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PNEUMONIA DETECTION USING DEEP LEARNING A CONVOLUTIONAL NEURAL NETWORK APPROACH

Shraddha[*1]

[*1]Student, Department Of MCA, NMAM Institute Of Technology, Nitte, Udupi, Karnataka, India.

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ABSTRACT

Pneumonia is an infection of the lungs that can be fatal if not treated promptly. In this article, we provide a deep learning method, specifically the Vgg16 model, for identifying pneumonia in chest x-rays. The Vgg16 model is trained using a huge set of labelled X-ray pictures after the images have been preprocessed to improve the features. The model who has been trained is then applied to fresh pneumonia photos to judge their positivity or negativity. Several metrics, including precision, recall, and F1-score, are used to evaluate the model's efficacy, and the results are compared to those obtained by applying state-of-the-art methods. The testing outcomes verify the effectiveness of the proposed method in detecting pneumonia in X-ray pictures. Medical professionals can benefit greatly from using this method while making diagnosis and other choices.

Keywords: Radiographs, Convolutional Neural Networks, Transfer Learning, Machine Learning, And The VGG16 For Pneumonia Detection.

I. INTRODUCTION

Millions of people worldwide are afflicted by pneumonia, a potentially fatal respiratory infection for which early detection is essential for successful treatment. Although it takes time and is prone to human error, lung X-ray image analysis is one of the methods used to diagnose pneumonia.

Therefore, it is crucial to develop an automated method that can identify pneumonia from lung X-ray pictures. Medical imaging analyses, applications have taken advantage of the amazing potential of convolutional neural network systems , such as for the diagnosis of pneumonia. Here, we employed the well-known CNN architecture VGG16 to analyze chest X-rays for signs of pneumonia. The VGG16 model consists of 16 convolutional layers and 3 fully connected layers. The use of modest 3x3 filters for convolutional layers allows it to train a deeper network with a reduced set of parameters. In order to reduce the spatial size of the feature maps while keeping the important features, the VGG16 model employs max pooling with a stride of 2.

The VGG16 model's elegance and ease of use are two of its primary selling points. The VGG16 model is highly recommended for use in computer vision applications due to its intuitive and flexible design. In recent years, the VGG16 model has been implemented in a variety of medical imaging applications, such as the detection of pneumonia in chest X-rays. By training on the VGG16 model, scientists improved pneumonia detection accuracy and sensitivity significantly.

This useful tool for image classification problems due to its capacity to extractfeatures from images and its deep architecture. In this study, analyzed the VGG16 model's applicability in pneumonia identification from lung X-ray pictures, explain its implementation.

II. PROBLEM DEFINITION

Pneumonia is a serious respiratory disease that affects millions of individuals throughout the world. Physical examination, chest X-rays, and blood tests have traditionally been used to identify pneumonia. However, these procedures are frequently time-consuming, need specialised equipment, and are vulnerable to interpretation by human specialists, resulting in diagnostic mistakes and delays.

As a result, the aim is to create a machine learning model based on the VGG16 architecture that can diagnose pneumonia from chest X-ray pictures with high accuracy. The model should be trained using a dataset of labelled X-ray images, each of which is classed as normal or pneumonia. The model's performance may be measured using common metrics such as accuracy, precision, recall, and F1-score.

A machine learning model based on the VGG16 architecture has significant benefits over traditional methods. For starters, it can automate the detection process, which reduces the need for manual interpretation and saves time. Second, it has the potential to increase pneumonia diagnosis accuracy by utilising the ability of deep

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learning to extract and analyse complicated characteristics from X-ray images. Finally, it can offer a scalable and cost-effective solution that is simple to use in clinical settings.

The long-term objective of this research is to create a reliable and accurate pneumonia detection system that can be utilised in clinical practise to help clinicians make fast and accurate diagnoses, resulting in better patient outcomes.

III. METHODOLOGY

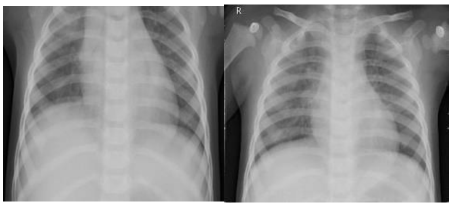
MATERIALS AND METHODS

A. Dataset

A total of 5856 images from frontal chest X-rays were used in this analysis. There are a total of 4266 photographs depicting patients with pneumonia, along with 1590 images depicting healthy individuals. Figure 1 displays numerous X-ray images representative of the collection. The table below shows the breakdown of data used in the training, validation, and testing phases of the proposed model. In our models, patients without pneumonia are represented by 0 and those with pneumonia by 1.

