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PERFORMANCE ANALYSIS OF PNEUMONIA DETECTION USING ResNets TECHNIQUE

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Abstract: Pneumonia is derived from the Greek word 'Pneuma' which means "Breath". Pneumonia is a serious disease related to the lungs. Due to Its rapid and intense spread, it has become an important issue that is to be taken care of in the field of medicine. This disease is more prevalent in people who are addicted to smoking. Results in different domains of image classification are remarkable in recent advances achieved in deep learning. In making better decisions there is a dire need for computer-aided diagnosis to assist clinicians. Concerned with Pneumonia detection, ResNet; the winner of the IMAGENET challenge has performed quite well on the image recognition task. ResNet is a classic neural network used as a backbone for many computers vision tasks. A ResNet architecture consists of two residual blocks; an identity block and a convolutional block. By using more deeper networks and algorithms, the performance of the models can be improvised. Using X-ray images, work can be extended to classify and both Pneumonia and lung cancer. This paper targets the analysis of detection of Pneumonia based on performance using different computer-aided techniques such as ResNet 18, 34,50,101 and152.

Keywords: Pneumonia detection, IMAGENET, ResNet, X-ray imaging

I. INTRODUCTION

Pneumoniadue to a bacterial, fungal, or viral infection that affects lung alveoli is a deadly lungs disease known as silent killer [1]. By 2030 nearly 11 million children mainly under five are likely to be killed by the infectious disease as per the report released on World Pneumonia Day [2]. Due to other medical conditions in the lungs like bleeding, lung cancer, volume loss, post-radiation, or surgery, the diagnosis of the diseases based on images becomes very complicated due to lack of expertise in the classification of Pneumonia using chest X-rays. This problem can be solved using the current development in the field of artificial intelligence by a computer-aided diagnosis can be a lot useful. To classify chest X-Ray images, Convolutional Neural Networks can be used to detect if the Pneumonia is present or not.Asoftware contest named ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was conducted by the ImageNet projectfor the detection and classification of images, in which different algorithms were analyzed. AlexNet, VGGNet, ResNet, InceptionNet, DenseNet, XceptionNet, and SENet are some of the CNN architectures [4]. All these architectures areILSVRC winners. By merging the above-said architectures, some other architectures are formed.Deeper neural networks of Deep Residual Learning for Image Recognition are more difficult to train. A residual network was presented to make the process easier.He et al. proposed a residual network structure (ResNet) [5] to solve these problems, by building a deep convolutional neural network of 152 layers, won the champion of multiple tasks on ILSVRC-2015.

PERFORMANCE ANALYSIS:

The performance analysis for any transfer learning model is evaluated using some measures, a few of the most common performance measures are Precision, F1 score, Recall, and Accuracy.

$$\text{PRECISION} = \frac{\text{True positive samples (TP)}}{\text{True Positive Samples (TP)+False positive samples (FP)}}$$

$$\text{RECALL} = \frac{\text{True Positive Samples (TP)}}{\text{True Positive Samples (TP)+False Negative samples (FN)}}$$

$$\text{F1 SCORE} = \frac{\text{2 x PRECISION x RECALL}}{\text{PRECISION+RECALL}}$$

$$\text{ACCURACY} = \frac{\text{True Negative Samples (TN)+True Positive Samples (TP)}}{\text{TN+TP+FN+FP}}$$

