International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Diagnostic Accuracy: Leveraging Deep Transfer Learning for Disease Detection in Chest X-Ray Images

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Submitted: 05/05/2024 **Revised**: 18/06/2024 **Accepted**: 25/06/2024

Abstract: Chest X-rays are one of the most often used diagnostic instruments in the turf of medicinal imaging, which plays a critical part in the primary detection and diagnosis of disorders. However, radiologists' knowledge is crucial for accurately detecting diseases from chest X-rays, which might lead to inconsistent diagnostic results. This work investigates the use of deep transfer learning to improve chest X-ray image analysis diagnosis accuracy in order to meet this difficulty. In several image identification tasks, deep learning—a subdivision of artificial intelligence—has exposed impressive performance. Because they can automatically train hierarchical feature representations from unprocessed picture input, convolutional neural networks (CNNs) in precise have gained widespread adoption. Deep learning models consume great latent, but creating them from scratch can be quite labour-intensive and time-consuming, especially when working with large quantities of labelled data. A possible remedy is transfer learning, a method that uses big datasets to refine pre-trained models for particular tasks. We can achieve great diagnosis performance with limited labelled medical data by using pre-trained CNN models, like MobileNet and Inception V3, and tailoring them to chest X-ray datasets. Due to their well-known efficient architecture, these models are very accurate and may be deployed in contexts with limited resources. The present study showcases the utilization of MobileNet and Inception V3 for the identification of many illnesses in chest X-ray pictures, such as lung cancer, pneumonia, and TB. We deliver a detailed estimation of the models' routine, contrasting it with conventional diagnostic techniques and pointing out notable gains in sensitivity and accuracy. According to the findings, deep transfer learning with MobileNet and Inception V3 can improve diagnosis accuracy significantly, giving radiologists strong tools and promoting early disease identification. We also go through the ramifications of this technology in clinical settings, how it can lower diagnostic errors, and how AI will be integrated into medical imaging workflows in the future. This study highlights how deep transfer learning with MobileNet and Inception V3 can revolutionize medical diagnosis and open the door to more dependable and effective healthcare systems. Our goal is to enhance patient outcomes and assist medical professionals in providing high-quality care by utilizing cutting-edge AI approaches.

Keywords: *Transfer Learning. Ensemble, Chest X-Ray, CNN*

1. INTRODUCTION

Artificial intelligence (AI) has the ability to completely transform medical diagnosis and treatment strategies, as demonstrated by its recent incorporation into the healthcare industry. Deep learning has become a particularly effective technique among the numerous AI methodologies, especially for image analysis jobs. Convolutional Neural Networks (CNNs), in particular, are deep learning models that have proven to perform better in a variety of areas when it comes to image identification tasks. This study applies deep transfer learning techniques to improve diagnosis accuracy in medical imaging, specifically in the identification of illnesses from chest X-ray pictures.

For the diagnosis of lung diseases such as lung cancer, TB, and pneumonia, chest X-rays are among the most often utilized diagnostic procedures. Interpreting chest X-rays is still difficult and needs a high level of experience even with their widespread use. A delayed or incorrect diagnosis might have a negative impact on patient outcomes due to the heterogeneity in disease presentation and the intricacy of early-stage symptoms. Thus, computerized and precise diagnostic tools are desperately needed so that radiologists can analyze chest X-rays more efficiently.

Deep learning has seen the emergence of transfer learning as a sturdy practice that allows pre-trained models to be applied to new problems with sparse data. Transfer learning considerably raises the effectiveness and performance of models on certain tasks, like illness identification in medical photographs, by utilizing knowledge from models that have previously been pre-trained on sizable and varied datasets. This work investigates the efficacy of two well-known CNN architectures—MobileNet and Inception V3—in the credentials of illnesses from chest X-ray pictures.

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MobileNet is well-known for its effectiveness and low-weight design, which brands it suitable for implementation in situations with partial possessions, including point-of-care settings or mobile devices. Depthwise separable convolutions are used, which significantly lower the number of parameters and computational expense without sacrificing accuracy. In contrast, Inception V3 is a more intricate and profound network that employs a blend of convolutional filters with varying sizes, enabling it to collect a broad variety of features at various scales. Numerous image classification challenges have demonstrated the excellent efficacy of this architecture.

