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Deep Learning Technique for The Classification of Lung Diseases from X-ray Images

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ABSTRACT

Pictures obtained from a chest X-ray can assist in diagnosing and screening various illnesses, including pneumonia, mass, lung opacity, TB, and nodules. The convolutional neural network (CNN) has been devised to predict pulmonary disease. In this investigation, we classify lung disease based on pictures from chest X-rays using a technique known as transfer learning. This method was chosen because it allows us to make more accurate diagnoses. Transfer learning has proven effective for detecting diverse anomalies in limited medical imaging datasets, leading to notable outcomes. This study involves utilizing a dataset comprising a collection of chest X-ray photos obtained from the Kaggle website, including nine different lung diseases (COVID, mass, effusion, lung opacity, nodule, pneumonia, pneumothorax, pulmonary fibrosis, and tuberculosis), as well as images of individuals without any lung ailments. The objective is to employ several transfer learning models (VGG19, Inception V3, Efficient Net V2m, Xception, Mobile Netv3, and Dense net201) to train these images, classify them, and then select the most influential Model for addressing this task. Most models yielded promising results, particularly dense net201, mobile net, and VGG19, which achieved more effective yields with 95.49%, 94.89%, and 93.69% accuracy rates, respectively.

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1. Introduction

Many different diseases can affect the lungs, yet they frequently appear with similar symptoms, such as decreased lung capacity and other symptoms. The diagnosis of these diseases can take a long time. Some of these diseases, such as tuberculosis, COVID-19, and pneumonia, can lead to death if they are not recognized early on, which can cause grief among persons who are given incorrect advice. It is generally agreed that chest X-rays and CT scans are among the most significant diagnostic tools for identifying lung illnesses[1].

It has been suggested that computer-assisted diagnosis (CAD) systems could be used to enhance the accuracy of diagnostic performance and reduce the likelihood of mistakes occurring in medical applications[2]. Deep learning has become an effective medical tool, successfully diagnosing various diseases. Due to the proliferation of new data and challenges, deep learning and machine learning have assumed a more significant role in various domains. Deep

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learning uses convolutional layers to process non-linear information[3] to create a more advanced network than traditional machine learning networks and more effective in handling big data sets.

Within the scope of this investigation, we will analyze and compare the overall performance of six different neural networks. (inception v3, efficient v2m, Xception, vgg19, dense net201, and mobile net) for the classification of chest X-rays. The neural networks utilized in this study were pre-trained by applying the transfer learning technique. On the website Kaggle, X-ray pictures of the most significant lung disorders were gathered and compiled. After that, data augmentation techniques were used on the images to boost accuracy and reduce redundancy. The results showed that dense net201, mobile net, and vgg19 achieved the maximum accuracy among the proposed networks, scoring 95.49%, 94.89%, and 93.69%, respectively.

2. related work

In recent years, deep learning algorithms have demonstrated their effectiveness in automatic feature extraction and high accuracy. Consequently, there has been a rise in researchers whose primary focus is diagnosing lung disease, particularly COVID-19 and pneumonia. In the following paragraphs, we will present a concise summary of the techniques based on deep learning that can be applied to diagnosing various lung problems. Previous studies are summarized in Table 1 below.

In 2019, CHENG WANG et al.[4]conducted research to classify lung images using the Inception V3 model and a deep learning technique. Their results were encouraging, coming in at 86.4% accuracy, 95.41% sensitivity, and 80.09% specificity. By 2020, Liu et al.[5] had used transfer learning methods to classify TB cases instead of non-TB cases. The researchers utilized six distinct models: DenseNet121, InceptionV3, NASNet, ResNet50, VGG16, and Xception. The classification was achieved by reviewing chest X-ray (CXR) pictures. Accuracy, sensitivity, and specificity were above average for the DenseNet121 model (83.50%, 82.20%, and 84.90%, respectively). Apostolopoulos et al.[6] published a study in 2020 using transfer learning methodologies to five different models: VGG19, MobileNetv2, Inception, Xception, and ResNetV2. The purpose of the research was to classify cases of pneumonia, COVID-19, and normal conditions by using X-ray images taken from a particular dataset. The results showed that Model VGG19 performed exceptionally well, with a sensitivity level of 92.81%, a specificity of 98.55%, and an accuracy of 93.32%.In 2020, Rachna Jain et al.[7] used transfer learning to train pre-trained models, including VGG16, VGG19, ResNet 50, and Inception V3. They built a model with two convolutional layers and another with three convolutional layers. The first Model had a validation accuracy of 85.26%, whereas the second Model increased this to 92.31%. In 2021, Hong et al.[8]used transfer learning to classify pulmonary diseases and healthy lung states using chest X-rays from the National Institutes of Health databases. Models such as VGG 19, efficient net B7, and dense net 201 were employed. The results showed that Model efficient Net b7 performed exceptionally well, with a sensitivity level of 79%, a specificity of 89%, and an accuracy of 85.32%. In 2022, Sungyeup Kim et al.[1] employed an end-to-end learning process where raw CXR images were directly inputted into a deep learning model (EfficientNet v2-M) to extract relevant features for disease classification and achieved validation performances of loss = 0.7658, accuracy = 82.20%, sensitivity = 81.40%, and specificity = 94.48%;