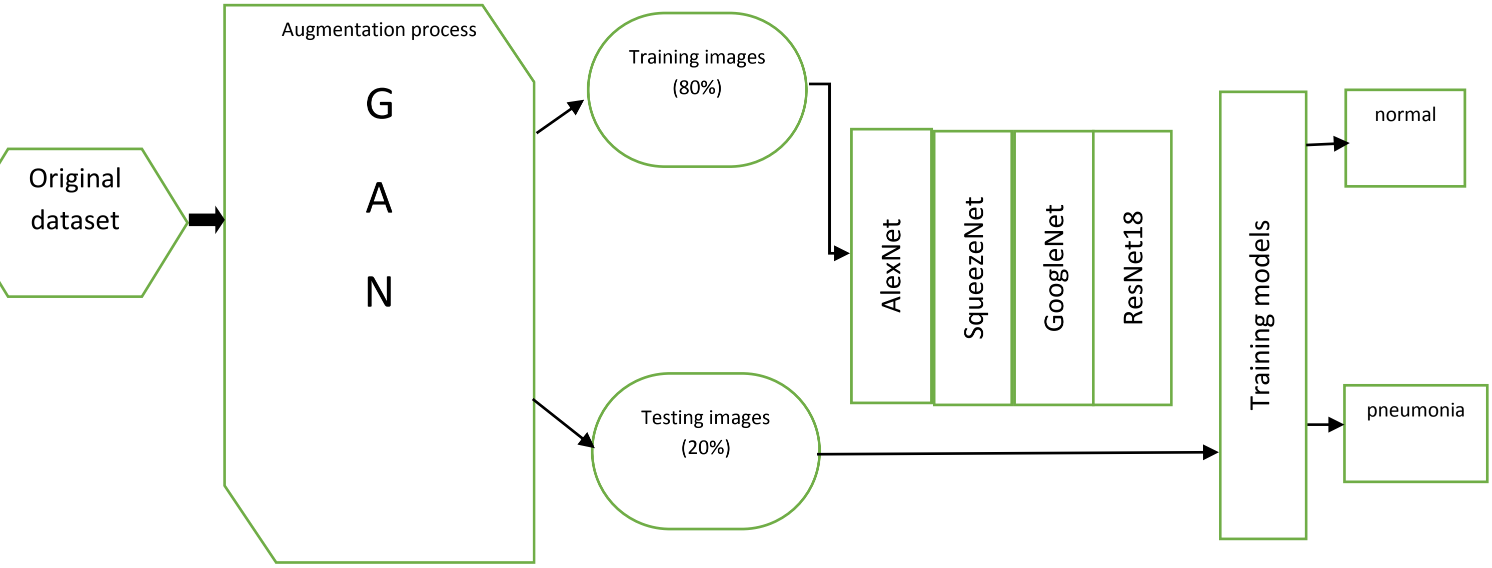
II LITERATURE REVIEW:

RESNET 18 MODEL:

The following model was proposed with Generative Adversarial Networks by Nour Eldeen M. Khalifa et al. [7] using the dataset used in the research [8], that was published in 2018 and it has been used in much research since then. It produced the highest testing accuracy rate of 99% among the other models that were tested. Hence, they concluded that the ResNet 18 was the ideal choice to use along with GAN.

They proposed a three-phased model based upon two deep learning models, with the first phase as the pre-processing phase that primarily does the augmentation process dependant on the first deep learning model, Generative Adversial Networks (GAN). The GAN consisted of two networks namely generative and discriminator. The augmentation process is accountable for the generation of contemporary images used in the testing phase as well as the training phase.

The second phase of the model, the training phase comprises the processes which split the data into two parts and train the models. The first part trains 80% of the dataset and the second part tests 20% of the dataset. The Deep transfer model is the second part of this phase. Several Deep Transfer models such as the AlexNet [10], SqueezeNet [11], GoogleNet [12] and ResNet 18 [13] were studied. These models have a smaller number of layers than the large deep learning models such as the Xception [14], DenseNet [15], and InceptionResNet [16] with 71, 201, and 164 layers respectively. This methodology was developed using MATLAB and the experimentation was carried out with 32 GB RAM, Titan X GPU, and i9 core (2 GHz).



Performance analysis for ResNet 18 model:

Model	Resnet18
Precision	98.97%
Recall	98.97%
F1 score	98.97%

RESNET-34 BASED U-NET:

Pant, Ayush et al. used a dataset from Kaggle [17], which contained 5863 Chest X-Ray Images in jpeg format and they were classified into Train, Test, and Validate which consisted of two main categories, Pneumonia and Normal [27].

The U-Net is a CNN model exclusively used for biomedical image classification since it gives the potential to be used as an Encoder-Decoder. It is highly effective once it is implemented in the application with the same input as that of output. A dense layer and an output layer are added at the end of U-Net. This is done to find out the output i.e., whether the image is of Pneumonia or Normal. The experimentation findings resulted in an accuracy of 0.82 and a high recall value of 0.99.

RESNET 34:

34-layer ResNet is virtually the same as the deeper network of VGG-19 with more convolutional layers. VGG19 model contains 3 fully connected layers, 1 SoftMax layer, and 5 MaxPool layers with 16 convolutional layers whereas, the ResNet 34 model contains 34 layers of convolutional neural network with the addition of shortcut connections to make the model, a Residual neural network. The increase in the number of convolutional layers results in decreased time complexity. Using the same Kaggle dataset, which contains 5863 X-ray images, Yuan Tian experimented to detect Pneumonia using ResNet-34 and gave an accuracy of 91% [28].

RESNET 50 MODEL:

The ResNet 50 model has 50 layered ResNet blocks with 2 or 3 convolutional layers in each block. The ResNet 50 was the winner in ILSRVC 2015 having an error of 3.57%. It has a 224 by 224 input image size.

RESNET 50 HYBRID MODEL:

Çınar et al. [17], introduced a hybrid ResNet 50 model and used the data from Kaggle’s website [18]. The data set contained the images of both classes i.e., 3,730 images of Pneumonia affected lungs and 1,341 images of Normal lungs.

