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Automated Diagnosis of Pneumonia from Classification of Chest X-Ray Images using EfficientNet

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***Abstract*—Pneumonia is a fatal contagious agent that causes respiratory disorders. The methodology utilized by an advisor to evaluate pneumonia through chest X-ray images is tedious and pricey. However, it also requires an experienced and skilled radiologist to correctly interpret the chest x-ray images. Moreover, the diagnosis can be confusing some times. Subsequently, researchers should pay attention to deploying a PC supported framework to recognize pneumonia. Again, clinical and experimental data can come from many different laboratories following different protocols and so databases are usually particularly disordered and noisy. To solve this issue, We have utilized EDA (Exploratory Data Analysis) to interpret the data set to clarify its basic traits. The class imbalance issue is reduced and data augmentation is also applied. A recently designed CNN (convolutional neural network) model EfficientNet is used to train the classifier by transfer learning and fine-tuning. The model has achieved a test accuracy of 96.33% and an AUC(Area Under Curve) of 0.991. We have also calculated other strategic objectives, such as precision, recall, and F1 score, to demonstrate the efficacy of our approach in finding pneumonia in the exclusion of trained physicians.**

***Index Terms*—Transfer Learning, Exploratory Data Analysis, Convolutional Neural Network, EfficientNet, Image Classification, Pneumonia identification.**

I. Introduction

The World Health Organization (WHO, Geneva, CH) has expressed that pneumonia is one of the world's highest reasons for mortality for kids younger than five years old, killing roughly 1.4 million, or around 18% of all kids below five years old around the world [1]. Infectious agents destroy pulmonary alveoli, causing them to be filled with pus and fluid, causing uncomfortable breathing and reducing oxygen intake. It is dangerous for children, people with other disabilities, people with weakened immune systems, aged persons, adults who have been hospitalized and put on a ventilation system, people with severe diseases such as asthma, and public smoking cigarettes.

Still in many communities that don't even have access to clinical imaging, such as MRI and CT, mostly in emerging countries, including the South Asian and African territories, where healthcare facilities are inadequate. Mostly as pain-free and non-invasive forms of testing, CXRAY images are the least expensive of many radio-logical tests, enabling the low-income public to have access to this type of prognosis. A thorough inspection of chest X-ray Images is obligated for the diagnosis of pneumonia, which in turn entails a proficient and trained radiologist. The assessment of chest x-ray pneumonia is a daunting prospect even for highly trained physicians. The appearance of pneumonia within X-ray images is often blurry, can confuse with other illnesses. These inaccuracies caused extensively biased decisions and diversities among radiologists in diagnosing pneumonia. Fig. 1. shows a normal chest x-ray image. Pneumonia-created pus and fluids trigger radiology sections (white regions) in the chest X-Ray image which is shown in Fig. 2.

However, to boost the classification efficiency of the proposed work, we have conducted scale conversion, rotation, and flipping procedures upon this image to extend the data-set. Furthermore, We have reduced the issue of class imbalance which affects the length of the training time due to the bias of cost function by the majority class on account of binary classification. Furthermore, to shorten the training time of the model and fast-tracking convergence, we have implemented a transfer learning system with fine-tuning.

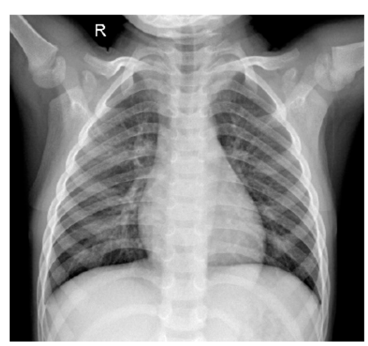

Fig. 1. Sample image of Normal chest X-ray

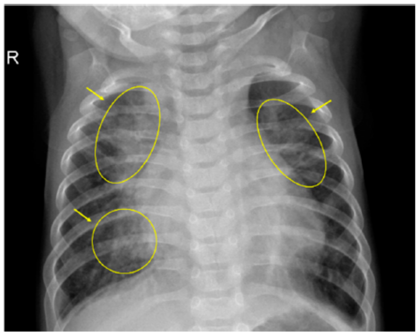

Fig. 2. Chest X-ray image of pneumonia patient in which fluid accumulation causes radiopaque segments

II. Related works

Modern developments in the field of deep learning, particularly convolutional neural networks (CNNs) showed abundant success in natural language processing, medical image classification [2], segmentation, object detection, and other tasks. CNN's accomplished very effective results in resolving medical complications such as brain tumor segmentation [3], breast cancer detection [4], skin lesion classification, Alzheimer disease diagnosis, etc.