Table 1: A summary of the literature on lung disease classification techniques

Year	Authors	techniques	Accuracy	sensitivity	specificity
2019	CHENG WANG et al.	Inception V3	86.4%	95.41%	80.09%
2020	Liu et al.	DenseNet121	83.5%	82.20%	84.90%
2020	Apostolopoulos et al.	VGG19	93.43%	92.85%	98.75%
2020	Rachna Jain et al.	Built Model	92.31%	-	-
2021	Hong et al.	EfficientNetB7	85%	77.97%	88.98%
2022	Sungyeup Kim et al.	EfficientNet v2-M	82.15	81.4	94.48

3. Database and processing techniques

3.1. Transfer learning

We used a database of chest X-ray pictures that we received from the Kaggle website and applied it to our research. The data collection consists of 5,000 different lung pictures. Figure (1) contains a sample of the data set and presents it in a format that varies according to the kind of disease, 500 images for every type of lung disease.

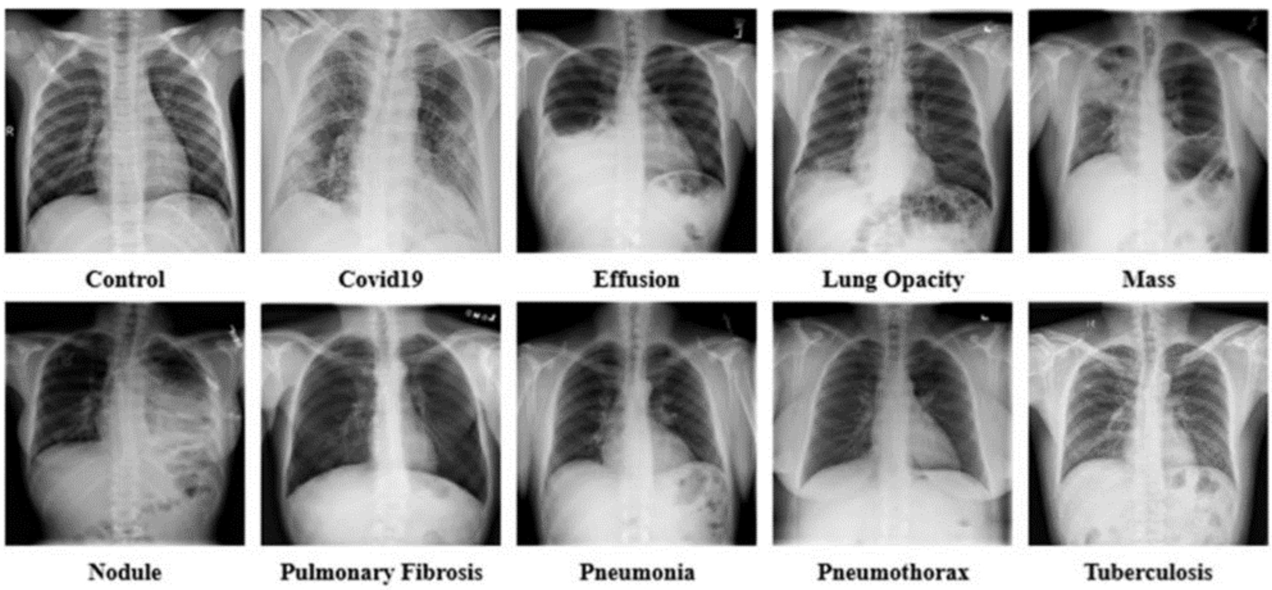


Figure (1). The sample dataset of the ten classes includes Control, COVID-19, Effusion, Lung Opacity, Mass, Nodule, Pulmonary Fibrosis, Pneumonia, Pneumothorax, and Tuberculosis.

