DETECTION OF PNEUMONIA BY USING NINE PRE-TRAINED TRANSFER LEARNING MODELS BASED ON DEEP LEARNING TECHNIQUES

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Abstract **- Pneumonia is a serious chest disease that affects the lungs. This disease has become an important issue that must be taken care of in the field of medicine due to its rapid and intense spread, especially among people who are addicted to smoking. This paper presents an efficient prediction system for detecting pneumonia using nine pre-trained transfer learning models based on deep learning technique (Inception v4, SeNet-154, Xception, PolyNet, ResNet-50, DenseNet-121, DenseNet-169, AlexNet, and SqueezeNet). The dataset in this study consisted of 5856 chest x-rays, which were divided into 5216 for training and 624 for the test. In the training phase, the images were pre-processed by resizing the input images to the same dimensions to reduce complexity and computation. The images are then forwarded to the proposed models (Inception v4, SeNet-154, Xception, PolyNet, ResNet-50, DenseNet-121, DenseNet-169, AlexNet, SqueezeNet) to extract features and classify the images as normal or pneumonia. The results of the proposed models (Inception v4, SeNet-154, Xception, PolyNet, ResNet-50, DenseNet-121 DenseNet-169, AlexNet and SqueezeNet) give accuracies (98.72%, 98.94%, 98.88%, 98.72%, 96.2%, 94.69%, 96.29%, 95.01% and 96.10%) respectively. We found that the SeNet-154 model gave the best result with an accuracy of 98.94% with a validation loss (0.018103). When comparing our results with older studies, it should be noted that the proposed method is superior to other methods.**

Index Terms - Pneumonia**, **Chest X-ray**, **Pre-trained transfer learning

I. INTRODUCTION

Pneumonia is an infection that causes the alveoli in one or both lungs to become inflamed. The alveoli may fill with fluid or pus (purulent substance), causing a cough with phlegm or pus, fever or chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia.

Pneumonia is one of the most common health problems in the world and is considered a respiratory problem that can be caused by bacteria, fungi or viruses. Pneumonia accounts for a large proportion of diseases and deaths. Early diagnosis and treatment of pneumonia is critical to avoid serious problems such as death.

Chest x-ray [1-3] is one of the most widely used radiological examinations for screening and treatment of many lung diseases. Medical X-rays are images that are commonly used to diagnose sensitive parts of the human body such as the skull, teeth, chest, bones, etc. Radiologists can diagnose a range of diseases by analyzing X-ray images such as pneumonia, bronchitis, infiltration, nodules, atelectasis, and inflammation Pericarditis, hypertrophy of the heart, pneumothorax, and fracture. But the main problem facing doctors is the correctness and accuracy of the diagnosis. It is known that the wrong diagnosis of the disease may lead to serious problems, including death. Therefore, researchers have become interested in recent years to search for techniques that make the diagnosis of X-rays more accurate, which helps doctors to make a decision [4].

There are different studies to identify pneumonia diseases with varying results, so it was necessary to choose advanced technologies with high efficiency such as artificial intelligence to identify pneumonia diseases. Artificial intelligence has witnessed a great development and the emergence of deep learning technology has been a great development because it has high accuracy in classifying and predicting the most complex problems, and it can deal with very large data that is difficult for other technologies to deal with. Many techniques have appeared in the field of deep learning and pre-trained models that perform the process of identifying pneumonia diseases, and they have shown good results. In this paper, artificial intelligence was used based on nine deep learning models (Inception v4 [5], SeNet-154 [6], PolyNet [7], Xception [8], DenseNet-169 [9], DenseNet-121, ResNet-

50[10], AlexNet [11] and SqueezeNet [12]) for the diagnosis of pneumonia using chest x-ray. The study can contribute as follows: (1) Solving the problem of accuracy in the diagnosis of pneumonia diseases, as previous studies showed less accuracy, while this study achieved high accuracy using artificial intelligence. (٢) Ease and reliability of diagnosis of the disease by using more than one model. In this study, nine models were used to classify pneumonia diseases. (٣) Ease of dealing with X-ray images, knowing that they are considered more difficult than images using magnetic resonance imaging (MRI) and computed tomography (CT) because of the low accuracy of their images, but with the use of the models proposed in the study, the process of identifying images became more effective and accurate.

his paper is organized as the following: In the next section 2, we discuss the relevant literature on pneumonia recognition. In Section 3, we present the proposed methodology for identifying pneumonia diseases. The results implemented for the proposed method are presented in Section 4. In the ٥ section, we present a comparison of the results of our study with the results of previous studies. Finally, Section 5 presents the conclusion of this paper.