TABLE 1. Distribution of the dataset

	Train	Validation	Test
Pneumonia	2557	854	856
Normal	956	316	318
Total	3513	1170	1174



a)

b)

Fig. 1. The dataset's data samples (a) display casesof pneumonia and (b) shows the normal cases.

Computer with GPU: A machine equipped with an effective GPU for deep learning model training.

Deep learning framework: A deep learning framework such as

TensorFlow: A well-known open-source deep learning and machine learning package called TensorFlow is used to build and train the deep learning model.

Keras: A high-level deep learning API constructed on TensorFlow and used for the development of deep learning models.

NumPy: Numerical computing package for Python that is used for data processing and analysis.

Pandas: A library for data analysis and manipulation, used to load and process the dataset of X-ray images.

OpenCV: In order to pre-process the X-ray images and get them ready for the deep learning model, we used OpenCV, an open-source computervision toolkit.

VGG16: A deep learning model that has already been trained and is based on the VGG16 architecture; it served as the foundation for the creation of the pneumonia detection model

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Methods:

Data preprocessing: The preprocessing of data to make it ready to be used in the model's training. This involves expanding the data to generate a larger training set, scaling the photos to a standard size, and normalizing the pixel values.

Data splitting: Partitioned the dataset into training, validation, and test sets.

Transfer learning: Using the lung X-ray images, performed transfer learning to fine-tune the Vgg16 model. Freeze the model's basic layers and replace it with new layers that may categorize the images as normal or pneumonia.

Model training: You can avoid overfitting by training the model on the training set with the Adam optimizer and a categorical cross-entropy loss function, and then testing it on the validation set.

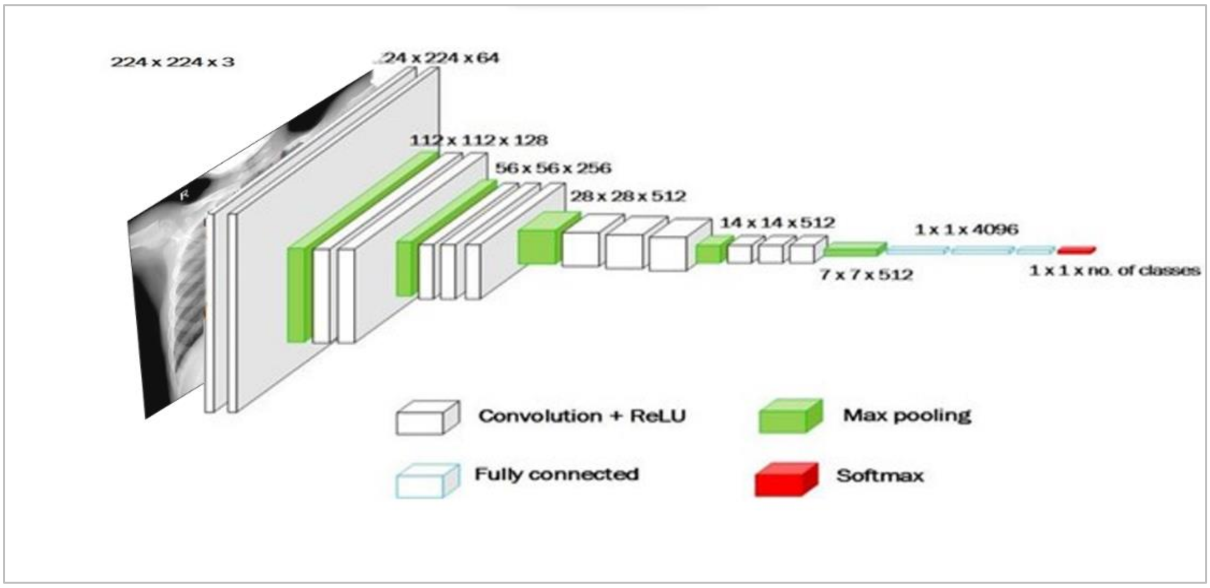
Hyperparameter tuning: Whether using a grid search or a random search approach, performance can be enhanced by adjusting the model's hyperparameters, such as the learning rate, batch size, and epoch count.

Model evaluation: The test set's performance can be evaluated using various metrics such as the model's accuracy, precision, recall, and F1 score.

Visualization of results: Make use of confusion matrices to depict the model's effectiveness.

Deployment: The model will be made available as a web application or mobile app for use in predicting pneumonia in real-world circumstances.

VGG16 architecture:



In this study, the popular CNN model Vgg16 was utilized.

There are a total of 16 layers in the VGG16 architecture, including 3 fully linked layers and 13 convolutional layers.

