Hybrid Reverse Propagation ANN Adaptive Algorithm Based Deep Learning Image Processing for Pneumonia Detection

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Abstract - *Pneumonia is a syndrome that is caused by bacterial lung disease. This disease is diagnosed using a chest X-ray. Early diagnosis is important for successful treatment. This disease can be diagnosed using X-rays. Sometimes it can be confused with another bacterial disease due to an unclear chest X-ray. Consequently, we need a computer-aided diagnostic system to guide doctors. In this, amalgam backhaul algorithms are introduced to achieve multilayer network erudition. System noise investigation is done using artificial neural network (ANN). The vgg19 convolution neural network model was used to create a user-friendly website for the diagnosis of this disease. Simulated artificial neural network hybrid adaptive back propagation algorithm used for deep learning image processing method in our training phase. The test results for the vgg19 network are with an accuracy of 0.91.*
Keywords: *Pneumonia; Transfer learning; Vgg19; Deep learning; Webpage*

I INTRODUCTION

With the current outbreak of COVID-19, well known as the coronavirus disease, it feels like history is repeating itself and we are going back in time to 1900 as part of the Spanish flu. The coronavirus is a harmful virus that has claimed hundreds of thousands of lives in countries around the world. Older adults and people who have serious underlying medical conditions or previous cases of pneumonia appear to be at higher risk of developing other serious complications from the virus. With the death toll rising and medical assets limited, doctors and health workers around the world are working around the clock to treat patients and prevent the spread of the virus. Severe forms of the virus can cause pneumonia, especially a higher risk of death. It is important to have rapid and direct detection of pneumonia so that patients can receive treatment in time, especially in poor areas.

With increasing scientific progress, there is potential to use tools based on fuzzy learning frameworks to detect pneumonia based on upper body radiographs. Confrontation here would help the closure process, which allows for faster treatment and better scientific results.

Pneumonia is a bacterial infection in one or both lungs that causes lung tissue to become inflamed. Worldwide, this disease affects more than 7% of the population, which is 450 million people, and 4 million die annually [8]. 158,176 deaths were reported in India during 2016 and we continue to have the highest number of child deaths globally. On Earth Pneumonia Day, a report was released that by 2030, more than 11 million children under the age of five will die from this communicable disease [7]. In the 19th century, the revolutionary father of modern medicine, Sir William Osler, said that pneumonia was "the captain of the men of death".

The 1virus can easily1 be transmitted from 1person 1to person1, which 1makes it 1spread rapidly. One of the common symptoms1 of COVID-191 that is easy to identify is 1 fever. Since1 the outbreak of the virus, thermal1 screening has been used in public places1 using infrared 1thermometers1 to check body temperature to identify the indicated1 infected in the crowd. This prevention 1is still missing1 because 1spends a lot1 time1 checking 1body1 temperature1 from 1every person and1most 1important is 1close contact1 of the infected can1 lead to spread1 to 1person who 1does the screening1 or 1from the person in charge of the screening1 to the screened1 people.

Clinical examinations such as chest X-ray, blood test and other techniques are used by doctors to diagnose pneumonia in patients. In this case, the chest X-ray is cheaper due to the development of technology in biomedical equipment. Sometimes doctors don't even detect this disease on X-rays because of defects in the images. Recent technologies such as artificial intelligence may be useful to alleviate the disease. In particular, convolutional neural networks (CNNs) show excellent results for image classification. The main idea behind CNN is that it is a simulated model of the visual cortex of the human brain. Based on the presence of pneumonia, chest X-ray images are classified into a convolutional neural network.

II LITERATURE SURVEY

Researchers [1] compared two CNNs to diagnose pneumonia. To train the model they used to transfer learning and tuning. The results of both networks are compared after the training phase. The accuracy of Xception and vgg19 are 0.82 and 0.87 respectively. And the accuracy for Xception is 0.86 and 0.82 for normal and pneumonia. Accuracy for vgg16 is 0.83 and 0.91 for normal and pneumonia. Here the exception blooms more in detecting pneumonia cases and vgg16 is better in detecting normal cases.