3.2. processing dataset

To ensure that the Model works effectively for CNN networks, which require high-quality images and large amounts of data, we must process the data before reducing it into the Model. In this study, the training phase included applying the data augmentation strategy to improve the effectiveness of the Model's performance. The data size was transformed to (224 * 224), and the actual data was split into 80% for training and 20% for testing.

4. Transfer learning and pre-trained models

4.1. Transfer learning

Transfer learning utilizes knowledge from solving one problem to tackle a distinct yet interconnected challenge. A standard method for transfer learning involves initially training a deep neural network (DNN) on a substantial dataset (referred to as the upstream dataset), followed by fine-tuning the DNN on a significantly smaller dataset (known as the downstream dataset). Pretraining enables us to choose the most advantageous initial weights that improve the learning process of the target task by utilizing current knowledge in the task domain[2]. The ImageNet dataset has been used to train multiple CNN designs, all of which have achieved high accuracy. Instead of arbitrarily starting over with the weights from scratch, you might use these weights to categorize an entirely new dataset. There are four different ways to transfer learning. One possible strategy involves removing the fully connected layers that were initially employed as classifiers, fixing the weights of the entire network, utilizing the pre-trained convolutional neural network (CNN) layers for feature extraction, and subsequently appending a classifier layer, such as a fully connected layer or an alternative machine learning classifier like a support vector machine[3]. The second approach involves removing the original fully connected layers, adjusting the weights of the whole network by fine-tuning with a shallow learning rate (LR), and, afterward, including a new classifier layer specifically designed for the new task[2]. The third methodology involves eliminating the fully linked layers, modifying the upper levels while keeping the bottom layers unaltered, and introducing a novel classifier layer designed for the new undertaking. Numerous studies have postulated that the lower layers of neural networks may be able to perceive rudimentary elements, such as edges and circles, while the upper layers can discern more intricate and specialized aspects[9]. The top layers are responsible for identifying extra features unique to the dataset. Because of this, numerous authors advise readers to adjust the topmost layers to perfection [9-11]. Utilizing cutting-edge infrastructure and beginning from scratch is the focus of the fourth approach. Training it from scratch means only utilizing the architecture shown to function on various complex datasets.

4.2. pre-trained modules

a) VGG19

The initial proposal of the pre-trained convolutional neural network (CNN) Model was put out by Simonyan and Zisserman [12]at the University of Oxford in the United Kingdom during the early months of 2014. The Model was given the tradename VGG network. The Visual Geometry Group model was trained using the ImageNet dataset, which encompasses 1000 distinct classes. The training process involved utilizing 100,000 images per class for training purposes, while an additional 50,000 images were allocated for validation. Compared to other models considered to be state-of-the-art, The VGG-19 architecture, a variant of the VGG architecture, comprises 19 layers that exhibit strong interconnections. The architecture of the Model consists of convolutional and fully-connected layers that exhibit strong interconnections. This design facilitates enhanced extraction of features and the utilization of Max pooling, as opposed to average pooling, for down-sampling before classification using the Soft Max activation function. Both of these factors contribute to the enhancement of the Model's performance[12]. Figure 2 depicts the architecture of the VGG-19.

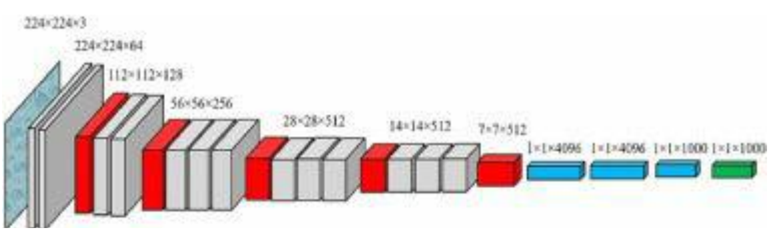


Figure (2): the architecture of the VGG-19

b) DenseNet-201

The Dense Convolutional Network, often known as DenseNet, was first presented by Huang et al.[13] Moreover, it features connections between all of the network's layers. This significantly reduces the total number of parameters, improves feature propagation and reuse, and eliminates the problem of vanishing gradients. After multiple convolutional layers, it can be challenging to differentiate between certain lung diseases since their symptoms are similar (for instance, pneumonia and COVID share many of the same characteristics). As a result of the lengthier route that must be traveled between the input and output levels, the information may become less clear before it reaches its final destination. DenseNet was developed to prevent vanishing gradient-induced accuracy losses in high-level neural networks[14]. Figure (3) displays the architecture of the DenseNet-201