II. Literature Review

present an overview of literature that relates to work presented here. These have been important topics of study in the literature for many years. To justify this claim here, we list the methods proposed by many authors in this field. In the last decade, various studies have determined the effect of pneumonia detection. In the initial work published in Mcnittgray et al. [13], it was described that the lung field segmentation method with features was first proposed. Gray size, local disparity measurement and local texture measurement have been the characteristics used. The method classifies each pixel of the CXR into one of the various anatomic categories (heart, sub diaphragm, upper mediastinum, lung, and background) using KNN, Linear Discriminant Analysis (LDA), and Feedback Network (NN) for back propagation. 70%, 70% and 76% of each classifier were right the right percentages were.

Novikov et al. [14] proposed a multiple image segmentation process based on U-net to segment the lung area by associating a loss function to the aforesaid class distribution and resolving data imbalance problems. In the cardiovascular and heart segmenting tasks this method also goes beyond the advanced methods.

Dai et al. [15] proposed an approach of Structure Correcting Adversarial Network (SCAN) which uses the CXR images segmentation to lung fields and the heart.

Gordienko et al. [16] proposed a method to detect Lung cancer by a deep learning process, demonstrating the effectiveness of the technique of bone suppression. The study found better accuracy and loss results for pre-treatment datasets without bones.

Paredes et al. [17] proposed a method to categorize the entire medical image, using small parts of medical images as regional features and k-nearest (k-NN) neighbor to achieve finally accurate start-to-art precision.

Vittitoe et al. [18] used information about spatial and texture to segment lung or non-pulmonary CXRs. Markov Random Field was used in the construction of a model with high sensitivity, specificity and precision.

Reference [19] proposed an approach using Lung ultrasound echography as proof of pneumonia, which has proven to be an important tool for detecting pulmonary consolidates. The application of ultrasound to detect pneumonia is limited by the picture analysis used by human experts for interpretation. During the analysis of pneumonia ultrasound images, the noise introduced by an image part of the skin complicates processing and interpretation. This methodology therefore helps to identify and remove the portion of the skin in ultrasound pulmonary imaging.

Reference [20] proposed a new approach by using image treatment techniques to detect pneumonia in Chest X-rays (CXR). In order to clean and extract images from the lung region, indigenous algorithms had been developed. Otsu thresholds from the pictures the lung region. The threshold Otsu was used to separate the healthy lung part from the cloudy areas that were infected by pneumonia. Tools like Python and OpenCV have been used to reduce expenses. Open sources. Only 40 analogy Chest X-rays were used for the study, which could lead to data overfitting. Moreover, it does not have the ability to be used as an application in real time. Antin et al. [21] proposed a differential classification method has been implemented in which the inputs are X-ray chest images and the outputs are either pneumonia or non-pneumonia in both groups. Many of the patients used multiple images to ensure that data from the same patient were not used over training and test sets. Before division into preparation, evaluation and test sets, the data is segregated by the patient. A perfect judgment limit is defined to accurately distinguish different groups. Pedro Cisneros-Velarde et al. [22] proposed a novel application for pneumonia detection ultrasound video analysis. This includes an algorithm for image processing that analyses some overall video statistics that can be used for pneumonia prediction. A number of clinical and use protocols have been used for testing the application. The images can however be hard to interpret and require experienced operators. Song [23] Proposed an approach which uses a fast diagnosis method for respiratory health issues based on low cost cell phones. A total of 367 breathing sounds collected from children's hospitals using the non-contact method to develop precise models of diagnosis and evaluation. A binary grading task: Pneumonia vs Non-working pneumonia was assessed. Even in the presence of environmental noises it was able to efficiently classify pneumonia. With 92,06% sensitivity and 90,68%

specificities, 91,98% precision is achieved. While this approach provides a low-cost pneumonia detection method, X-rays continue to be necessary for a better interpretation.