In [2], researchers tried a dissimilar technique for minimizing dimensionality. They used the JSRT dataset, which has 247 X-ray images. The BSE-JSRT dataset can be extracted after removing the bone shadow (dataset 02). Segmented JSRT (dataset 03) and we can have segmented BSE-JSRT (dataset 04). The T-SNE technique is used to remove outliers (dataset 05). Here, the highest accuracy is obtained from dataset 05 which is 0.71 and the lowest accuracy is dataset 04 which is 0.56. From the bone contour 02 dataset, we get an accuracy of 0.65.

In this work [3], the authors used ANN tool to detect lung diseases such as pneumonia, TB. The pre-processing techniques are lung segmentation, which removes the image classification. Back-propagation and feed-forward networks are used for image classification. Using a data set from the Sassoon sanatorium of 80 patients. They achieved an accuracy of 0.92. The limitation is when the CXR position and size change, there is no robustness. In this [4], researchers used CNN techniques such as resnet-50 to diagnose chest diseases using chest X-ray. In preprocessing techniques, the global division takes input and the local branch is trained after discovering a local region of lesions. Here, resnet-50 has an average accuracy of 0.841. AG-CNN increases the accuracy up to 0.868

Researchers in [5] created a cheXNet algorithm that, as a CNN with 121 layers, diagnosed pneumonia. They reduced the image size to 224*224. In addition to normalization, it is based on the standard deviation and mean. The accuracy of cheX Net is 0.435.

The proposed artificial neural network model by Kumar et al. (2021) [6] as an Adaptive Hybrid Backpropagation Algorithm (ANNHBPAA) to remove flapping. ANN adaptive clap termination has been implemented on the image signal and an intelligent real-time noise suppression method based on neural networks.

Here [7] [8] [9] the author took data from 3 different hospitals to detect pneumonia. They used the cheXNet model for classification. And 0.2.0 is used for PyTorch model training. Overall, they scored 0.815 accuracy. But CNN doesn't do well on external data.

Kumar et al. (2020) [10] on active noise control (ANC) systems and achievable simulated results for trans-image facsimile systems. The working principle of the expected intelligent adaptive filter-based noise suppression system is an extension of previous work

III PROPOSED SOLUTIONS

The production and detection of X-rays is – due to the very temperament of the physical exchanges that take place – a "random" process. In the output, the improbability is caused by the laws of nature that govern what happens. From the thermal emission of electrons starting from the X-ray tube filament to the production of X-ray photons as these electrons are accelerated and collide with the anode, every step of the generation process is "statistical" in nature.

For a given level of exposure, the number of x-rays incident on the sufferer is different at different locations on the patient's body. These confrontational x-rays pass through the patient's composition. Some are enveloped by the patient, while others pass through and are absorbed by the imaging detector—another statistically driven process with inherent noise characteristics. Once the x-rays have passed through the patient, the image "information" is contained in the spatial distribution of the x-ray flux.

The patient's anatomy shapes variations in the concentration of X-rays that the imaging system uses to create the image. But superimposed on this image "signal" is the inherent arithmetic "noise" associated with the X-ray production process.

In contrast, when using a large amount of radiation, the visibility of arithmetic noise is very low, perhaps even imperceptible. While this may result in a visually pleasing image, it may mean that an unnecessarily high level of exposure has been used, resulting in overexposure of the patient.

Up to this point, the noise associated with the statistical nature of x-ray production and its subsequent amalgamation by the patient converses. These processes are governed by indispensable laws of nature and determine the basic limit of image quality for any given radiograph.

The final displayed image is brought to a basic image quality threshold, which characterizes the amount of "extra" noise that the detector introduces into the image over and above the noise that was natural when the X-rays were incident, as the detectable quantum efficiency (DQE) of the detector. This is essentially the ratio of the signal-to-noise in the final image to the "unique" signal-to-noise present in the incident X-ray. The detector always adds some amount of noise to the image, so the DQE is forever less than 1, as shown in Figure 1A, 1B and 1C

The variance increases as thicker areas of the corpse - such as the chest - are displayed. Conventional methods of decreasing scatter are collimation, anti-scatter gratings and/or the use of an air gap.