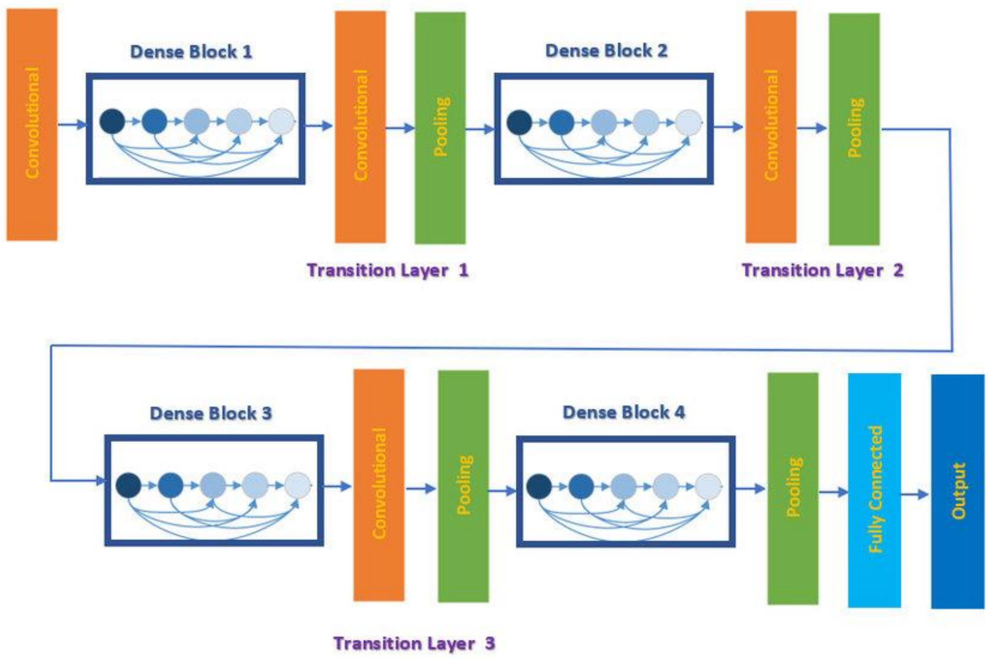


Figure (3): the architecture of the DenseNet-201

c) MobileNetV3

It is a convolutional neural network first presented by Howard et al.[15]. The system's design was intended to achieve optimal performance on mobile phones' central processing units (CPUs). The accomplishment was achieved by utilizing the Neural Architecture Search (NAS) technique, which was improved after incorporating the NetAdapt algorithm. Furthermore, novel architectural enhancements were implemented to augment the system's performance further. The architectural design has modules called squeeze and excitation, which generate output feature maps by assigning unique weights to each channel generated from the input. This differs from the uniform weighting scheme employed by conventional convolutional neural networks[16]. This is in contrast to CNN's standard provision of equal weight. Figure (4) displays the architecture of the MobileNetV3.

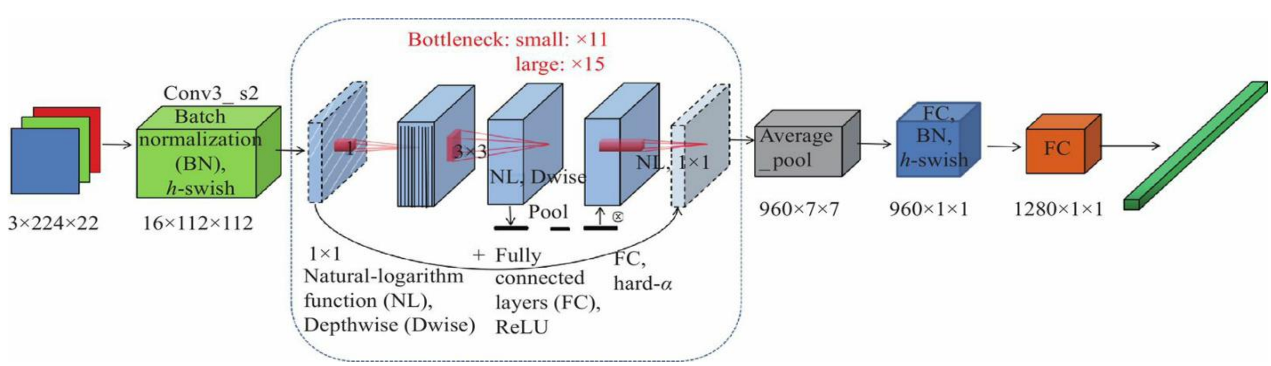


Figure (4): the architecture of the MobileNetV3

d) Inception v3

This Model is extensively employed for picture recognition and has been empirically proven to get an accuracy rate above 78.1% when evaluated on the ImageNet dataset[17]. The Model is the conclusion of several concepts that numerous researchers have investigated over an extended period[18].