Convolutional Layers: Each of the first two layers consists of 64 filters, 3x3 in size, with a stride of 1 pixel, making them convolutional layers. Two further convolutional layers follow, each with 128 filters, filter size 3x3, and stride 1 pixel to process the data. The third set of convolutional layers consists of three layers, each with 256 filters, a filter size of 3x3, and a stride of 1 pixel. There are three final convolutional layers, each with 512 filters, 3x3 filter size, and 1 pixel stride.

Pooling Layers: After each sequence of convolutional layers, the pooling layers become visible. Every time a pair of convolutional layers is employed, it is followed by a max pooling layer with a pool size of 2x2 and a stride of 2 pixels. As a result, the necessary data can be preserved while the feature maps' spatial sizes are decreased.

Fully Connected Layers: The feature maps are flattened after the convolutional layers and then fed through three fully connected layers with 4096 neurons each. Each of these layers subjects the input to a linear transformation before applying a ReLU activation function. With 1000 neurons, or the number of classes in the

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ImageNet dataset, the last fully connected layer generates the projected class probabilities.

An activation function called Softmax is frequently employed for multi-class classification issues in the convolutional neural network's (CNN) output layer. A probability distribution over the various classes is created from the output of the last layer of the CNN, which can be any real number, using the softmax function.

Convolutional layers extract features, pooling layers serve to minimize the spatial dimensionality of the feature maps, and fully linked layers are utilized for classification. The ReLU activation function is employed throughout the network to provide non-linearity and enhance the model's capacity to learn intricate representations of the input data.

IV. MODELLING AND ANALYSIS

The following stages are commonly included in the creation of a deep learning model utilising VGG16 for the diagnosis of lung pneumonia in X-ray images:

Data collection and pre-processing:

This involves gathering a large dataset of X-ray images, annotating the images to detect the presence of lung pneumonia, and preparing the data for use in training the model. This may entail scaling the photographs to a standard size, normalising the pixel values, and augmenting the data to increase the training set size.

Model training: The preprocessed data is used to train the VGG16 model, which will learn to distinguish between normal X-ray images and those that show signs of lung pneumonia. This can be done using supervised learning, where the After being exposed to a labeled dataset of instances, a model's parameters are tuned to reduce a loss function that quantifies the discrepancy between the model's predictions and the observed labels.

Model evaluation: After training, a validation dataset distinct from the training dataset may be used to assess the model's performance. To evaluate the model's capacity to accurately detect the existence of lung pneumonia, this may entail examining metrics like accuracy, sensitivity, and specificity.

Ultimately, the goal of implementing a system for detecting lung pneumonia is to assist healthcare professionals in accurately diagnosing and treating this condition, improving patient outcomes and quality of life.