There are many studies that tried to find solutions to detect pneumonia using artificial intelligence models, and these studies gave different results, and we will give some examples of these studies.

Bar et al. [24] proposed a transfer learning algorithm with CNN and GIST for pneumonia detection from chest X-rays.

Yao et al. [25] presented A CNN combination and a recurring neural network for the exploitation of label dependencies. They used a DenseNet10 as a CNN backbone that was completely adapted to and trained on X-ray data. The findings for this official split are published by authors and Reference [26] devised a deep learning network to identify fourteen diseases and one of them is pneumonia Wang et al. [27] used the application of the CNNs to CXR classification with the use of computer vision domain. Based on the encoded display settings authors carried out simple preprocessing while reducing pixel depth to 8 bits. Furthermore, without preservation of the aspect ratio, each image has been resized to 1024 pixels.

Shi et al. [28] suggested an approach to segmentation of the lung region in CXRs was unmonitored. The segmentation of lung fields by using the Gaussian kernels and space restrictions. Fuzzy C-means (FCM). The method has been tested on 52 CXRs of the.

dataset JSRT and has an accuracy of 0.978 ± 0.0213.

Li et al. [29] presented a pathology and localization framework using CNNs.

Suzuki et al. [30] developed a method for suppressing the contrast in a multi-resolution, large-scale, Artificial Neural Network training chest between ribs and clavicles. The subtraction of the bone image from the corresponding radiograph of the thoroughfare results in an image of the soft tissue that significantly reduces the rib and the clavicle.

Nguyen et al. [31] The separation from the rips and other parts of the lung is by means of independent component analysis (ICA). The results showed that 90% of the ribs could be fully and partially inhibited and 85% of the cases increased the visibility of the nodule.

Demner-Fushman et al. [32] presented a dataset of chest radiograph containing hypertrophic heart disease and pleural effusion, where the disease pictures are presented frontally and lateral.

Parveen and Sathik. [33] proposed method that classify and detect Pneumonia from X-rays has been researched. In addition, the authors extracted features through discrete wavelet transforms and using Fuzzy C means to detect pneumonia.

Caicedo et al [34] proposed method to classify medical images with state-of- the-art accuracy, use the Scale-Invariant Function Transform (SIFT) as local descriptor and use the SVM (support vector machines) graph. But a patent algorithm is SIFT.

Qing et al. [35] used ConvLayer customized CNN for classifying lung illness images patches. The authors also found that the system can be extended to other datasets for medical images. Furthermore, it has been found in other research that CNN-based system can be trained with the large-chest X-ray (CXR) film dataset, as well as state-of- the-art with high precision and sensitivity data, such as Stanford normal diagnostic radiology data set with more than 40000 CXR and the new ChestX-ray8 (108 948 frontal view CXR) database (108 948 frontal view CXR). In addition, it is difficult to train an appropriate model using limited data.

Vianna. [36] proposed a transfer learning which used as the critical component of a computerized diagnostics system, to build an X-ray image classification. The authors found a transmission learning system with an increase in the data efficiently relieves overload problems and yields better results than two other models: scratch training and a model transference learning with a last classification layer only retrained.

Moh'd Rasoul et al. [37] suggested an approach for the treatment of pneumonia using image recognition algorithms and artificial neural networks. A group of infected and normal X-ray images are prepared using the Self-Organizing Map (SOM) algorithm for classification using segmentation and feature extraction using many processes. The Artificial Neural Network also uses a database of various cases of infected and normal pneumonia X-rays, a network for detecting the infected image, the used network was a high-performance Learning Vector Quantization Network.

Ronald Barrientos et al. [38] presented an approach based on analyzes of patterns from digital ultrasonic images in rectangular segments. Neural networks are used to describe the characteristic vector features obtained. The correct classification of vectors with high sensitivity and specificity evidence of pneumonia was obtained. But ultrasound scans do not yield highly detailed and clearly defined images.

Khobragade et al. [39] proposed an approach using image classification feed-forward technique to detect major lung conditions, such as TB, lung cancer and pneumonia, by using Artificial Neural Network Back Propagation. The preliminary identification requirement for lung disease is radiography. For the detection of lung borders, simple image processing techniques such as intensity-based methods and discontinuity-based methods are used. For image classification purposes, statistical and geometric features are extracted. Chest x-rays contain thoracic anatomy, which is the cheapest in comparison with other imaging techniques like CT scanning. Chest x-rays are good for tests, but diagnoses are sometimes poor.