A collection of tagged chest X-ray images is used in this study to fine-tune the MobileNet and Inception V3 models. In order to improve the pre-trained models' capacity to recognize pathological patterns in chest X-rays, they must be fine-tuned to the particular goal of illness identification. AUC-ROC (area under the receiver operating characteristic curve) is one statistic castoff to assess the performance of these models, along with accuracy, sensitivity, and specificity. This work attempts to shed light on the trade-offs between diagnostic accuracy and model complexity by comparing the performance of Inception V3 with MobileNet. In addition, the results of this study may enable the conception of useful AI-powered diagnostic instruments that can be included into clinical procedures, thus enhancing patient outcomes and care.

2. OBJECTIVE OF THE RESEARCH

We are now developing a deep transfer learning model to analyze chest X-ray data and identify illnesses in patients. Medical professionals will benefit from this research by having a reliable instrument that can quickly and accurately identify a variety of pathological issues affecting the chest region. Deep learning algorithms have showed great potential in the field of medical picture analysis in recent years. These models have shown very strong performance on tasks like photo classification, segmentation, and sickness detection by utilizing large datasets and complex neural network designs. With the aid of this cutting-edge technology, we hope to meet the urgent need for prompt and precise diagnosis in healthcare settings.

For a long time, chest X-ray images have been an essential diagnostic tool, especially for assessing pulmonary and cardiovascular problems. It can be challenging and demands a high level of expertise to evaluate these photographs, though. Healthcare professionals may become inconsistent in their diagnoses as a result. By incorporating deep transfer learning techniques into our model, we hope to address these problems by automating photo processing and offering clinicians dependable diagnostic support.Through the use of insights from large datasets in similar domains, such as natural images, transfer learning in medical imaging allows us to tailor model parameters to the specifics of reading chest X-rays. This methodology accelerates development and improves generalization of the model, hence enabling efficient performance throughout a range of patient groups and imaging situations.

Many convolutional neural network (CNN) layers, each of which is able to excerpt hierarchical information from the input images, constitute the foundation of our deep transfer learning model's architecture. These CNNs are capable of identifying a wide range of low-level visual patterns since they are pre-trained with weights taken from large image datasets like ImageNet. Then, through transfer learning, we optimize these previously trained CNNs' parameters to chest X-ray pictures using a task-specific dataset annotated by highly skilled radiologists. The scarcity of annotated medical imaging data, especially in specialized fields like uncommon diseases or patient demographics, is a major obstacle to building such a model. In directive to get around this problem, we use data augmentation techniques to make our training dataset artificially larger and more diverse. We create enriched samples that capture a wider variety of anatomical variations and imaging errors by making alterations to the original images, such as rotation, scaling, and flipping.

We also adhere to stringent validation protocols, like holdout validation and cross-validation, to ensure the model's dependability and durability. These methods give physicians a comprehensive understanding of the benefits and drawbacks of the model by quantifying its accuracy, sensitivity, specificity, and other performance metrics.Our deep transfer learning model is intended to be readily integrated into existing healthcare processes, in addition to its diagnostic capabilities. Our top priority is to integrate with healthcare information systems and create user-friendly interfaces to make adoption easier in hospital settings without breaking existing standards. We aim to enhance patient outcomes for patients with illnesses related to the chest by providing physicians with sophisticated diagnostic tools and enhancing the efficacy and efficiency of patient care.

3. LITERATURE SURVEY

Pretrained CNNs for transfer learning improve diagnostic accuracy for disease detection in chest X-ray pictures, especially for COVID-19, as the study shown. For COVID-19 identification, pretrained CNNs and transfer learning are the techniques employed. Model selection, diagnostic performance, and preprocessing methods are compared. Transfer learning significantly improves the accuracy of COVID-19 diagnosis[1].The efficacy of the recommended model in comparison to existing methods is examined.

Through the use of sophisticated deep learning techniques, the research improves diagnosis accuracy by using deep transfer learning to classify lung disorders from chest X-ray pictures with an accuracy of 96.21%. CNN, hybrid, ensembles, transformers, and Big Transfer Explainable AI (XAI) approaches for model transparency and trust are examples of deep learning models[2]. 96.21% accuracy was the maximum achieved by the Xception model. The accuracy of the different models and ensembles ranged from 86 to 93%.