The core component of the Inception-v3 is a deep neural network consisting of 42 layers. The Inception-v3 model comprises many building pieces, including convolutions, maximum pooling layers, average pooling layers, dropout layers, and fully connected layers. These components may be categorized as either symmetric or asymmetric. Figure (5) displays the architecture of the Inception-v3 version[19].

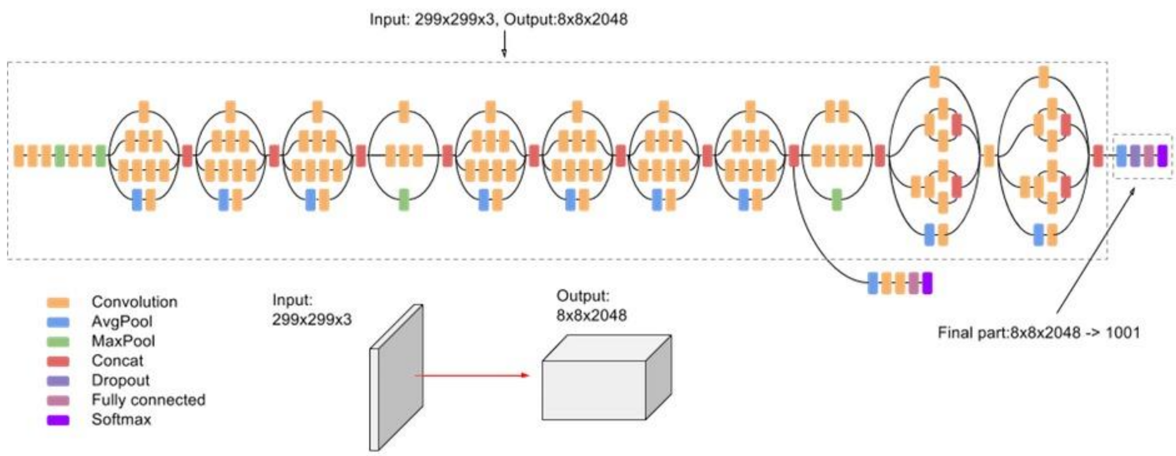


Figure (5): the architecture of the Inception-v3

e) Efficient v2 M

This novel convolutional neural network (CNN) architecture is designed to enhance the training efficiency and optimize the network's parameters for improved performance. To accomplish this objective, a methodology including training-aware neural architecture search and compound scaling was implemented[20]. Incorporating both MBConv blocks and Fused-MBConv blocks facilitated a more efficient training procedure. Figure (6) displays the architecture of the Efficient v2 M.

Figure (6): the architecture of the Efficient v2 M

f) Xception

Francois Chollet improved the Inception idea by inventing the Xception architecture[21]. The architecture comprises a sequence of depth-separable convolutional layers integrated with residuals. The purpose of the depthwise separable convolution is to minimize the memory and computational demands. Among Xception's fourteen modules, all save two have 36 convolutional layers, which include linear residual connections. The Xception separable convolution algorithm partitions the feature learning process into separate operations focusing on individual channels and spatial dimensions.

Additionally, the He et al. [22]residual link provides a direct channel in the sequential network, resolving the representational bottleneck and vanishing gradient problems. Instead of aggregating the outcomes of several layers, this shortcut link enables them to serve as input for the following layer. The shortcut link enhances the processing speed by circumventing the concatenation step and directly conveying the output of one layer to the next through a summation operation. Figure (7) displays the architecture of the Xception.