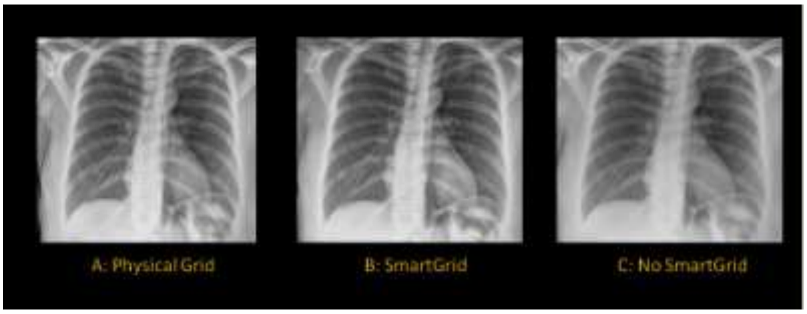

Figure 1 (A) (left): Erect Portable Chest @ 105 kVp, 3.2 mAs with 6:1, 103 In/in Grid; (B) (center): Same patient, same SID @ 95 kVp, 2.8 mAs, no Grid, processed with Smart Grid and (C) (right): Same capture as B without Smart Grid

In a voice communication system, noise suppression using an adaptive digital filter is a well-known technique for extracting a desired speech gesture by removing noise from a noise-encrusted speech signal. Different gradient adaptive grids (GAL) and LMS algorithms are used for noise suppression. Recently, hybrid adaptive neural network algorithms have gained popularity in suppressing the noise available in the communication system. The working principle of the planned intelligent adaptive noise cancellation filter system (AFNCS) is a continuation of the previous work (Kumar et al. [10]), which is further empirically designed and simulated to improve the performance of the input synthetic signal with respect to noise cancellation.

This intelligent hybrid backpropagation algorithm includes both GAL and LMS algorithm. The main objective of the proposed intelligent AFNCS is to obtain a signal as a reference signal and an output noise signal, in the middle of this signal, the noise is eliminated by subtracting the reference signal and the noisy signal from the original signal. Using AFNCS can significantly restore the original signal by eliminating noise through adaptive control and weight adjustment through ANN. The following Figure 2 shows the block representation of the AFNCS which receives an input signal "i(t)" and generates an output signal "O(t)" using an adaptive system and a reference signal "R(t)". Finally, the signal with errore(t) is calculated by finding the difference between the reference signal and the output signal as shown in (1).

$$e(t) = R(t) - O(t) \tag{1}$$

Where't' represents the number of iterations.

Adoption of the hybrid algorithm considers this error signal e(t) as the generating function for execution. This function calculates the required filter coefficients. A minimum error rate indicates that the output signal is the same as the original signal. Here, backpropagation algorithms are used to evaluate the error rate of each neuron. The following Figure 2 shows the structural diagram model of the backpropagation layer of the ANN network. The layer diagram of ANN consists of three layers including input layer, hidden layer and output layer. A hidden layer is active between the input and output layers, which connects the two layers. The overall backpropagation network is affected by the error of a single neuron. The network enables the propagation of an audio or speech signal using ANN and provides an output signal. As shown in Eq. (1) the error results of the output layer are calculated and this error is passed back to the participation layer through the hidden layer until the desired output is obtained.

Further, to reduce its error signal, a weight fine-tuning is performed for each neuron. The proposed hybrid algorithm combines both LMS and GAL backpropagation algorithm, which helps to initiate slow convergence.

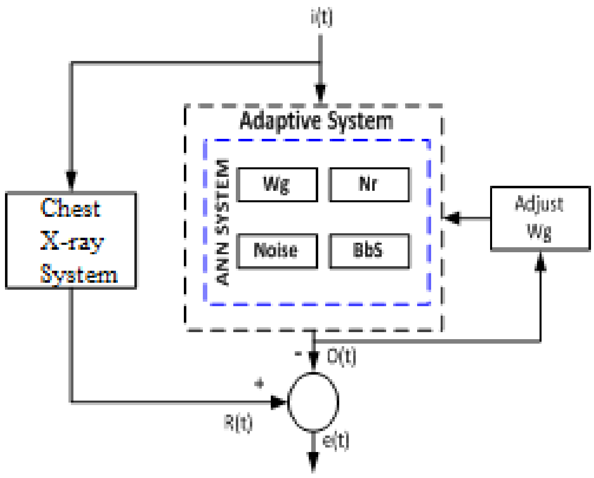

Figure 2 Proposed Adaptive Filter Based Noise Cancellation System (AFNCS)

The proposed AFNCS revealed in Fig.1 adopt adaptive filtering for carrying out of ANN and also adopts a control system for fine-tuning of adaptive filtering parameters. The elements association is trained with ANN by weight fine-tuning. The output of ANN can be obtained by using below formula as given in (2). The following table 1, indicates the parameters used in design.

$$ANN_{out} = \sum i(t) \times W_g \tag{2}$$

Each of the input are accompanied by a weight.