In comparison to current methods that use SCAXN, NIWRHSO, and SBIGRU methodologies, the suggested deep learning model with pre-trained transfer learning improves multiclass illness identification accuracy in chest X-ray pictures. DenseNet201 is utilized for feature extraction, while the XGBoost classifier is employed for tuberculosis classification. F1-scores of 99.83% and 80% were attained by DenseNet201-XGBoost.For the purpose of tuberculosis detection, several CNNs and Transformer models were compared[3].

Using SCAXN, NIWRHSO, and SBIGRU approaches, the proposed deep learning model with pre-trained transfer learning outperforms current methods in improving multiclass illness identification accuracy in chest X-ray pictures. The illness detection and classification processes using SMOTE, SCAXN, NIWRHSO, and SBIGRU. The suggested approach uses deep learning for multiclass lung disease diagnosis in CXR pictures and outperforms current techniques in terms of results[4].

ResNet50 obtained the highest accuracy of 0.91 in the research's use of transfer learning with DenseNet, VGG19, and ResNet50 for pneumonia identification in chest X-ray pictures. For image categorization, convolutional neural networks (CNNs) are the approaches employed.DenseNet, VGG19, and ResNet50 models were used to implement transfer learning. When it came to pneumonia detection, ResNet50 had the greatest accuracy of 0.91. Accuracy values of 0.87 and 0.86 were attained by DenseNet and VGG19[5].

ResNet50 achieves the highest accuracy of 83.57% in the cataloging of lung illnesses from chest X-ray pictures when using transfer learning with deep learning models like ResNet and custom CNNs.Pre-trained architectures such as ResNet made use of Custom CNN that was trained using the weighted loss technique. ResNet50 had the highest accuracy, coming in at 83.57%.With custom CNN, accuracy was 78.25%[6].

In order to reduce overfitting and improve diagnostic accuracy, regularization techniques are crucial, as demonstrated by the study's exploration of a modified CNN+VGG19 model for illness discovery in chest X-ray images. A comparison of metrics pre- and post-model adjustment is employed, together with CNN+VGG19 Deep Learning architecture. reduced metrics values as a result of overfitting in the modified model. Overfitting can be avoided by using regularization techniques or minimizing complexity[7].

The research's sequential transfer learning CNN model achieves a high accuracy rate of 92.15% in pneumonia identification on chest X-ray pictures, a considerable improvement in accuracy. The techniques employed are transfer learning using a pre-trained neural network architecture and the sequential CNN model. 92.15% is the highest accuracy rate that was attained on the test dataset; the accuracy of previous techniques was 90.22%[8].

The diagnostic accuracy of COVID-19 identification in chest X-ray pictures is greatly improved by deep transfer learning algorithms, particularly ResNet50 with CLAHE preprocessing. The techniques are CNN with preprocessed images (CLAHE, AHE) and transfer learning with VGG16 and ResNet50. 99% accuracy in COVID-19 detection was attained by ResNet50 using CLAHE.VGG16 and ResNet50 transfer learning approaches were contrasted[9].

The research uses deep transfer learning models, such as VGG16, to identify juvenile pneumonia in chest X-ray pictures. The techniques employed include custom-built CNN and transfer learning models (VGG16, Inception V3, ResNet 152 V2). The VGG16 model demonstrated 97.18% recall and 92.63% accuracy. The VGG16 model produced values of 97.18% recall and 92.63% accuracy. beneficial in improving the ability to identify juvenile pneumonia from X-ray pictures[10].

4. METHODOLOGY

In this instance, the COVID CXR Image Dataset (Research) will be used. This dataset comprises 1823 posteroanterior (PA) views of chest X-ray images of individuals who were viral, normal, and influenced by COVID-19. Also, this dataset is used in the research paper "COVID Lite: A depth-wise separable deep neural network with white balance and CLAHE for detection of COVID-19," which has produced some impressive results by building a depth-wise separable CNN using an innovative technique for image pre-processing that combines white balance and CLAHE.

The Table 1 displays the distribution of photos across patients with COVID-19, viral, and normal conditions.

