chest X-rays are taken from the dataset provided which contain various x-rays images differentiated by two categories “Pneumonia and Normal". A deep learning model is created which actually tells whether the person is having pneumonia diseases or not.

On the basis of the investigations about pneumonia diagnosis realized by computer vision technology, most of the researchers have put their interest on CNN. Even if some of them achieve a good performance in pneumonia diagnosis. CNN indeed requires a high computational power. Therefore, it is essential to reduce computation complexity of the entire automatic diagnosis mechanism. To this end, this work-on-progress chooses a machine learning-based method combined with a pre-process mechanism that offers the ability of dimensionality reduction for image data, or reduction of computational complexity.

2. Literature Survey

Pneumonia

Pneumonia is actually a lung infections mainly caused due to a variety of organisms, like viruses, bacteria etc. When this infection caught the victim the windpipe (air sacs) of the patient became inflamed and pus-filled up in air sacs. All over the world pneumonia is at the top of those diseases which are causing death all over the world. Every year more than 50000 people, mostly old age, die because of pneumonia. All this is due to the lack of early diagnosis of disease. Therefore it's not possible to recognize or identify the disease by just looking at the X-Ray. There were many methods and techniques introduced inthe previous studies by the help of Artificial Intelligence

Facts and Finding

This survey is categorized into two major Al divisions: machine learning and deep learning. Further methods of machine learning and deep learning are explained below. Machine learning is a subfield of Artificial Intelligence (Al). The goal of machine learning generally is to understandthe structure of data and fit data into modelsthat can be

seen and utilized by people In machine learning tasks are by and large characterized into supervised and unsupervised.

Deep Learning

As we know deep learning is a very well-known method used in Al. There are many researchers who work for pneumonia detection using deep learning methods Jae Hyun Kim et al took advantage and used commercial deep learning in their research. An exploration Clinical approval of deep learning calculation for identification of pneumonia on chest radiographs in crisis division patients with intense febrile respiratory disease was proposed by JaeHyun Kim et al (2020). Deep learning calculation is being utilized in this exploration to identify the pneumonia in crisis office patients. 377 sequential patients dataset were gathered and the calculation applied on their X-beam to recognize the pneumonia. This examination results that the proposed calculation works productively and gets pneumonia obvious on the chest x-ray beams. Deep learning-based methods are already being used in various fields [7-11].

Convolutional Neural Network

LeCun et al. [4] first used CNN, in 1989, for handwritten zip code recognition. This is a type of feed-forward network. The main advantage of CNN compared to its predecessors is that it is capable of detecting the relevant features without any human supervision. Pneumonia is a diseasewhich kills around 50000 people each yearglobally therefore adequate treatment and cure for this must be made important for precaution of the deaths. This research tried to obtain some of the state-of-the-art results for the detection of pneumonia using chest X-rays. For the detection purpose convolution neural architecture was leveraged which allowed us to obtain the spatial significance of the data in the images to correctly classify the chest X- rays to be prone to pneumonia or not. George Thomas et al (2018) disclose to us how we might identify pneumonia by utilizing CNN techniques just as group the viral bacterial pneumonia based on perception and assessment in CNN. For usage of this technique Pediatric CXRs dataset was utilized. This examination results that by applying CNN-put together a choice emotionally supportive networkwith respect to the dataset one can identify and recognize various kinds of pneumonia Rachna Jain et al., as of late in (2020) introduced this exploration where they prepared the system which can group the pictures into pneumonia and non- pneumonia classification. Datasets for the usage of this model were gathered from theKaggle site. The system is utilized progressively. This investigation results that the introduced models are profoundly precise and steady. The moderator points later on to improve the precision of grouping of their introduced models. Accuracy recall and F1 performance models were used. U-Net [14], SegNet [15], and CardiacNet [16] are some of the prominent architectures for medical image examination.

Deep learning algorithm based on neural network were implemented to detect pneumonia. X-Ray image dataset was usedto implement the organized trained model. This steady concludes that the performanceis mostly due to the deep framework of CNN that uses the power of extracting different stage features, which resulted in a better generalization ability.