If, $\sum W_g \geq Th$

then the output of ANN will be 1 given in (3)

$$ANN_{out} = 1 \tag{3}$$

A. Data

In this study, a dataset consisting of 5842 chest X-rayimages provided by Guangzhou Women and Children's Medical Centre, Guangzhou. The x-ray images in the dataset are of different resolutions such as 1328x1160 and1762x1535. The number of no pneumonia is 1576, and pneumonia is 4266. Fig. 3 shows some x-ray image samples from the dataset. In our models 0 represents normal cases, 1 represents pneumonia cases.

Table 1 Distribution of Dataset

	Train	Test
Normal	1341	234
Pneumonia	3875	390
Total	5216	624

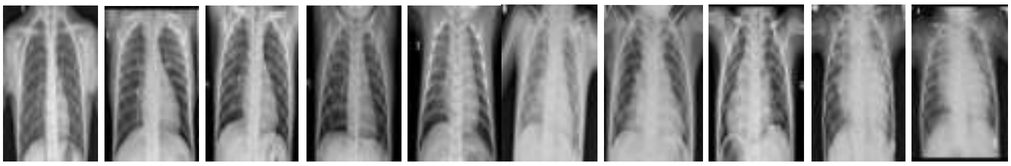

Figure 3: Data samples from the dataset, (a) Pneumonia dataset, (b) show normal case

B. Pre-processing

In Deep learning, we need to get more data for better and reliable results. However, for some problems, there may not be more data or not enough data, especially when it comes to health problems. To avoid this, experts have several solutions to solve this problem. One is data augmentation, which prevents overcrowding and increases accuracy. It is supported in the Keras deep learning library through the image data generator class shown in Figure 4. Here we use scale, shear range, zoom range, horizontal flip. We preprocess the dataset of our X-ray images before using them to diagnose pneumonia. Preprocessing was done as follows:

Unification of X-ray images. Before inserting the images into our model, we shrink the images to 224 * 224 and convert them to NumPy arrays. It may be suitable for feature extraction using VGG. Perform image data argumentation methods is supported in the Keras deep learning library through the Image Data Generator class. Here we use rescale, shear range, zoom range, Horizontal flip.