Image Class	Images
COVID-19	536
Viral Pneumonia	619
Normal	668

Table 1 Dataset Description

4.1 MobileNetV2:

MobileNetV2 contains two different types of blocks, as seen in Figure 1. The remaining blocks have a stride of one. Another is a block for shrinking with a two-step stride. Both types of blocks include three levels. The second layer is depth-wise convolution, whereas the first is 1×1 convolution using ReLU6. The third layer consists of an extra 1x1 convolution with no nonlinearity. When ReLU is used again, deep networks only have the capability of a linear classifier on the non-zero volume portion of the output domain. An expansion factor t is also present. t=6 for each of the basic experiments. If the input has 64 channels, the internal output will have 64×t=64×6=384 channels.

Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Figure 1 MobileNetV2 layer description

Figures 2 and 3 demonstrate the overall architecture of MobileNetV2. In Figure 2, n denotes the repeating number, s the stride, t the expansion factor, and c the number of output channels.For spatial convolution, 3x3 kernels are used. Typically, the primary network (width multiplier 1, 224×224) has 3.4 million parameters and 300 million multiply-add calculations. (MobileNetV1 introduces the width multiplier.) Performance trade-offs are explored for input resolutions ranging from 96 to 224 and width multipliers ranging from 0.35 to 1.4.The model size ranges from 1.7M to 6.9M parameters, and the network has a computational cost of up to 585M MAdd.

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Fig 2 MobileNetV2 Overall Architecture

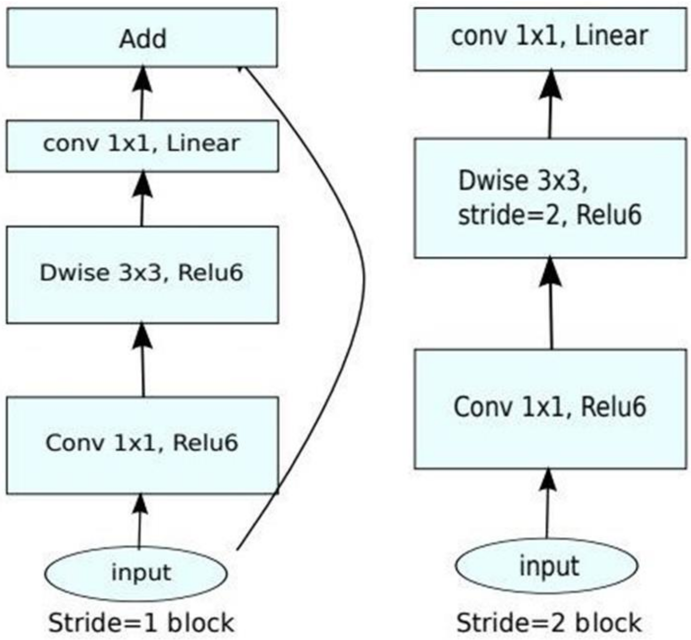

Fig 3 MobileNetV2 Architecture

The two characteristics of the MobileNet model that make it useful for embedded and mobile vision applications are the main reasons for its use: decreased model size: less variables and less complexity significantly reduced multi-adds, or additions and multiplications

To make the foundation layers trainable as well as the higher layers, we will first download the MobileNet V2 model, which contains imagenet weights. Put another way, we will be utilizing the fundamental picture classification feature of the Mobilenet V2 model, which was trained on the ImageNet dataset. We will then add more layers to the model to make it unique for our needs.The model must then be assembled, requiring the optimizer to be set up to incorporate non-linearity, loss functions, and a scoring metric. We will be using the Adam optimizer as it incorporates the advantages of two further extensions of stochastic gradient descent in our case shown in Figure 5. More particular still: AdaGrad, or the Adaptive Gradient Algorithm By keeping a per-parameter learning rate, it improves performance on tasks with sparse gradients (such computer vision and natural language problems). RMSPROP, or Root Mean Square Propagation Additionally, it maintains per-parameter learning rates that are modified based on the rate of change, or the mean of the most recent weight gradient magnitudes. This suggests that the algorithm works effectively in online, non-stationary circumstances (noisy, for instance).