As well as in the future, the addition of more data augmentation techniques can increase the productivity of training and use larger datasets to increase accuracy results. Min-Jen Tsai et al. (2019) introduced their examination on

pneumonia location utilizing Machine learning. Creatorproposed a calculation which was 144 layers Convolutional neural system prepared on chest X-Rays . The datasets were utilized ImageNet dataset and Chest Net dataset. They think about the two outcomes from pre-prepared and after-prepared. This investigation finishes up following a few focuses:

- A well-tuned CNN provides better results than a CNN trained through scratch;
- The proposed model only detectspneumonia, not the subtypes;
- Classifiers quality can be increased. Because the focus is on the classification there is no segmentation for detection of pneumonia.

The principal goal of creators was to make a classifier which can distinguish pneumonia from the chest- X-Ray of patients. They picked the dataset for this reason from the Kaggle site. The three diverse prepared models can recognize the pneumonia from the frontal perspective on X-beam which was proposed in this exploration. This exploration presumes thatthis research can better social insurance framework.

Pre-Trained CNN Method

Dimpy Varshini et al., used pre-trained CNN models with supervised classifier algorithms in the state of art of pneumonia detection. They used the Chest X-ray 14 dataset that was released by Wang et al. Author said that the limitation with their model was that there is no history of the inclusive patient considered in the presented evaluation model and only.

Frontal Chest X-Ray were used for the experiments. Early diagnosis of a diseases is the basic need of this or for this regard Katie Stipanskaya et al., proposed an algorithm to detect pneumonia from chest X-ray. Publicly available dataset were used to apply the proposed algorithm. Extended ChesNet used here to classify multiple thoracic pathologies. The suggested algorithm detects pneumonias from frontal view chest X-ray images and also detects multiple diseases outperforms previous state-of-the-art on Chest X-ray.

Sheikh Rafiul Islam et al., proposed their research on the automatic detection of pneumonia. Author suggests a compressed sensing-based deep learning framework to detect pneumonia to help out the medical practitioners. Experiment on Mendeley CXR image dataset was performed using the proposed methodology of this research. This study concludes that an automatic computerized system using CNN methods could be used to detect pneumonia which is proposed here in this research and in the future proposed method may be extended as a generalized automatic computerized system to assist the medical field. Network which was used was a simple multilayer network with Convolutional and 3 fully connected layers and there was a reconstruction model for compressedsensing Image

In 2018 the radiography group proposed their exploration on distinguishing proof of pneumonia by utilizing chest radiographs, Open source profound learning technique was being utilized in the article recognition which incorporates worldwide and neighborhood includes discovery capacity 3000 chest radiographs were remembered for the test procedure. This investigation reasons that three elements are significant in the method of pneumonia location:

- An architecture that includes local and global context;
- Use a good sense for backgroundand foreground;
- Accuracy.

Transfer Learning (TL)

It is a technique in deep learning that focuses on taking a pre-trained neural network and storing knowledge gained while solving one problem and applying it to new different datasets. Pan and Yang [12] used domain, task, and marginal probabilities to propose a framework for better understanding transfer learning. In this article, knowledge gained while learning to recognize 1000 different classes in ImageNet would apply when trying recognize the diseases.