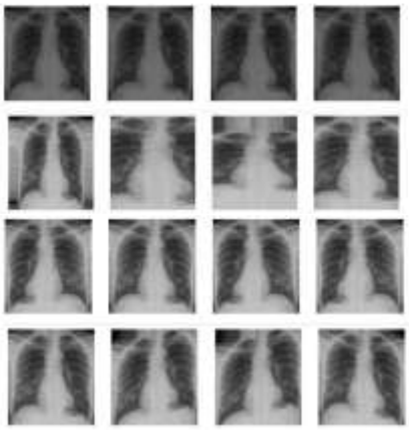

Figure 4 (a) Rescale, (b) Zoom range, (c) Horizontal flip and (d) Shear range

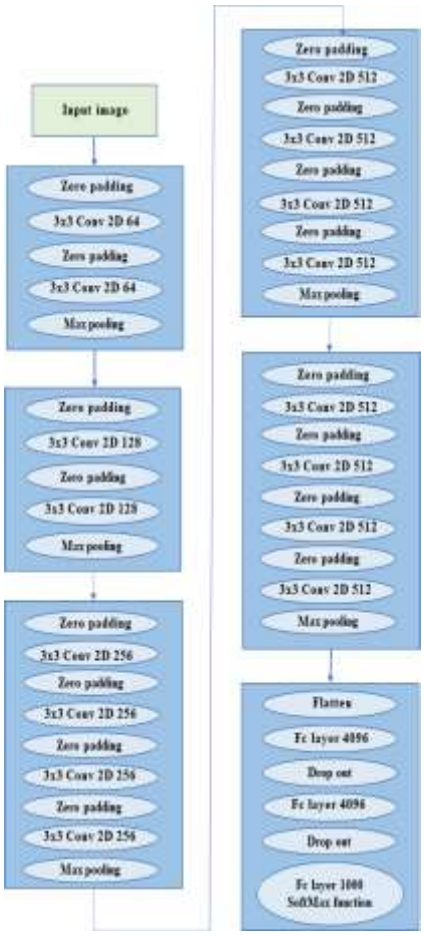

Figure 5 Vgg19 network

A. Architecture

AlexNet, AlexNetOWTBn, GoogleNet, VGG models are most often used in transfer learning. They are a stack of many convolution layers. we have many problems with deep convolutional neural networks, they are network optimization, vanishing gradient problem and degradation problems. VGG NET brings a new idea. It is used to solve complicated tasks and also increases the detection accuracy. VggNet aims to solve the difficulties in the training process of deep convolutional neural networks, saturation and accuracy degradation. In this paper, we used the Vgg19 architecture shown in Fig. 5. The Vgg19 Vgg19 network has 19 layers (16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and 1 SoftMax layer).

3*3 filters are used in the first and second layers in the convolutional layer. Here, a total of 64 layers are used in the first and second layers, resulting in a volume of 224*224*64 as the same convolution used. 3*3 filters are always used with step 1. The next layer is the pooling layer, here to reduce the width and height volume from 224*224*64 to 112*112*64 we will use a max pool size of 2*2 and step 2 Next are 2 convolution layers which as 128 filters. Therefore it gives a new dimension of 112*112*128. Here again a pooling layer is used to reduce the size to 56*56*128. Now 256 filters with 2 convolution layers are added and then reduced to 28*28*256 down sampling layer. Then the stack of 3 convolution layers is separated by 1 max-pooling layer. Finally, in the last pooling layer, we get a volume of 7*7*512, which is flattened into a fully connected layer with a total channel of 4096 and 1 class of soft Max output.

IV HARDWARE EXPLANATION

In the proposed method, the rate of convergence of the increase of the error signal with the value of the St. mechanism is LMS adopted in the proposed method due to its easier implementation, easy calculation, dynamic use of memory capacity and is performed by adjusting the filter coefficient for error reduction.

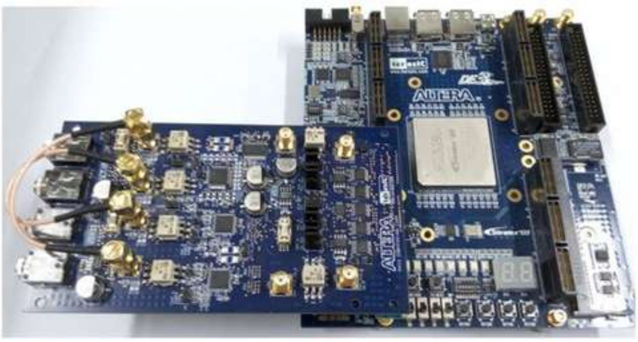

Figure 6 Hardware experimental board

To estimate the performance of the proposed adaptive noise suppression algorithm by replication, the proposed algorithm is implemented on an experimental panel. As seen in Fig. 6, the experimental board includes one main board and one D-to-A/A-to-D converter card. A 16-bit D/A converter card is used to generate two signals. One signal is the communication signals, which are different from the SaS noise. Another signal is SaS noise with a variable time delay. Then these two signals are processed by the proposed algorithm after 16-bit A/D anti-noise conversion.

Initially, the temporal obstacle estimation performance and noise suppression performance in different mixed SNR environments are evaluated in that order. Second, the noise suppression performance of the proposed algorithm is evaluated when the time delay between the primary input and the reference input is changed.