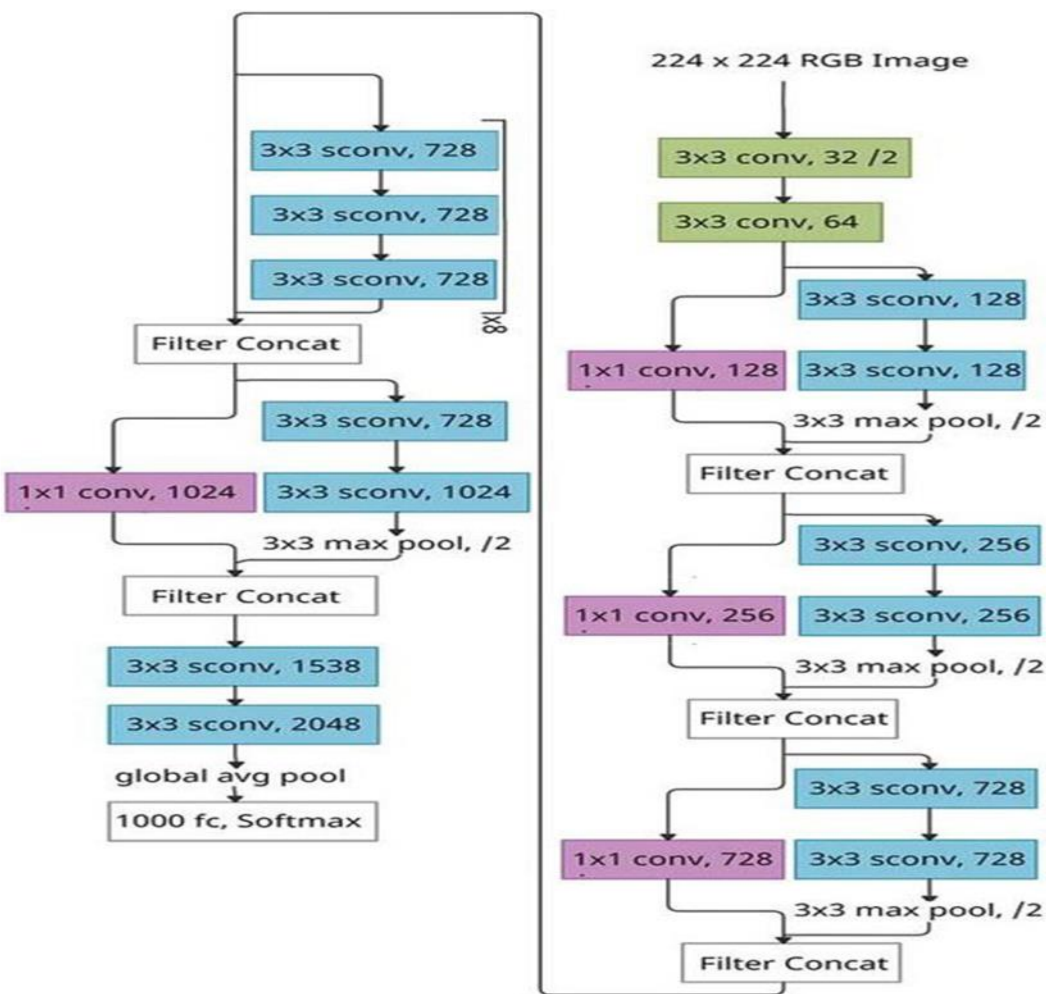


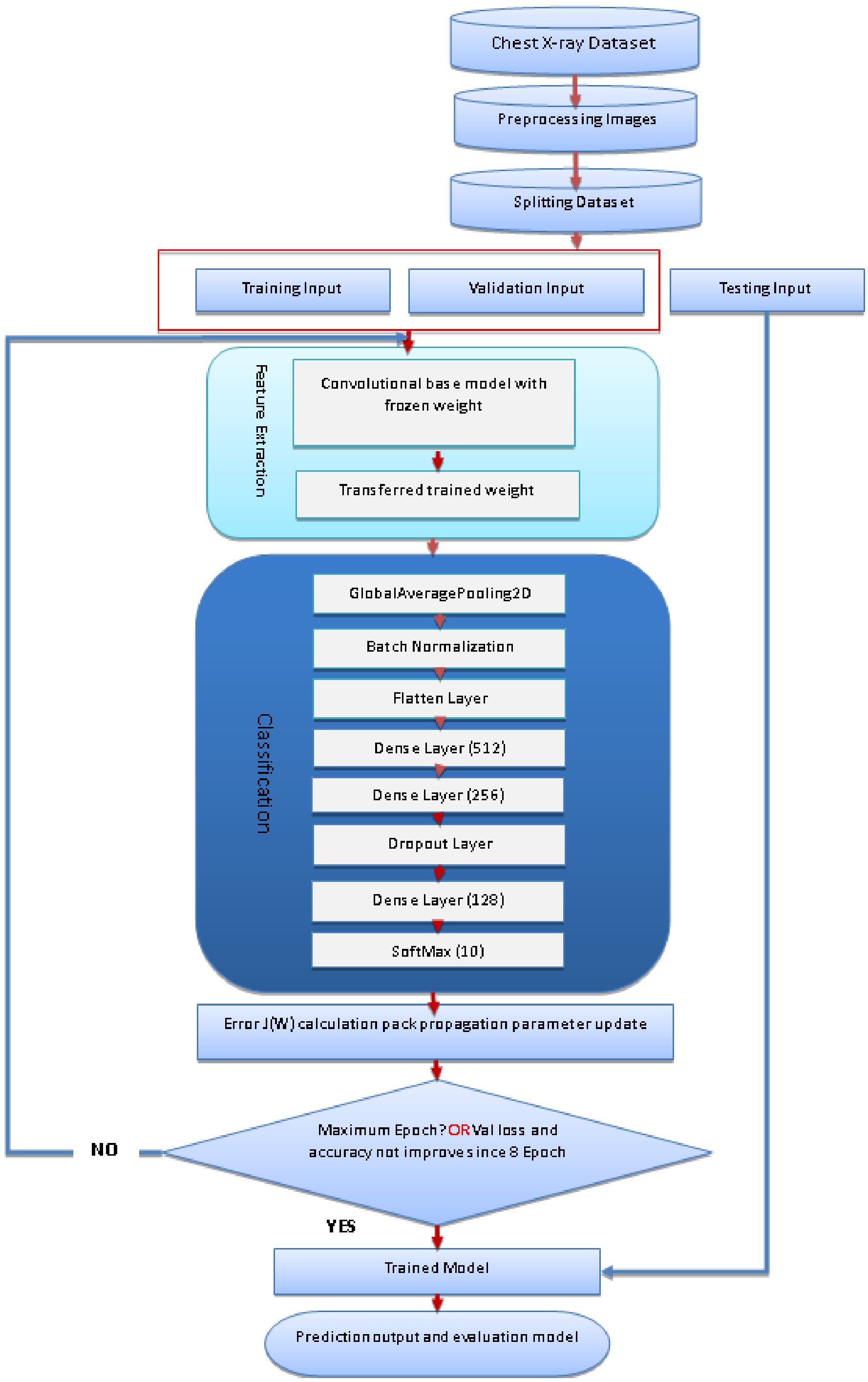
Figure (7): the architecture of the Xception

5. Research Methodology

In this study, we altered the structure of convolutional neural networks (inception v3, efficient v2m, Xception, vgg19, dense net201, and mobile net) to be more suitable for our classification of lung disorders. We divided the dataset after loading it with preprocessing and augmentation. In Table 2, you can see the values of the parameters and hyperparameters that we used in our models. Before proceeding with feature extraction and transfer learning, we loaded the pre-trained models and ran convolution on 224x224 input images while freezing the ImageNet weights. We continued by adjusting the Model's upper, unfrozen layers using an average pooling layer to prevent overloading, a batch normalization layer to speed up training and make the network more resistant to overloading, three dense layers, and a dropout layer, in addition to a prediction layer that uses the SoftMax function for categorization. Figure (8) explains the proposed strategy.

Table 2: models hyperparameters and tuning

Hyperparameters	**Setting**					
	inception v3	**efficient v2m**	**Xception**	**vgg19**	**dense net201**	**mobile net**
Input Size	224 x 224	224 x 224	224 x 224	224 x 224	224 x 224	224 x 224
batch size	32,16	32,16	32,16	32,16	32,16	32,16
Seed	42	42	42	42	42	42