In 2017, Rajpurkar et al. [5] recommended a 121-layer convolutional neural network dependent on DenseNet and named CheXNet. They molded their calculation with 10,000 front-screen chest X-beam pictures of 14 human illnesses. Kermany et al. [6] applied the transfer learning of the InceptionV3 model to recognize pneumonia from the Chest X-ray sample in the Mendeley data collection. Liang et al. [7] used transfer learning and a deep residual Network oriented approach and dilated convolution for the classification of pediatric pneumonia images. Sirazitdinov et al. [8] recommended a group of RetinaNet and Mask R-CNN networks for the recognizable proof of pneumonia. From the start, the networks recognized the pneumonia-influenced areas and after that, the non-maximum concealment was acted in the expected lung areas. Stephen et al. [9] built a CNN from scratch to distinguish pneumonia in the chest X-ray images. Enes Ayan et al. [10] used transfer learning by Xception and Vgg16 models. Ayush et al. [11] proposed an ensemble of ResNet-34 based U-Net and EfficientNet-B4 based U-Net. The process of training a deep CNN model such as DenseNet, ResNet, Xception or EfficientNet from scratch necessitates lots of data because it includes millions of training parameters in which a limited dataset will be inadequate to obtain a successful generalization of the model.

This paper makes a major contribution to the use of the latest transfer learning model called EfficientNet, which is trained on the Imagenet dataset with fine-tuning. We have proposed one way to deal with resolve the class imbalance issue of the dataset and augmentation of data is consolidated.

III. Materials and Methods

A. Dataset

The dataset [12] we have used in this work is divided into three folders; train, test, and validation that contain subfolders for every image type, pneumonia, and normal. The data collection includes 5,863 X-Ray images, comprising 4273 pneumonia images and 1583 images in normal cases. As there is an extremely limited quantity of information particularly in the validation set, we have consolidated all pneumonia pictures in one dataset and all ordinary pictures in another dataset. At that point, we have divided the information into 60%, 20%, and 20% for preparing validation, and testing set correspondingly which is appeared in Table I.

TABLE I: Dataset Information

Dataset	Number of Normal Images	Number of Pneumonia Images
Training dataset	950	2563
Validation dataset	317	855
Testing Dataset	316	855

B. Data preprocessing and augmentation

In Deep learning, big quantities of data are needed to generate the right results. There is low availability of data in the dataset. Data augmentation strategy is applied to resolve this issue, which also alleviates over-fitting. After this, the amount of data is boosted, which is crucial for the effective transferability of the model. The shape of the images becomes 128*128 after resizing. The techniques used for data augmentation are displayed in Table II.

TABLE II: Techniques of Data Augmentation

Techniques of Data Augmentation	Values
Re-scale	1.0/255
Shear Range	0.2
Width Shift Range	0.2
Height Shift Range	0.2
Rotation Range	30
Horizontal Flip	True
Zoom Range	0.2

C. Exploratory data analysis

It is imperative to be especially cautious with the data, to ensure that the data are valid across the whole extraction phase, and to have numerous checks accomplished in the process. We have continued with the study of the data folder and the images stored in it.

D. Class Imbalance

In the newly rearranged sets, we get an equal proportion of Pneumonia/Normal images on every subset. But the dataset is still imbalanced by a varying amount of Pneumonia/Normal images for each collection. To reduce this issue, we have computed the class weights to solve the imbalance in our model data using the 'CLASS WEIGHTS' parameter.