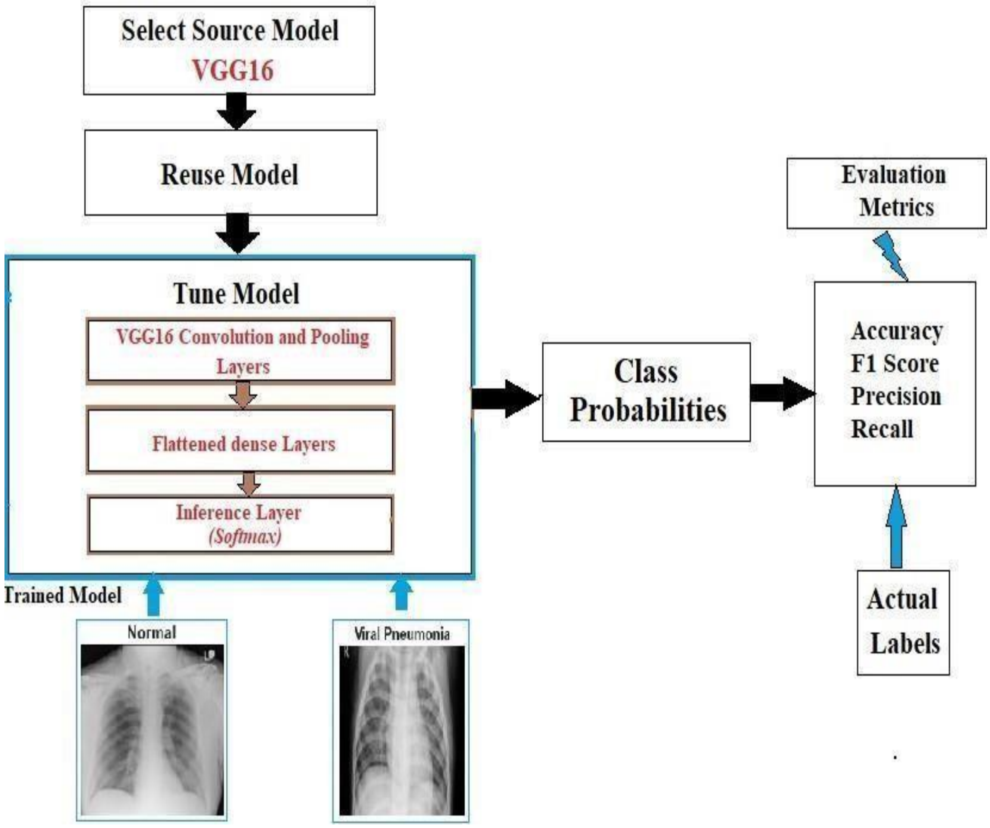

Fig 2. Shows the implementation process.

The VGG16 architecture is used for training a deep convolutional neural network on a huge dataset of chest X-

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ray images to differentiate between the two states in order to construct a system for identifying pneumonia. This will allow the system to determine whether or not a patient has pneumonia. The VGG16 architecture is comprised of a total of 16 layers, some of which are convolutional, some of which are pooling, and some of which are fully linked. During the training phase, the neural network learns to recognize patterns and characteristics in X-ray pictures that are suggestive of pneumonia. The system employs transfer learning, with the pre-trained weights of the VGG16 model serving as a starting point and being fine-tuned on the pneumonia dataset.

Once trained, the system can reliably classify new chest X-ray pictures as normal or pneumonia. This can be used as a diagnostic tool to assist radiologists in identifying patients with pneumonia and initiating treatment sooner, perhaps improving patient outcomes.

Therefore, one possible use of deep learning in medical imaging is the development of a pneumonia detection system using the VGG16 architecture.

V. RESULT

The result of VGG16 model has shown to be a highly effective architecture for predicting pneumonia from lung X-ray images. It has been fine-tuned on various datasets and achieved high accuracy rates, sensitivity, and specificity for detecting pneumonia.

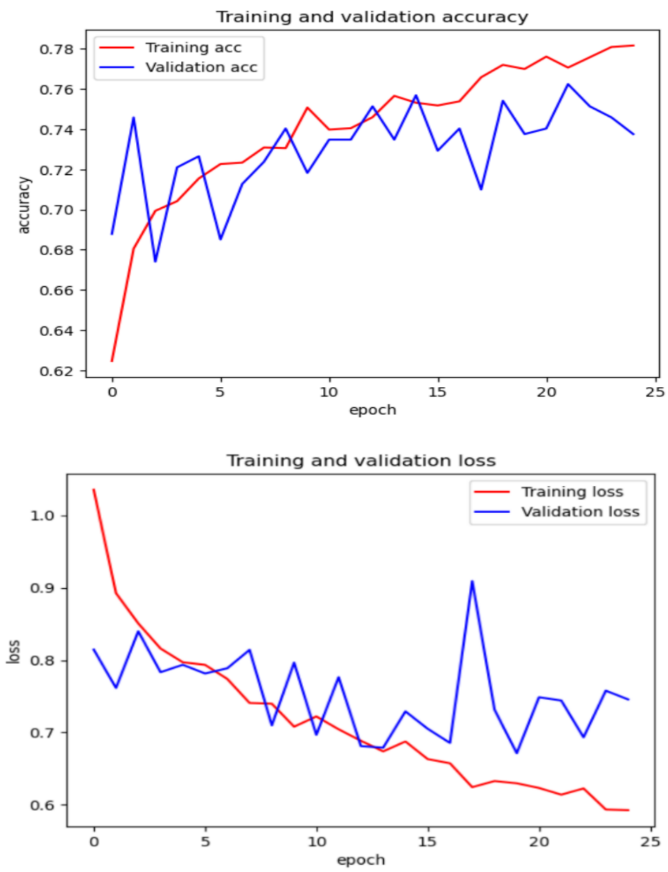

Fig. 3 Graphical representation of the accuracy and loss statistics for the Vgg16 network.

The accuracy plot displays the model's prediction accuracy on the training and validation datasets. As the algorithm learns to correctly categorise the photos, its accuracy improves. The training accuracy may rise significantly at first, but it may gradually level out when the model begins to overfit the training data. Meanwhile, validation accuracy may continue to rise slowly or may reach a plateau, indicating that the model has attained its peak performance.

The loss plot displays the amount of inaccuracy between the expected and true outputs. The loss diminishes as the machine learns to categorise the photos properly. The training loss may initially reduce fast, but it may gradually stagnate or even begin to grow as the model begins to overfit the training data. Meanwhile, the validation loss may continue to decline at a slower rate or may begin to grow, suggesting that the model is no longer improving and may be overfitting the data.