Abiyev R.H et al. [40] suggested three methods (backpropagation neural networks (BPNNs), competitive neural networks (CpNNs) and convolutional neural networks (CNNs)) for pneumonia detection. Experiments were conducted on the networks used, and the CNNs showed from the comparative results to be the best.

Rajaraman et al. [41] proposed two models (CNN and VGG16) that classify and detect Pneumonia based on bacterial and viral types in pediatric CXRs. The proposed model is implemented using CNN and VGG16. Every model shows independent performance. The best result is obtained using VGG16 with 96.2% accuracy.

Kermany et al. [42] suggested a transfer learning algorithm to detect pneumonia that was used to detect the retinal OCT images. The best result is obtained with 92.8 % accuracy.

Togacar et al. [43] proposed an ensemble of deep learning algorithms (AlexNet, VGG-16 and VGG-19) to extract the features and reduce their number. And then pass the features to the models (decision tree, k-nearest neighbors, linear discriminant analysis, linear regression, and support vector machine learning models) to predict pneumonia disease. The best result is obtained using linear discriminant analysis with 99.41 % accuracy.

Saraiva et al. [44] proposed a convolutional neural networks and multilayer perceptron for pneumonia detection from chest X-rays. The best result is obtained using CNN model with 94.40% accuracy.

Ayan et al. [45] proposed VGG16 and Xception for pneumonia detection. The best result is obtained using Xception model with 87% accuracy.

Stephen O et al. [46] The authors build their model from scratch. The aim of this paper is to use CNNs model for classification and detection the pneumonia from chest X-ray image.

Chouhan et al. [47] proposed a transfer learning based on deep learning to detect pneumonia. They are used to extract features from chest X-rays different models of neural networks that features were passed into a predictor classifier. They proposed an aggregate model that combines the outputs of the all models to obtain a single output. The best result is obtained with 96.4 % accuracy.

III METHODOLOGY

There are methodologies for identifying pneumonia diseases [40-47]. In this section we will present the proposed methodology for identifying pneumonia using nine pre-trained transfer learning models (Inception v4, SeNet-154, PolyNet, Xception, DenseNet-169, DenseNet-121, ResNet-50, AlexNet and SqueezeNet). Our proposed method can be shown as the following: data collection, Image Preprocessing, training phase, testing phase, and recognition of pneumonia diseases.

A. . Data Collection

In this study, the dataset was obtained from [42], and it contains 5216 x-ray images of the chest in the training phase and 624 images in the testing phase.

B. . Image Preprocessing:

This step is aimed to resize the images to have the same dimensions (224x224 pixels) and convert them into grayscale level.

C. . Training Phase

In the training phase, series of steps are applied to the dataset. As shown in figure 1, the training phase consist of four steps:

1) ***Data* gathering**: In this step we are preparing the dataset that we will train in the network.
2) ***Training Phase:***

- ***Training using Pre-trained model:*** the dataset is trained with the proposed models (Inception v4, SeNet-154, PolyNet, Xception, DenseNet-169, DenseNet-121, ResNet-50, AlexNet and SqueezeNet).
- ***Trained model*:** After the training process, the final weights are saved in a model that is able to detect pneumonia in chest x-ray images and classify each image into pneumonia or normal.