The input layer of the introduced hybrid ResNet 50 model received the input data as 224*224*1. The new model has a base that includes an input layer, convolutional layer, activation layer, pooling layer, fully connected layer, SoftMax, and classification layers

Accuracy	97.22
Sensitivity	95.78
Specificity	97.69
F-Measure	94.51

with an additional 2 fully connected layers. To make the model run more stable and faster, a Batch Normalization layer was added to Normalize each layer in the neural network. A Dropout layer is adjoined to prevent the model from retaining the training data. The SoftMax activation function assists the fully connected output layer in classifying the data. The total number of layers in this hybrid model is 182. This improvised hybrid model produced an accuracy rate of 97.22% whereas for the ResNet 50 model 96.35% was obtained using the same dataset.

Performance analysis for the devised hybrid model:

250	18
11	763

Confusion matrix:

Performance analysis for the ResNet 50 model:

Confusion matrix:

Accuracy	96.35
Sensitivity	92.91
Specificity	97.54
F-Measure	92.91

RESNET 50 SVM:

Varshini et al. used the ResNet 50 model followed by classifiers such as SVM (rbf kernel), Naïve Bayes, k-nearest neighbours, Random Forest and obtained the accuracies of 77.49%, 68.91%, 72.98%, 57.93% respectively. The highest accuracy is observed at ResNet 50-SVM [19].

A Support Vector Machine is a learning algorithm especially used for binary classification whose performance is dependent upon the appropriate selection of kernels. For the above data, the SVM is best suited to classify the images and was able to find the best hyperplane for classifying the data points.

RESNET 101:

ResNet-101 is a 101 deep layer of convolutional neural network. The network can classify images of the 1000 objects into several different categories, like keyboard, mouse, and pencil [31]. As an outcome, the network has learned rich feature representations for a good range of images. The image input of the network is 224-by-224[29].

Comparison of results of different networks.

Network	MS
Mask R-CNN	0.2181
DeepConv-DilatedNet+Soft-NMS	0.35087

Abiyev and Ma'aitah [32] compared their work with that of others, as shown in Table 1. MS is defined as the mean score for every image with overall threshold (ranges from 0.4 to 0.75 at a step size of 0.05) values; they have predicted that their outcome is 10.9% higher than those obtained by Abiyev and Ma'aitah [32] using Mask R-CNN, which concludes that model is reliable for detecting pneumonia.A comparison was made with 4 different AP indexes with different IoU thresholds and the mAP values ($t \in$ 0.4, 0.5, 0.6, 0.7) are calculated as shown in Table

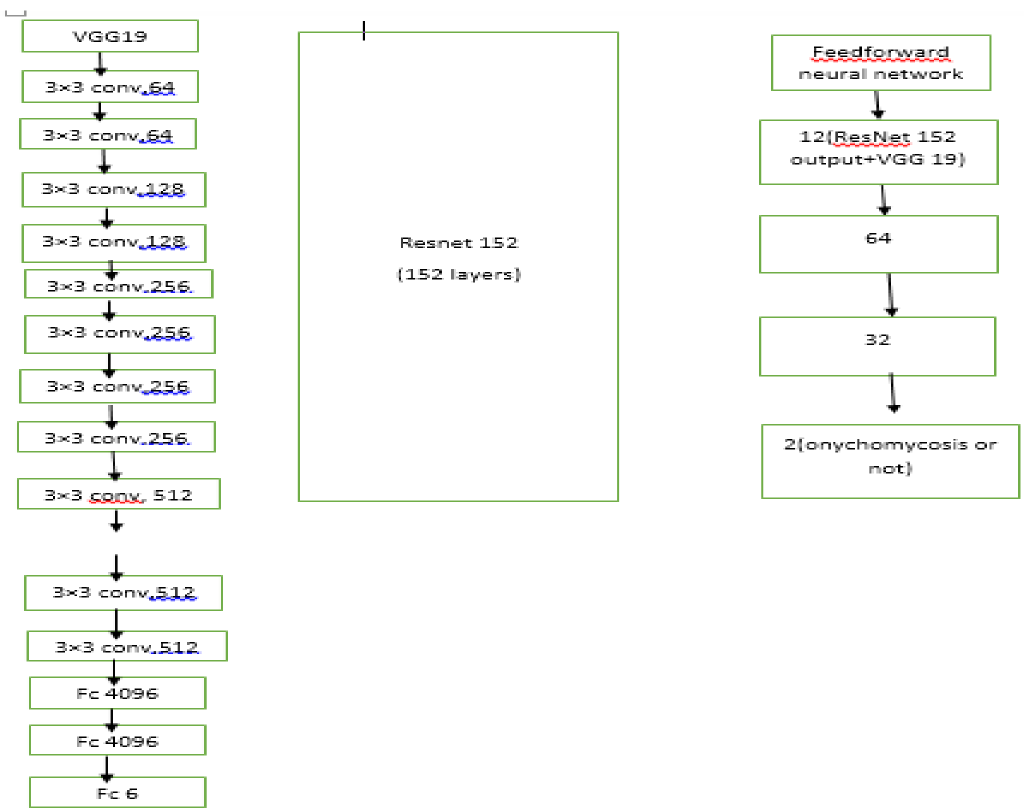
Assessment results for different IoU thresholds