V EXPERIMENTAL METHOD

To verify the feasibility of the proposed algorithm, an FPGA-based adaptive noise suppression system is built, which is shown in Fig. 7. A sine signal with a frequency of 10 kHz is generated by a signal generator and is amplified by an amplifier. Then the signal is transmitted by a loop antenna, the diameter of which is 20 cm. The transmitted magnetic signal is received by a three-channel tunnel magnetoresistive (TMR) sensor (TMR2305). The Y channel of the TMR sensor is parallel to the axis of the loop antenna. The Y channel and X channel of the TMR sensor are analogous to the horizontal plane. The Z channel of the TMR sensor is perpendicular to the horizontal plane. The three channels are perpendicular to each other. After amplifiers, filters and 16-bit A/D converters, the received signals are processed by the FPGA. A switching power supply is used as a noise source to generate impulse noise. A contrast is made between the original signal and the filter output to illustrate the noise suppression effectiveness of the proposed algorithm.

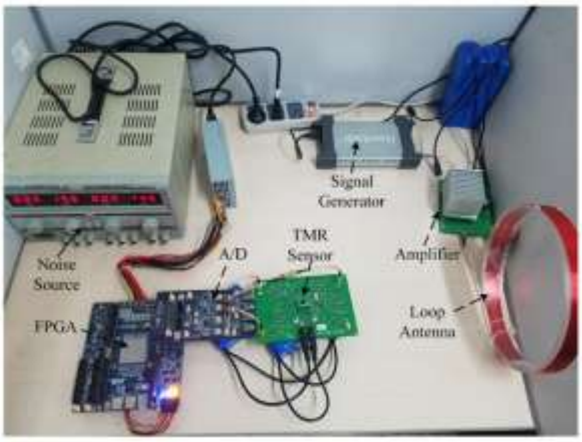

Figure 7 Adaptive noise cancellation system

V ALGORITHMS

In a numerical computational environment, the proposed AFNCS is modeled using the design and implementation of an algorithm based on soft computing. The system specifications that are required to know the performance of the AFNCS algorithm include a 64-bit operating system, an x64-based processor supported by 4.00 GB of installed memory (RAM), where the processor type is Intel® Core™ i-8250U, CPU@ 1.60 GHz , 1.80 GHz. The following algorithm shows the steps associated with the AFNCS design goals to achieve cost-effective adaptive noise cancellation from a sinusoidal (speech) signal.

5.1 PERFORMED TESTS

We tried a lot of testing in different experimental settings to analyze the performance of the proposed model. We changed several network parameters and instructions to build the model. We split the total dataset into 80% for training and 20% for validation. We then experimented on the dataset with our proposed model.

A. Fine-Tuning

Fine-tuning is a method used to increase the efficiency of a feature. Makes small changes to improve the result. Changing the parameters is so fundamental that any change will greatly affect the training process in terms of computation time, convergence speed, and utilization of process units. The parameter settings for the proposed model are shown in Table 2. This fine-tuning process was repeated over and over to improve the accuracy of our model.

Table 2 Parameters setup for the proposed model

Parameter	Value
Batch size	32
Steps per epoch	5216
Epoch	20
Validation steps	624
optimizer	Adam optimizer

B. Training

We collected a total of 5842 radiographs as our database from Guangzhou Women and Children's Medical Center, Guangzhou, where the number without pneumonia is 1576 and pneumonia is 4266. All images are classified into 2 classes (NORMAL & PNEUMONIA) by professional graders and used to train the model . And it is tested with 624 frames.

To train the model, we used a pre-trained vggNet which is initialized using the weights trained on ImageNet, which gave better results.

C. Performance of the Proposed Model

The model we created will start training with a training dataset that consists of both real images and augmented images. We then used the validation dataset to generalize the model.

Furthermore, we can see the distribution of losses (both training loss and validation loss) in the number of epochs in both the training phase and the validation phase.

In this paper with the proposed model, the size of the X-ray images was changed to 224*224. We then performed data augmentation. We used the weights of the pretrained vgg19 model. We used the Adam optimizer and used the SoftMax activation function and the batch size is 32. In our model, we set the learning rate, decay and momentum as default values.

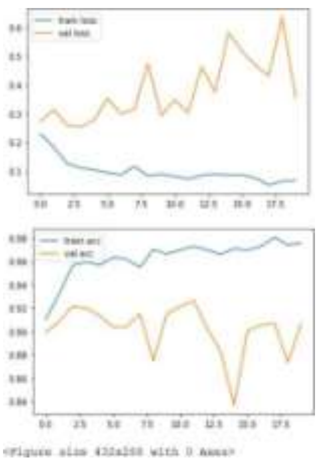

Figure 8 Pretrained VGG-19 performance forpneumonia prediction task

Then we started training our vgg19 model, after training, we have got the accuracy score of the model which is 0.91 where we have used the standard ImageNet weights to train the model shown in figure 8 & 9

We have trained our model up to 20 epochs; the training was stopped owing to the absence of further improvement in both accuracy and loss.