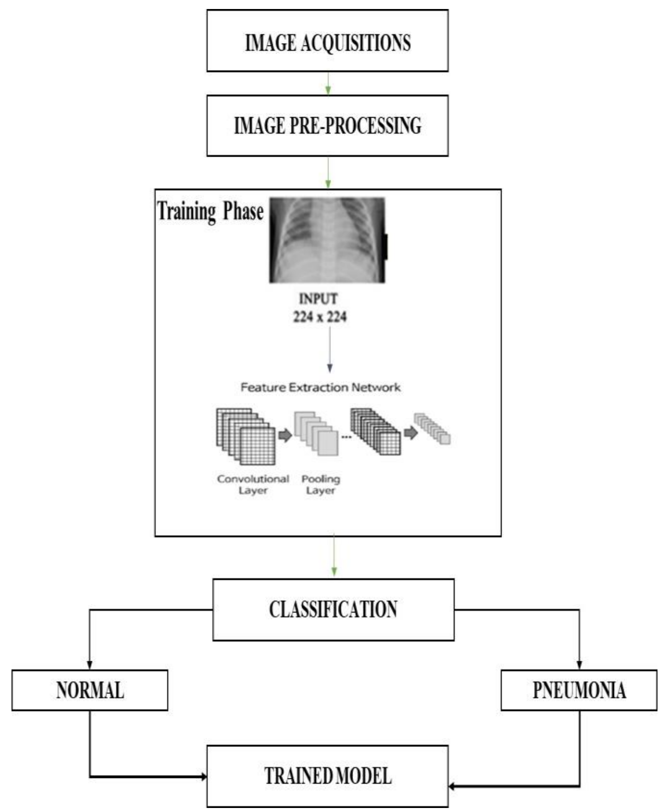

Fig. 1. Workflow of Training Phase.

D. Testing Phase

In this phase, we aim to use a dataset of Chest X-ray images as examples to test the trained model and assess the performance it. As shown in figure 2, The testing phase consists of following steps:

- ***Generation of test data:*** we are preparing the dataset that was gathered for testing.
- ***Pre-processing image*:** this step is aimed to resize the images to have the same dimensions (224x224pixels) and

convert them into grayscale level.

- ***Classification phase (normal or pneumonia):*** Classification of chest X-ray images is the last step. The proposed models classify the images into a normal or a pneumonia.

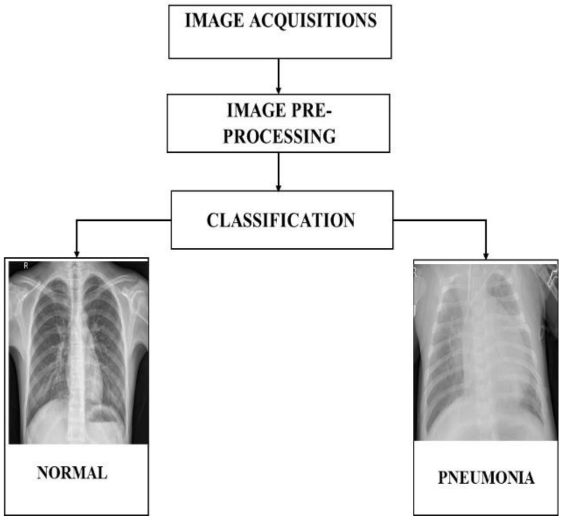

Fig. 2. *Workflow of testing phase.*

E. Deep Learning Technique

The proposed model uses deep learning with Convolution Neural Networks and Transfer learning consist of nine pre-trained models.

1) Convolution Neural Networks (CNN)

Algorithm is used here due to its vital role in image classification tasks. The power of CNN is in the hidden layers, which are located between the input layer and the output layer. For the classification tasks by CNN shows high performance findings. Figure 3 illustrates the architecture of CNN.

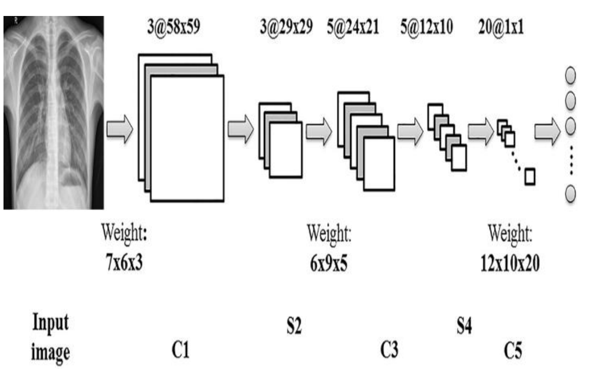

Fig. 3. Architecture of CNN

2) Transfer Learning

Transfer learning is a new technique that has been used recently. The most important advantage of this technique is reducing the required time and resource for training. Instead of training from scratch that takes more time and GPU resource and large dataset of images, the pre-trained models (Inception v4, SeNet-154, PolyNet, Xception, DenseNet-169, DenseNet-121, ResNet-50, AlexNet and SqueezeNet) are used to transfer the knowledge and perform the task. A brief description of this models as following:

1. *Inception v4*: with 43 million parameters and an upgraded Stem module, Inception-v4 is touted to have a dramatically improved training speed due to residual connections. With an ensemble of three residual and one Inception-v4, it achieves 3.08% percent top-5 error on the test set of the ImageNet classification (CLS) challenge.
2. *SeNet-154*: SENet-154 is constructed by incorporating SE blocks into a modified version of the 64×4d ResNeXt-152 which extends the original ResNeXt-101 by adopting the block stacking strategy of ResNet-152. Further differences to design and training of model are as the follows:

(a) Number of first 1 × 1 convolutional channel of each bottleneck block building is halved to reduce computational cost of the model with a minimal decrease in performance.