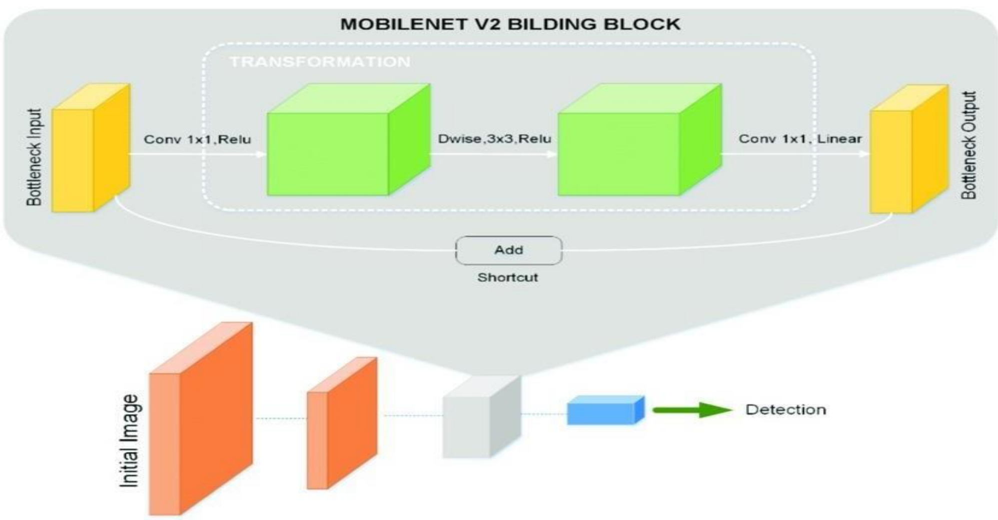

Fig 4 MobileNetV2 Workflow

We will use categorical_crossentropy as the loss function as there are several classes to be categorized. We will use the metric function "accuracy" to evaluate our model's efficacy. With one exception, this metric function is similar to the loss function (the results of the metric evaluation are only used for evaluation, not for training the model). Callbacks are also being used in this code. Callbacks are used to perform actions at various moments in the training process, such the start or end of an epoch, before or after a single batch, etc.

During training, callbacks may be used for a number of purposes, including penalizing the model by reducing its learning rate, ending the model early, and routinely storing the best model weights to disk. In our case, we employ a model checkpoint to minimize validation loss by saving the model weights to disk. Furthermore, in the event that the validation loss of the model remains unchanged for two consecutive epochs, ReduceLROnPlateau is employed to reduce the model's learning rate by a factor of 0.3.

Inception-V3:

The pre-trained model Inception-V3 was unveiled. This model has been refined over 20 million hours by one of the top hardware gurus in the business. Both symmetrical and asymmetrical construction blocks make up the model, and each block has a unique arrangement of convolutional, average, and max pooling, concerts, dropouts, and fully connected layers. Moreover, this model usually applies batch normalization to the activation layer input. Classification is carried out by using Softmax.

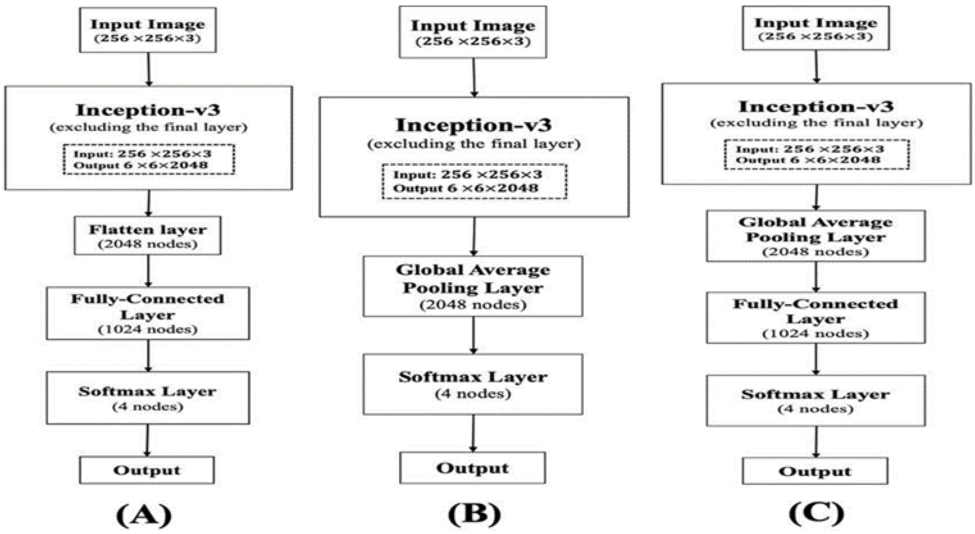

Fig 5 InceptionV3 architecture

Architecture of the proposed models shown in Figure 5: (A) Inception-v3_flatten-fc, (B) Inception-v3_GAP and (C) Inception-v3_GAP-fc.