optimizer	Adam	Adam	Adam	Adam	Adam	Adam
learning rate	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Epochs	10	10	10	10	10	10
loss function	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy	Categorical cross-entropy
Early Stopping	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving	8 patience for 'min' Val-loss and 'max' Val-accuracy not improving
Total params	23031722 (87.86 MB)	53980734 (205.92 MB)	1991858 (83.89 MB)	20456138 (78.03 MB)	19484490 (74.33 MB)	3660618 (13.96 MB)
Trainable params	1218698 (4.65 MB)	823946 (3.14 MB)	1120138 (4.27 MB)	429194 (1.64 MB)	1152906 (4.40 MB)	659466 (2.52 MB
Non-trainable params	21813024 (83.21 MB)	53156788 (202.78 MB)	20871720 (79.62 MB)	20026944 (76.40 MB)	18331584 (69.93 MB)	3001152 (11.45 MB)



Figure(8): An illustration of the proposed strategy

6. Research Methodology

6.1 Results

The trials were carried out with the help of Python. To classify lung diseases based on chest X-rays, we carried out trials with models that had been pre-trained. Images were split into two groups: the training group, which comprised 80% of the total, and the test group, which comprised the remaining 20%. Table 3 displays the results of all convolutional neural networks. The results indicate that the dense net 201, mobile netv3, and vgg19 networks achieved the best classification accuracy compared to the rest of the CNN networks, with 95.49%, 94.89%, and 93.69%, respectively.