(b) First 7 × 7 convolutional layers are replaced with 3 consecutive 3 × 3 convolutional layers.

(c) The 1 × 1 down-sampling projection with stride-2 convolution is replaced with a 3 × 3 stride-2 convolution to preserve information.

3. *PolyNet*: The Very Deep PolyNet, designed following this direction, demonstrates substantial improvements over the state-of-the-art on the ILSVRC 2012 benchmark. Compared to Inception-ResNet-v2, it reduces the top-5 validation error on single crops from 4.9% to 4.25%, and that on multi-crops from 3.7% to 3.45%.
4. *Xception*: Xception has 71 layers and 23 million parameters. It is based on Inception-v3. Xception was heavily inspired by Inception-v3, albeit it replaced convolutional blocks with depth-wise separable convolutions. Xception practically is a CNN based solely on depth-wise separable convolutional layers
5. *DenseNet-169:* DenseNet-169 is a CNN with 169 layers deep. The densenet-121 model for image classification is among the DenseNet models group. DenseNet-169 has 224-by-224 size of image Input. Each layer receives extra inputs from all previous layers in DenseNet and passes its own function maps on to all subsequent layers.
6. *DenseNet-121:* DenseNet-121 is a CNN with 121 layers deep. The densenet-121 model for image classification is among the DenseNet models group. DenseNet-121 has 224-by-224 size of image Input. Each layer receives extra inputs from all previous layers in DenseNet and passes its own function maps on to all subsequent layers.
7. *ResNet-50:* ResNet-50 has 50 layers deep of ResNet blocks (each block having 2 or 3 convolutional layers), ResNet 50 had 26 million parameters. ResNet-50 has 224-by-224 size of image Input and has 3.8 billion FLOPs. ResNet-50 takes the 1st place on (ILSVRC 2015) with 3.57 % error.
8. *AlexNet:* AlexNet is a CNN with 8 layers deep, 3 fully-connected and 5 convolutional. AlexNet had 60 million parameters. AlexNet winner in ILSVRC 2012. The 2nd top 5

error rate was around 26.2 percent, which was not a CNN difference.

9. *SqueezeNet:* SqueezeNet is a CNN with 18 layers deep. They are offering the SqueezeNet small CNN architecture with 50x fewer parameters.

IV. Result

In this section, we will show the results obtained during the implementation in the training phase and the testing phase, where we divided the dataset into two parts, 5216 X-ray images of the chest for training and 624 images for the test. In the training phase, the network was trained with 250 epochs and batch size of 32 and was implemented on nine models (Inception v4, SeNet-154, PolyNet, Xception, DenseNet-169, DenseNet-121, ResNet-50, AlexNet and SqueezeNet). Training loss and training accuracy were used as a measure of performance in the training phase, as in the figures (4-5).

As we can see from Figures (٤ and ٥) and Table 1, the results that were obtained in the training phase only, it was found that the least training loss was obtained by the SeNet154 model, while the highest training accuracy was obtained by the two models (Inception v4 and PolyNet).