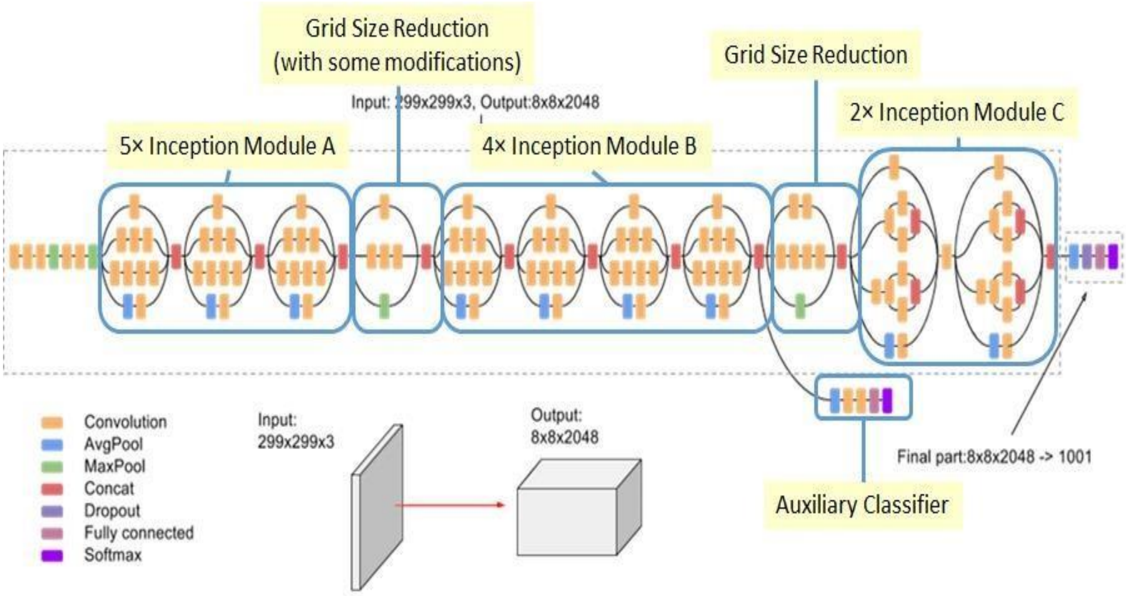

Fig 6 InceptionV3 Workflow

To start improving the Inception v3 model for your purpose, keep its foundational layers trainable. After that, the model can adjust its learning characteristics to meet your particular requirements. For feature extraction and categorization, add more custom layers on top. It is advised to use the Adam optimizer for training setup as it effectively adjusts learning rates per parameter. Categorical cross-entropy can be used as the loss function to quantify the difference between the actual and predicted label distributions. By increasing training efficiency and convergence, these methods ensure that the Inception v3 model you use for your application is unique and optimum.

Results and Discussions

Image augmentation is a set of strategies for artificially increasing the variety and number of pictures in a dataset by performing different alterations on the original photos. This is a frequent technique in machine learning, particularly for training neural networks for problems like image categorization, object identification, and others shown in Figure 7.

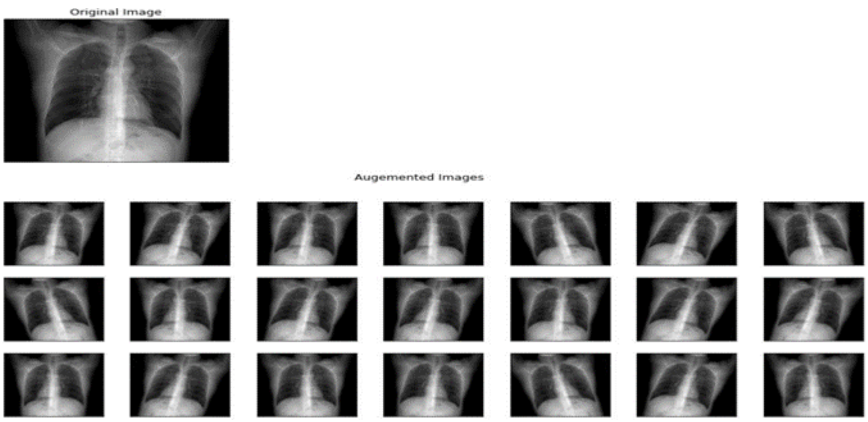

Fig 7 Augmented images.