Here are some standard mathematical equations used in evaluating machine learning models:

Accuracy: This measures the proportion of actual results (both true positives and negatives) among the total number of cases examined.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision: This is the ratio of true positives to all positive results (including false positives).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (Sensitivity): This measures the proportion of actual positives that are correctly identified.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score: The F1 Score is the harmonic mean of precision and recall, balancing the two.

Where:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

Table 3: Result of different modules

Network	accuracy (%)	Precision(%)	Recall (%)	F1-score (%)
Dense net 201	95.49	96	96	96
Mobile net v3	94.89	95	95	95
VGG-19	93.69	94	94	94
Efficient v2M	88.28	90	89	89.5
Inception v3	85.49	87	87	87
Xception	80.76	81	81	81

6.2 Discussion

According to the findings, the convolutional neural networks have demonstrated their usefulness in automatically extracting fundamental characteristics from chest X-rays. The research could be strengthened by gathering additional patient information for in-depth analysis. Models that have been tested and shown to be effective, such as those that have achieved high accuracy on some X-rays of reality, tend to be confirmed on a broader range of medical images to demonstrate their reliability. This is because testing the models tends to reveal flaws in the models themselves. In Figure 9, we can see how our proposed techniques stack up in terms of accuracy.

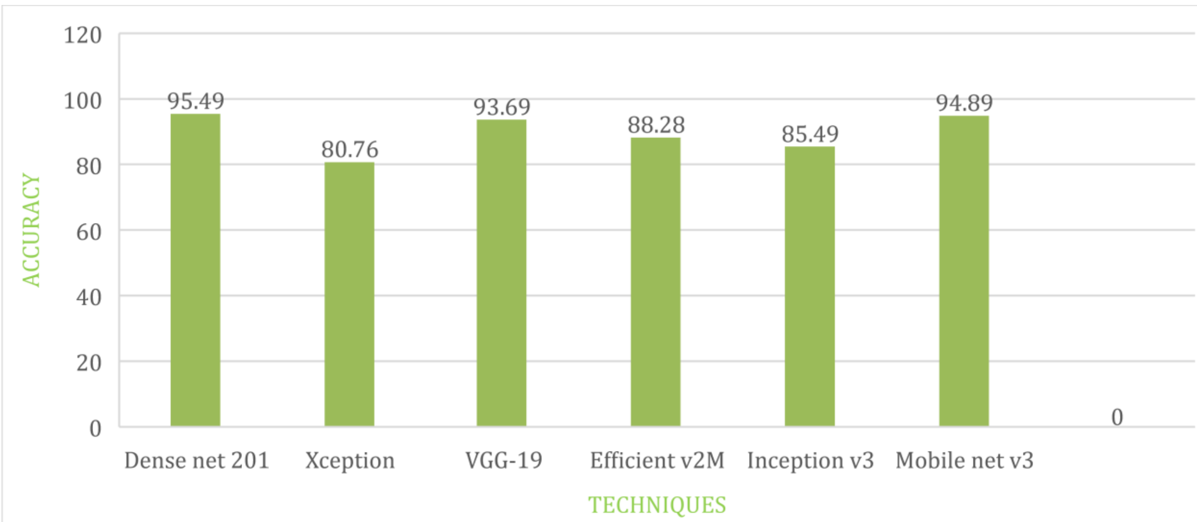


Figure 9: The comparison of the accuracy score of proposed models

7. Conclusion

The present investigation centered on assessing the efficacy of several convolutional neural network architectures in classifying pulmonary disorders. This study investigated the classification capabilities of six pre-trained deep learning models, namely VGG19, Inception V3, Efficient Net V2m, Res Net152, Mobile Net v3, and Dense net201. The findings indicate that the VGG19, Dense net201, and Mobile Net v3 models outperformed the other models regarding classification performance. Enhanced training through utilizing a larger quantity of pictures can facilitate the extraction of intricate characteristics in real-time scenarios and aid in the precise localization of models. The study has produced several significant contributions, which may be succinctly stated as follows: A total of six pre-trained models were examined, and further adjustments were implemented only to the last layer of each Model. During the analysis, three high-performance models were examined to categorize lung illnesses. The efficacy of these models was evaluated using real-world photographs, demonstrating a notable level of accuracy in their predictive capabilities.

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