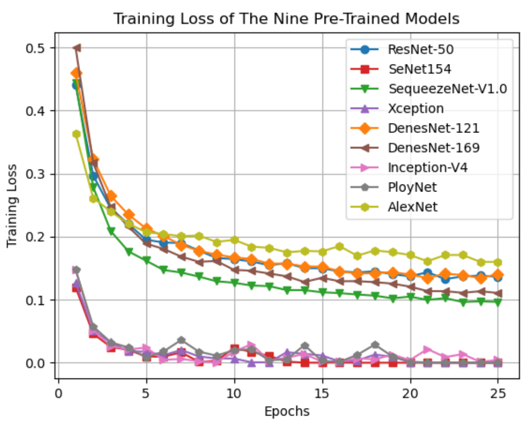

Fig. 4. *Training loss of the nine pre-trained models.*

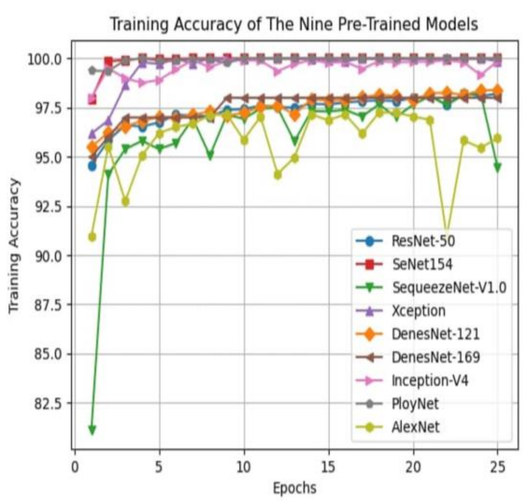

Fig. 5. *Training accuracy of the nine pre-trained models.*

While in the testing phase, the network was tested on 30% of the dataset by using the trained model obtained in the training phase from the nine proposed models (Inception v4, SeNet-154, PolyNet, Xception, DenseNet-169, DenseNet-121, ResNet-50, AlexNet, SqueezeNet) .The validation loss and validation accuracy were used as a measure of performance in the testing phase as shown in (6-7). As we can see from Table 1, the validation loss and validation accuracy values obtained from the SeNet154 model were the best among all the models, while the DenseNet-121 model had the lowest validation accuracy.

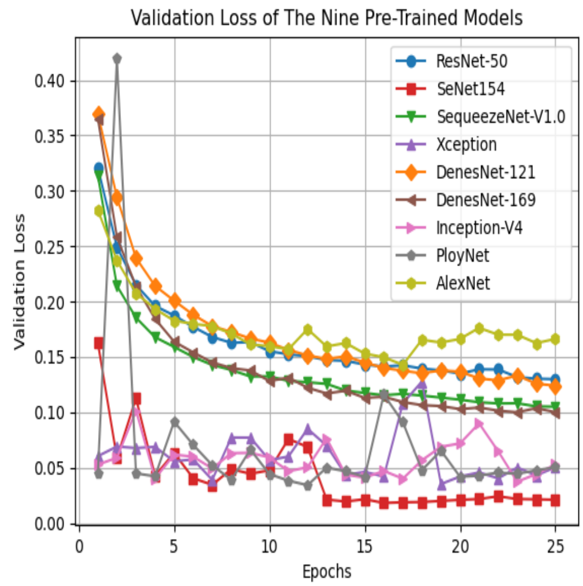

Fig..6 Validation loss of the nine pre-trained models.

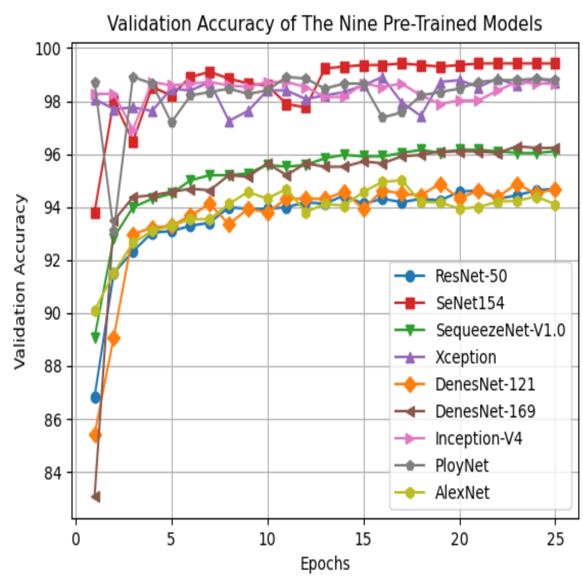

Fig.7. *Validation accuracy of the nine pre-trained models.*

The performance metrics of nine pre-trained models are given in Table 1, which summarizes the results of training loss, training accuracy, validation loss and validation accuracy.