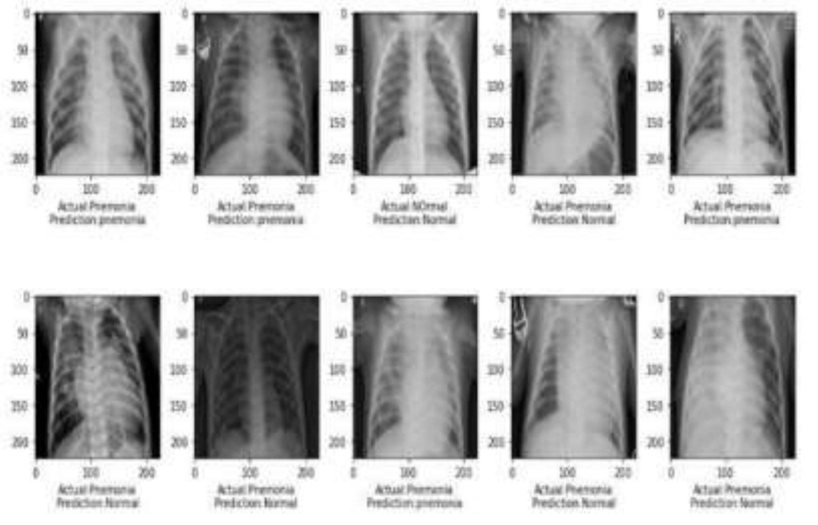

Figure 9 Output of the model predicted with real data

VI RESULTS

To predict pneumonia disease, we have created a webpage using flask API. Once Flask API is designed. We can add the trained h5 file in the flask API then we can use the flask run command in the command prompt to run the flask file and create a running webpage link which we can put in the browser to see the webpage.

Figure 10 Webpage which predicts the disease when input is given

Figure 10 shows the pneumonia disease input screen. Where user can input their x-ray image by pressing the upload button, Once the user clicks on the predict button it will return whether the patient has pneumonia disease or not Fig 6 shows the output of the predicted results.

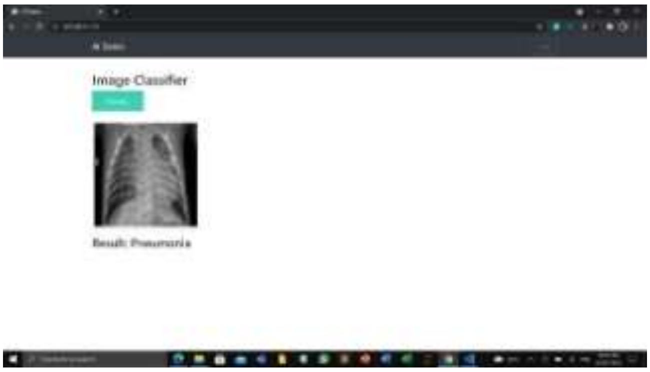

Figure 11 Predicts the disease

Benchmark

In the base paper they have used vgg16 and Xception model for performing training. We have used extension of vgg which is vgg19, which as more trainable parameter and gives better accuracy than vgg 16 which used in our base paper. In vgg 16 we have 138million parameter and in vgg 19 we have 144 million parameters. Vgg 19 is the deeper version vgg 16.

Table 3 Performance attainment

	Algorithm	accuracy
Base paper Result	Vgg16, Xception	0.87, 0.82
Performance attainment	Vgg19	0.91

VII CONCLUSION

A convolution neural network used to automatically identify pneumonia. We used the transfer learning method to train this model and made fine tuning to improve the performance of the model, our model can distinguish between 2 classes of pneumonia or normal. The Vgg19 model we used showed significant performance. The obtained results confirm the achieved valid accuracy up to 0.91 for pneumonia classification shown in Table 3. Finally, we conclude that our model is of great practical importance.

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