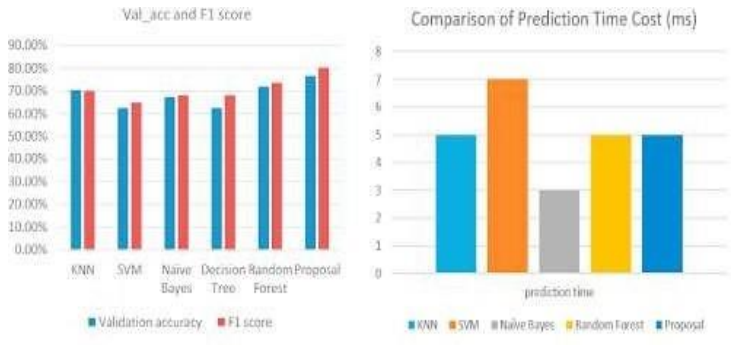

Figure 2. The evaluation result of the validation accuracy

3. System Analysis

Existing System

There is interest in using convolutional neural networks (CNNs) to analyze medical imaging to provide computer-aided diagnosis. In recent years, more than one million adults are hospitalized with pneumonia and around 50,000 die from thedisease every year in the US alone. Chest X-rays are currently the best available method for diagnosing pneumonia, playing a crucial role in clinical care and epidemiological studies. However, detecting pneumonia in chest X-rays is a challenging task that relies on the availability of expert radiologists. Zech et al., presented a mechanism on the basis of CNN that automatically detects pneumonia fromchest X-rays. However, the image dataset trained in their work is inaccessible for other researchers. This kind of condition lasts, until Daniel et al. presented their investigation works and opened their chest X-ray image dataset in 2018.

Disadvantage of the Existing System

- Diagnosis is based on symptoms and physical examination which may out be accurate at all times;
- The computation complexity of the existing solution is more where additional algorithm are used to reduce them.

Proposed System

Fast the model uses the Batch Normalization to normalize images so that the data have a similar distribution which yields faster convergence during the training. Normalized images are then split into training and testing images.

80% of the images are training images and the remaining 20% images are placed into the testing set. The images were split in a way that retains the same proportion of classes in the train and test sets that are found in the entire original dataset, meaning that the proportion of healthy and unhealthy lungs in the training and testing dataset are identical. The new model follows the structure of convolutional layer, batch normalization layer, activation layer, whichis finally followed by a pooling layer.

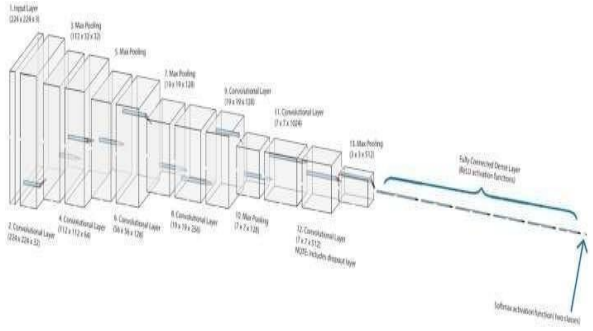

Figure 3. Structure of the proposed network model

The Overall Workflow of the Project

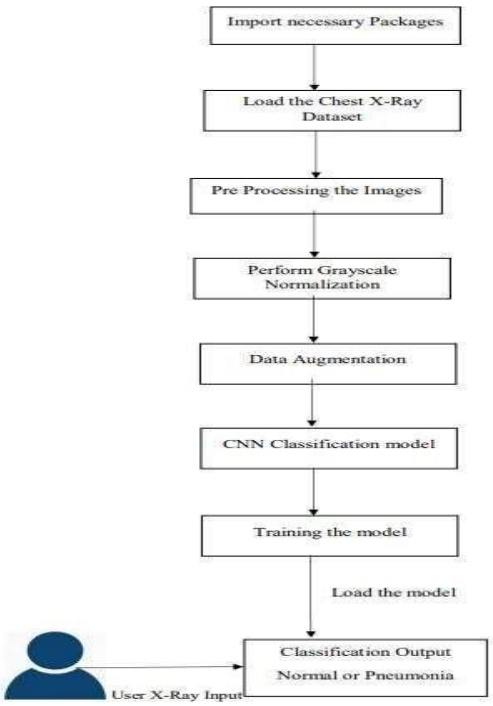

Figure 4. Workflow of the study

As depicted in Figure 2, the model follows the pattern of convolutional layer followed by pooling layer, Filters are essentially the elements that enable the neural network to pick up on specific patterns such as edges. Filters are often initialized in many ways but ultimately that can be omitted, because the purpose of the convolutional layer is to learn the specific features duringthe training, they are basically the mechanism needed for feature extraction. At last the matrices are flattened and are then connected to the dense fully connectedlayers, which are responsible for the classification. It is worth nothing that within each convolutional block in the model's architecture there is a batch normalization layer. Pooling layers usually follow convolutional layers in order to reduce the number of

parameters and dimensions of the feature maps. The experimental results show that the accuracyrate of this project is 92.6%, the precision rate is 93%, the recall rate is 96%, and the FI score accuracy rate is 94%.