Table 1. *Performance metrics results*

	Training Phase		Testing Phase	
Metrics	**Training Loss**	**Training Accuracy**	**Validation Loss**	**Validation Accuracy(Testing Accuracy)**
Inception v4	0.013661	99.97%	0.037313	98.72%
SeNet154	0.000294	100%	0.018103	**98.94%**
Xception	0.009546	100%	0.035201	98.88%
PolyNet	0.004015	99.97%	0.034165	98.72%
ResNet-50	0.065344	98.2%	0.083816	96.2%
DenseNet-121	0.140600	96.06%	0.124040	94.69%
DenseNet-169	0.110994	97.10%	0.099953	96.29%
AlexNet	0.169739	95.84%	0.142768	95.01%
SqeezeNet	0.096505	96.99%	0.105027	96.10%

V. Comparative Analysis

Here we compare the results of the proposed method with other approaches in pneumonia detection. In table 2, we list the accuracy of different method related works. Abiyev R.H et al. (2018) proposed a CNN model, and trained it on the 1000 images. They reported an accuracy of 92.4%. Rajaraman et al. (2018) have achieved 92.2% accuracy by exploiting VGG16 model with 5856 images. Kermany et al. (2018) proposed a transfer learning for pneumonia detection and achieved an accuracy of 92.8%. The dataset is composed of 5856 CXR images. M.Togacar et al. (2019) combined an ensemble of different deep learning algorithms (ResNet18, DenseNet121, InceptionV3, MobileNetV2 and Xceptio) for pneumonia detection, And the dataset consists of 5849 images. They reported an accuracy of 96.84%. Saraiva et al. (2019) proposed a CNN model and achieved an accuracy of 95.30%. And the dataset in this study consists of 5840 images. Ayan et al. (2019) proposed a transfer learning of Xception and VGG16 models for pneumonia detection, and trained it on the 5856 images. They achieved the best an accuracy of 87% with Xception model. Stephen O et al. (2019) used a CNN model, and trained it on the 5856 images dataset. They reported an accuracy of 93.73%.

Chouhan et al. (2020) By applying an ensemble of different deep learning algorithms (AlexNet, DenseNet121, InceptionV3, resNet18 and GoogLeNet neural networks). have achieved an accuracy 96.39%, And the dataset consists of 5232 images.

Table 2: *Comparison of pneumonia detection technique*

Citation	Technique	Results
Abiyev R.H et al. [40]	CNN model	92.4
Rajaraman et al.[42]	VGG16	96.2
Kermany et al. [46]	Transfer learning	92.8
M.Togacar et al.[43]	ResNet18,DenseNet 121,InceptionV3, MobileNetV2, Xception	96.84
Saraiva et al.[44]	CNN	95.30
Ayan et al. [45]	Transfer learning of Xception and VGG16. Best: Xception	87
Stephen O et al. [41]	CNN model	93.73
Chouhan et al.[47]	AlexNet, DenseNet121, InceptionV3, ResNet18 and GoogLeNet neural networks.	96.39
Proposed Models	Inception v4	98.72%
	SeNet154	98.94%
	Xception	98.88%
	PolyNet	98.72%
	ResNet-50	96.2%
	DenseNet-121	94.69%
	DenseNet-169	96.29%
	AlexNet	95.01%
	SqeezeNet	96.10%

from the above table 2, we can see that the proposed method is better than the other work in this area in terms of accuracy. The best result is obtained using SeNet-154 pre-trained model which reached 98.94% in terms of accuracy.

Conclusion

This paper aims to identify the diseases of pneumonia that have become widespread in the recent period with high accuracy. 5856 images were collected for classification and divided into 5216 images for training and 624 images for testing. A method has been proposed using nine pre-trained models (Inception v4, SeNet-154, Xception, PolyNet, ResNet-50, DenseNet-121, DenseNet-169, AlexNet, and SqueezeNet) and these models achieved accuracy (98.72%, 98.94%, 98.88%, 98.72%, 96.2%, 94.69) %, 96.29%, 95.01%, 96.10%) respectively. We found that SeNet-154 model gives the best result with validation loss (0.018103) and accuracy 98.94%. Vividly, the experimental findings show the effectiveness of the proposed method. In the future we plan to improve and increase the accuracy of these models. In addition to use other models such as VGG16, ResNet-152, SE- ResNet-50 and etc.

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