	AP@0.4	AP@0.5	AP@0.6	AP@0.7	mAP
DetNet59	0.6317	0.4201	0.2068	0.0657	0.3311

ResNet50	0.6066	0.3791	0.1863	0.0513	0.3058
ResNet101	0.5539	0.3508	0.1540	0.0406	0.2748
VGG16	0.5506	0.3559	0.1881	0.0660	0.4210
DeepConv-DilatedNet	0.6419	0.4570	0.2732	0.0746	0.3617

Firstly, DesNet59 as the backbone they compared with various detection effects and the method using Vgg16, ResNet50, and ResNet101 as the backbone, respectively.As shown in the figure that Faster R-CNN with Deep Cony-Dilated Net as a backbone is higher than when compared with the DetNet59, ResNet50, ResNet 101, and VGG16 network models on each AP with different thresholds [30].

RESNET 152:



Resnet 50 can be used as a starting point of the transfer learning where we will code a smaller version of Resnet 152. However, simply stacking layers together does not work by increasing network depth.The ResNet-152 convolutional neural network was customized to recognize pneumonia from radiography images with the transfer learning technique. Kaiming et al. produced a Recognition success of 97.4% in the detection of pneumonia disease with this customized architecture without any pre-processing of raw data or manual feature extraction on radiography images [24].

Deeper neural networks are hard to train. To ease the training of substantial networks, we present residual learning deeper than those used previously. We certainly reformulate the layers regarding the layer inputs as learning residual functions, instead of learning unreferenced functions. These residual networks are easier to optimize and can gain accuracy from the considerably increased depth that provides comprehensive empirical evidence. Residual nets are evaluated on the dataset ImageNet having lower complexities with a depth of 152 layers which is 8 times deeper than VGG nets [25].

III DISCUSSION:

Various datasets used for the performance analysis of the different ResNet models included X-ray images of bacterial, viral pneumonia, and non-Pneumonia. Also, it included frontal view and lateral view images. Some datasets also included images of pleural effusion, tuberculosis, and COVID-19. In the end, any CNN model performs higher if it is trained with a large quantity of data. It requires a lot of time to train with a large amount of data. With the use of Graphics Processing Unit (GPU), the training time can be reduced [33]. The GPU runs the operations all at once rather than running them one by one.

The ResNet18, 34, 50 showed better performances with the incorporation of specific algorithmic architectures such as the GAN, UAN, and SVM respectively. In other ways, the ResNet101 and 152 showed better performances without any other incorporation of algorithmic architectures. It is because of the additional layers of residual blocks present in them.

IV CONCLUSION:

Pneumonia causes high mortalities globally. The image classification technique can identify the class of Pneumonia if provided with the training images of the different classes of Pneumonia such as lobar pneumonia, bronchopneumonia, and interstitial pneumonia. These three types of Pneumonia are named based upon the part of the lung involved in affection. Furthermore, the same image recognition technology can be used to classify and differentiate the coronavirus disease from the other types of Pneumonia as well as lung cancer. This type of detection of diseases will minimize the erroneous conclusions made by the physicians using traditional methods. The accuracy of various ResNets models from the literature survey is listed in the table. It is important to note that, different datasets were used by the different models to obtain the performance analysis of each model.

From the table, the Resnet18+GAN and the ResNet152 have the highest accuracy rates. The ResNet152 has the least top-1 and top-25 error rates compared to shallow ResNet models. The ResNet101 encoder has a higher IoU metric on Semantic Segmentation Challenge. It is noted that the models show improved performance with an increase in the number of cascaded blocks. Thus, the deeper ResNet models produce better results than the shallow models.

RESNET MODEL	CITATION	ACCURACY
ResNet18+GAN	Nour Eldeen M. Khalifa et al.	98.97%
ResNet34+UAN	Pant, Ayush, et al.	82%
ResNet34	Yuan Tian	91%
ResNet50	Çınar et al.	96.35
ResNet50 Hybrid Model	Çınar et al.	97.22
ResNet50+SVM	Varshini et al.	77.49%
ResNet101	R. H. Abiyev and M. K. Ma’aitah	87.02%
ResNet152	Kaiming He et al.	97.4%

Table.1 Summary of Performance Analysis

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