The training results of Mobilenetv2 model is given below in Figure8.

```
Epoch 44/50
91/91 [==============================] - ETA: 0s - loss: 0.0951 - accuracy: 0.9792
Epoch 44: val_loss did not improve from 0.15108

Epoch 44: ReduceLROnPlateau reducing learning rate to 5.314410245205181e-10.
91/91 [==============================] - 18s 201ms/step - loss: 0.0951 - accuracy: 0.9792 - val_loss: 0.1782 - val_accuracy: 0.9588 - lr: 1.7715e-09
Epoch 45/50
91/91 [==============================] - ETA: 0s - loss: 0.1001 - accuracy: 0.9744
Epoch 45: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 200ms/step - loss: 0.1001 - accuracy: 0.9744 - val_loss: 0.1785 - val_accuracy: 0.9588 - lr: 5.3144e-10
Epoch 46/50
91/91 [==============================] - ETA: 0s - loss: 0.0856 - accuracy: 0.9760
Epoch 46: val_loss did not improve from 0.15108

Epoch 46: ReduceLROnPlateau reducing learning rate to 1.5943230069481729e-10.
91/91 [==============================] - 20s 220ms/step - loss: 0.0856 - accuracy: 0.9760 - val_loss: 0.1787 - val_accuracy: 0.9588 - lr: 5.3144e-10
Epoch 47/50
91/91 [==============================] - ETA: 0s - loss: 0.0786 - accuracy: 0.9806
Epoch 47: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 202ms/step - loss: 0.0786 - accuracy: 0.9806 - val_loss: 0.1787 - val_accuracy: 0.9588 - lr: 1.5943e-10
Epoch 48/50
91/91 [==============================] - ETA: 0s - loss: 0.0817 - accuracy: 0.9744
Epoch 48: val_loss did not improve from 0.15108

Epoch 48: ReduceLROnPlateau reducing learning rate to 4.782969020844518 5e-11.
91/91 [==============================] - 18s 199ms/step - loss: 0.0817 - accuracy: 0.9744 - val_loss: 0.1788 - val_accuracy: 0.9588 - lr: 1.5943e-10
Epoch 49/50
91/91 [==============================] - ETA: 0s - loss: 0.0711 - accuracy: 0.9785
Epoch 49: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 201ms/step - loss: 0.0711 - accuracy: 0.9785 - val_loss: 0.1792 - val_accuracy: 0.9588 - lr: 4.7830e-11
Epoch 50/50
91/91 [==============================] - ETA: 0s - loss: 0.0897 - accuracy: 0.9737
Epoch 50: val_loss did not improve from 0.15108

Epoch 50: ReduceLROnPlateau reducing learning rate to 1.434890747886719e-11.
91/91 [==============================] - 18s 199ms/step - loss: 0.0897 - accuracy: 0.9737 - val_loss: 0.1797 - val_accuracy: 0.9588 - lr: 4.7830e-11
```