Advantage of the Proposed System

- The diagnoses for the images were graded by two expert physicians before being cleared for training the Al system;
- A grayscale normalization is performed to reduce the effect of illumination differences. Moreover, the CNN convergesfaster on [0.1] data than on [0.255];
- In order to avoid over fitting, the dataset is to be expanded artificially. The existing dataset can be made even larger by the process of Data Augmentation techniques.

4. Design

System Architecture

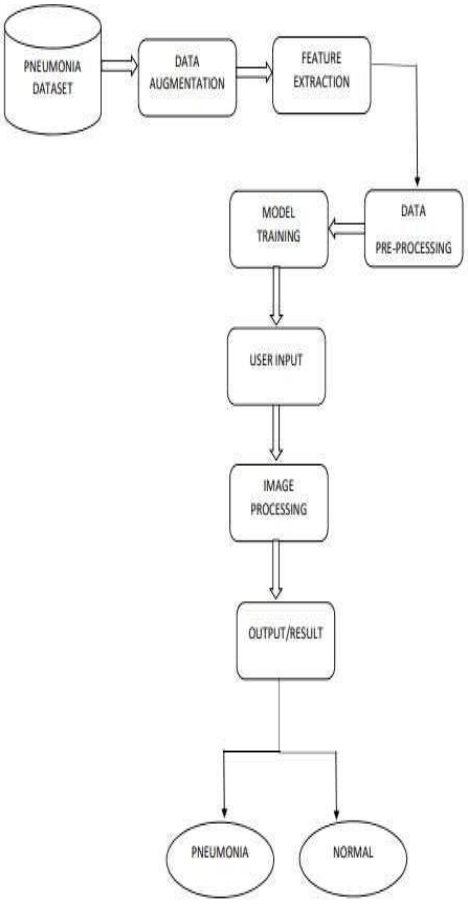

Figure 5. System Architecture

User Interface

Login Page

Login page is accessed by any user who has this application (mainly doctors) with the Email ID and password given to them.

Figure 6. Login Page

Sign Up Page

This page is to make the user register or sign up for the application.

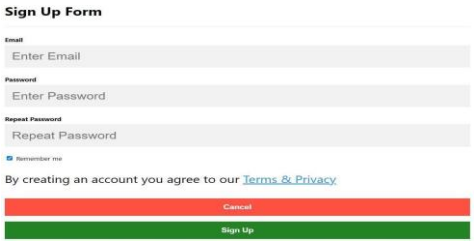

Figure 7. Sign up page

Database Schema

Signup Details Table

This page contains the details of the user who is new and signs up with his/her new account.

SignUp

Email	Password
lkj@gmail.com	abcd&1
Tsk@gmail.com	tsk%123

Figure 8. Signup details table

Pneumonia Detection Module

This page is the final page where the analysis result is obtained.

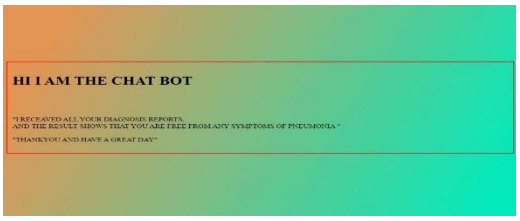

Figure 9. Prediction page

5. Modules Description

User Interface Module

This module deals with the login interface and retrieval of data from the database in the server. The client login with the given login id and password.

Image Preprocessing

Normalization

The images fed to the network models are RGB images, previously resized to the following dimensions 224x224x3. Upon resizing the images, they are normalized by dividing each of the pixel values across the three channels by 255 in order to make the calculations faster and more effective. It is important to normalize images so that the data have a similar distribution which yields faster convergence during the training. Normalized images are then split into training and testing images, 80% of the images are training images and the remaining 20% images are placed into the testing set.

Data Augmentation

In order to avoid overfitting, the dataset needs to be expanded artificially. The existing dataset is made even larger. The idea is to alter the training data with small transformations to reproduce the variations. Some popular augmentations people use are grayscales, horizontal flips, vertical flips, random crops, color jitters, translations, rotations and much more.