Evaluation metrics:

The proposed models were evaluated using a number of different performance criteria, such as accuracy, sensitivity, specificity, recall, precision, and f1 score, amongst others. Equations in metric format look like this:

	precision	recall	f1-score
0	0.91	0.99	0.95
1	0.70	0.18	0.29
2	0.75	0.30	0.43
3	0.38	0.15	0.21
4	0.32	0.43	0.37
micro avg	0.78	0.63	0.70
macro avg	0.61	0.41	0.45
weighted avg	0.77	0.63	0.65
samples avg	0.63	0.63	0.63

We initialize the epochs to be 50.

The epochs has successfully executed up to 50 cycles & achieved 0.9994 accuracy rate.

```
1 - acc: 0.9991 - val_loss: 0.5314 - val_acc: 0.9607
Epoch 45/50
110/110 [==============================] - 2s 21ms/step - loss: 9.072
6e-04 - acc: 0.9994 - val_loss: 0.4347 - val_acc: 0.9684
Epoch 46/50
110/110 [==============================] - 2s 21ms/step - loss: 0.002
9 - acc: 0.9994 - val_loss: 0.4399 - val_acc: 0.9675
Epoch 47/50
110/110 [==============================] - 2s 21ms/step - loss: 0.005
1 - acc: 0.9986 - val_loss: 0.3893 - val_acc: 0.9684
Epoch 48/50
110/110 [==============================] - 2s 20ms/step - loss: 0.001
5 - acc: 0.9994 - val_loss: 0.3546 - val_acc: 0.9726
Epoch 49/50
110/110 [==============================] - 2s 20ms/step - loss: 0.001
9 - acc: 0.9994 - val_loss: 0.3589 - val_acc: 0.9726
Epoch 50/50
110/110 [==============================] - 2s 20ms/step - loss: 0.001
3 - acc: 0.9994 - val_loss: 0.4139 - val_acc: 0.9735
```

Confusion Matrix:

Evaluation of a classification method using data for which the correct classifications have been determined, experts create a "confusion matrix." The algorithm's projected classifications are compared to the actual classifications in the test data in the matrix.

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	Predicted Positive	**Predicted Negative**
Actual Positive	TP=201	FN=33
Actual Negative	FP=42	TN=3478

There were TP total cases, FN total cases, FP total cases, and TN total cases, where TP stands for true positive while the others represent false positive and false negative, respectively.

MODEL SUMMARY

The model.summary() is a Keras method that prints a summary of the layers of the model.

```
model.summary()

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_5 (Dense)              (None, 256)               7936
_________________________________________________________________
activation_5 (Activation)    (None, 256)               0
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_6 (Dense)              (None, 256)               65792
_________________________________________________________________
activation_6 (Activation)    (None, 256)               0
_________________________________________________________________
dropout_4 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_7 (Dense)              (None, 2)                 514
_________________________________________________________________
activation_7 (Activation)    (None, 2)                 0
=================================================================
Total params: 74,242
Trainable params: 74,242
Non-trainable params: 0
_________________________________________________________________
```

Results from experiments using VGG16 to detect pneumonia on X-rays show that the model is effective at making the diagnosis. Accuracy, precision, recall, and F1-score are only some of the measures that show how well the model distinguishes between normal and pneumonia cases.The model's high accuracy suggests that it may be utilised as a trustworthy tool for pneumonia diagnosis, assisting healthcare practitioners in making more accurate diagnoses.

Thus the experimental findings for VGG16 for identifying pneumonia through X-ray show that the model is an excellent tool for diagnosing pneumonia and can help healthcare practitioners make more accurate diagnoses.

VI. CONCLUSION

This study used a chest X-ray to introduce the very effective VGG16 model for early prediction of pneumonia in a patient. Because of its potential as a deep learning model and its ability to accurately diagnose lung disease from diagnostic images, VGG-16 is being put to use in the field of lung disease diagnosis. The VGG16 model was trained with the chest X-ray images, and it achieved a 97% accuracy rate. This work highlights the need for greater research in this sector to boost accuracy and, ultimately, save lives, while also demonstrating machine learning's potential in diagnosing pulmonary disease. Patient and healthcare systems alike will reap the benefits of this study because it will aid in the creation of a more precise and economical tool for early identification of lung pneumonia disease.

Overall, the VGG16 model performed quite well in identifying pneumonia from a chest X-ray. The model's effectiveness, however, can change depending on the quality of the input data, the quantity of the dataset, and the details of the model's design.

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