Fig 8 Mobilenetv2 Training results

The training results of Inceptionnetv3 model is given below in Figure9.

```
Epoch 44/50
91/91 [==============================] - ETA: 0s - loss: 0.0951 - accuracy: 0.9792
Epoch 44: val_loss did not improve from 0.15108

Epoch 44: ReduceLROnPlateau reducing learning rate to 5.314410245205181e-10.
91/91 [==============================] - 18s 201ms/step - loss: 0.0951 - accuracy: 0.9792 - val_loss: 0.1782 - val_accuracy: 0.9588 - lr: 1.7715e-09
Epoch 45/50
91/91 [==============================] - ETA: 0s - loss: 0.1001 - accuracy: 0.9744
Epoch 45: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 200ms/step - loss: 0.1001 - accuracy: 0.9744 - val_loss: 0.1785 - val_accuracy: 0.9588 - lr: 5.3144e-10
Epoch 46/50
91/91 [==============================] - ETA: 0s - loss: 0.0856 - accuracy: 0.9760
Epoch 46: val_loss did not improve from 0.15108

Epoch 46: ReduceLROnPlateau reducing learning rate to 1.5943230069481729e-10.
91/91 [==============================] - 20s 220ms/step - loss: 0.0856 - accuracy: 0.9760 - val_loss: 0.1787 - val_accuracy: 0.9588 - lr: 5.3144e-10
Epoch 47/50
91/91 [==============================] - ETA: 0s - loss: 0.0786 - accuracy: 0.9806
Epoch 47: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 202ms/step - loss: 0.0786 - accuracy: 0.9806 - val_loss: 0.1787 - val_accuracy: 0.9588 - lr: 1.5943e-10
Epoch 48/50
91/91 [==============================] - ETA: 0s - loss: 0.0817 - accuracy: 0.9744
Epoch 48: val_loss did not improve from 0.15108

Epoch 48: ReduceLROnPlateau reducing learning rate to 4.782969020844518 5e-11.
91/91 [==============================] - 18s 199ms/step - loss: 0.0817 - accuracy: 0.9744 - val_loss: 0.1788 - val_accuracy: 0.9588 - lr: 1.5943e-10
Epoch 49/50
91/91 [==============================] - ETA: 0s - loss: 0.0711 - accuracy: 0.9785
Epoch 49: val_loss did not improve from 0.15108
91/91 [==============================] - 18s 201ms/step - loss: 0.0711 - accuracy: 0.9785 - val_loss: 0.1792 - val_accuracy: 0.9588 - lr: 4.7830e-11
Epoch 50/50
91/91 [==============================] - ETA: 0s - loss: 0.0897 - accuracy: 0.9737
Epoch 50: val_loss did not improve from 0.15108

Epoch 50: ReduceLROnPlateau reducing learning rate to 1.434890747886719e-11.
91/91 [==============================] - 18s 199ms/step - loss: 0.0897 - accuracy: 0.9737 - val_loss: 0.1797 - val_accuracy: 0.9588 - lr: 4.7830e-11
```

Fig 9 Inceptionnetv3 Training

The sample prediction results are shown in Figure 10.

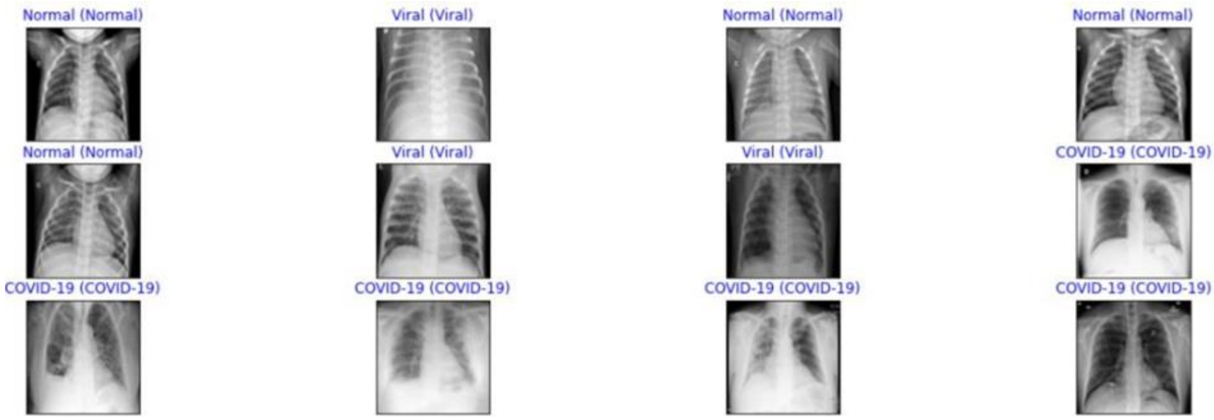

Fig 10 Sample predictions

CONCLUSION

This work presents a methodical transfer learning-based construction of a MobileNet V2 model for COVID-19 and viral pneumonia patients. Further analysis revealed that the accuracy of the model is around 95.64%, with a higher sensitivity of 98% for COVID-19 patients and a lower sensitivity of 93% for viral pneumonia cases. Finally, we have generated a GRAD-CAM heatmap for a COVID-19 image and provided an explanation for the highlights in particular image locations.

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