Image Data Generator

Keras Image Data Generate class provides a quick and easy way to augment your images. It provides a host of different augmentation techniques like standardization, rotation, shifts, flip brightness changes, and many more.

For the data augmentation, it is chosen to:

Randomly rotate some training images by 10 degrees;

Randomly Zoom by 20% some training images;

Randomly shift images horizontally by 10% of the width;

Randomly shift images vertically by 10% of the height;

Randomly flip images horizontally. Once the model is ready, the training dataset is fitted.

Training the Model

Sequential Model

Batch Normalization

Batch Normalization normalizes the activation between the layers in neural networks to improve the training speed and accuracy. Batch normalization receives as input the output of the convolutional layer. First, it applies a standard normalization to assure zero mean and unit variance and then performs scaling and shifting. This result is then passed to the activation function, which finally provides the input for the next convolutional layer.

Max Pool 2D

Pooling layers usually follow convolutional layers in order to reduce the number of parameters and dimensions of the feature maps. This is performed so that the algorithm could learn faster and become more efficient by

downsampling features it has detected. Overall the main concept behind pooling layers is that they summarize the key points of the feature map, by applying some kind of pooling to it. In this case, max pooling was applied, with both the strides and filter size equaling to 3×3.

Conv 2D

The convolutional layer is data that represents the features learned from the layer. This data is stored in a matrix which at this point gets flattened out so neurons could have full connections to all activations in the previous layer. This allows the network to learn the combinations of these features (in a non-linear way) to make the best possible prediction.

Dropout

Adding dropout layers to a convolutional neural network is one of many regularization techniques commonly used to prevent the network from overfitting. It is worth nothing that dropout layers are only used during the training phase. Dropout layers prevent the model from relying on only a few important weights or features.

Flatten

layer flatten() method is used for converting a multi-dimensional array into one dimensional flatten array or say single dimensional array.

Dense

The dense layer's output shape is altered by changing the number of neurons/units specified in the layer.

6. Implementation

Dataset for Pneumonia Diagnosis

The normal chest X-ray (left panel) depicts clear lungs without any areas of abnormal opacification in the image. Bacterial pneumonia (middle) typically exhibits a focal lobar consolidation, in this case in the right upper lobe (white arrows), whereas viral pneumonia (right) manifests with a more diffuse "interstitial" pattern in both lungs.

Figure 10. Illustrative example of chest X-ray in patient with pneumonia sources

A total of 5863 Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care. For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the Al system. In order to account for any grading errors, the evaluation set was also checked by a third expert. Viral pneumonia

manifested with a more diffuse "interstitial" pattern in both lungs, which was detected by all the fine-tuned architectures [13].

7. Conclusion

Due to the requirements of high prediction accuracy, and limitations of computation complexity, automatic pneumonia diagnosis in a realistic environment becomes a challenge. In this project, a CNN model is proposed to provide an efficient and accurate solution for the pneumonia detection problem based on X-ray images. The main novelty consisted of the placement of a dropout layer among the convolutional layers of the network. Compared with the existing technical methods, the research has achieved the expected results on the currently available datasets. Experiments have shown that the proposed model performs better than its counter candidates in terms of accuracy and efficiency, achieving recall and precision well above 92.6 %. The main finding of this study is the beneficial effect of the dropout layer placed in the convolutional part of a CNN architecture. Besides providing quicker convergence at training, it produces better accuracy at validation and prediction. The application of the proposed network model in infant pneumonia detection based on CXR images represents another proof that smaller CNN architectures built from scratch can easily outperform larger models deployed via transfer learning.

8. Future Scope

(1) In future research work, data preprocessing is further strengthened, improving model generalization capabilities, and continuing to optimize the methods so that research can be applied to a wider range of medical technologies; (2) It proceeds to reflect on realizing other feature clustering algorithms to further reduce the computation cost as well as improving classification accuracy of the entire system; (3) Application migration from desktop to mobile; (4) Diagnosing pneumonia from other imaging modalities such as CT and Ultrasound.

Declarations

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This research did not receive any grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing Interests Statement

The authors declare no competing financial, professional, or personal interests.

Consent for publication

The authors declare that they consented to the publication of this research work.

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