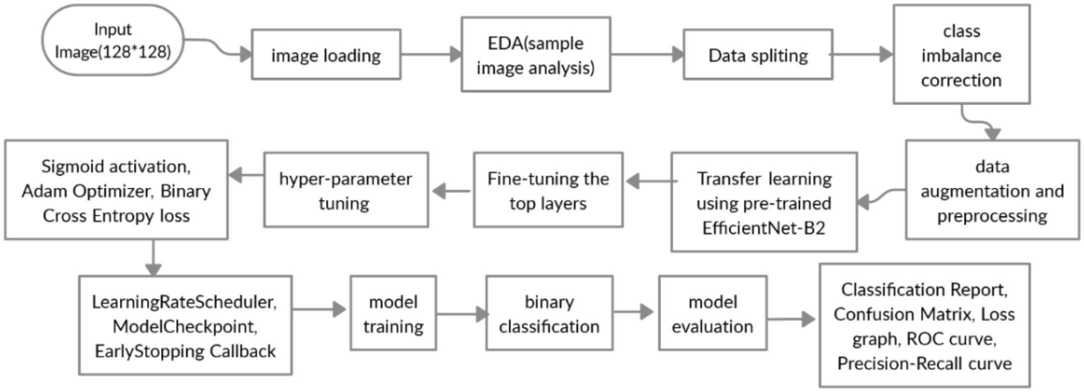

Fig. 3. Workflow

E. EfficientNet

The principle part of Efficientnet is the Mobile Inverted Bottleneck Conv (MBconv) Block, in addition to squeeze-and-excitation blocks presented in [13]. The thinking behind the EfficientNet people group is to work from a high caliber yet compacted benchmark model and reliably measure every one of its boundaries with a fixed number of scaling coefficients. The model is created by Google AI in May 2019 which is accessible from Github repositories. We have applied transfer learning using the pre-trained EfficientNet model and the weights are taken from Imagenet.

F. Fine-tuning

We have frozen the earlier layers to extract common low-level features or patterns from the chest X-ray images and the top layers are modified. In convolutional neural networks, the first several layers learn very specific and basic features that generalize to almost all kinds of images. As we kept going up, the features became gradually more unique to the data set upon which the model was trained. The purpose of fine-tuning is to adjust these unique features to function with the currently fed data-set of Chest X-Ray. On top of the base model, we have added a newly designed classifier and trained to adjust the weights according to new distributions and patterns.

TABLE III: Top Layers and parameters of the proposed model

Layer type	Output shape	Param#
global_average_pooling2d	1408	0
Dense (with activation 'RELU')	128	180352
Dropout (30%)	128	0
Dense (with activation 'RELU')	64	8256
Dropout (20%)	64	0
Dense (with activation 'sigmoid')	1	65
Total parameters: 7,957,235		
Trainable parameters: 7,889,667		
Non-trainable parameters: 67,568		

G. Hyper-parameter tuning

We have used LearningRateScheduler, a callback function that is used to control this hyper-parameter over time (number of iterations/epochs). We have defined a function that takes an epoch index as input and returns the new learning rate as output. Then we have modified the learning rate based on the epoch. As the decay argument is specified in the equation, it has decreased the learning rate from the previous epoch according to the argument.

We have applied ModelCheckpoint and Earlystopping callback function where patience is set to 10 and validation loss is monitored. The workflow is presented in Fig. 3.

IV. RESULT ANALYSIS

To monitor the execution of our proposed strategy, we carried out the experiment using all eight EfficientNet models. (i.e. EfficientNet-B0 to B7). The models are small and because of using the depthwise separable convolution in MBconv block in EfficientNet, the computational complexity is minimized. This is why EfficientNet is chosen. We have calibrated the batch size, the shape of the image, learning rate, and other hyper-parameters to deliver the expected output. The fine-tuning of the top layers is also modified every time to get a better response. Adam optimizer(learning rate=0.001) is utilized to limit the loss function of Binary cross-entropy. Finally, we have got the best result using EfficientNet-B2 with an image size of 128×128, batch size of 128, and, using the top layers given in Table III. Kaggle's kernel is used for training with GPU as an accelerator and the execution time is 2099.6 seconds. The algorithm is implemented using Keras Framework. We have used Tensorflow, Scikit-learn, OpenCV, etc. for different functionalities. We have trained the model using 3513 images, validated it with 1172 images, and tested the model with 1171 images. The model has attained an optimum result at the 29th epoch with an early stopping callback. Then we have judged the performance using evaluation metrics of precision, recall, f1 score, and accuracy. According to the result in Table IV, the model has demonstrated a high precision and recall value which indicates that there are very low false positive and false negative values. In this manner, the model has few wrong predictions thus the model is trustworthy in diagnosing pneumonia reasonably.

TABLE IV: Result

Model	Label	Test Accuracy	Precision	Recall	F1 score	AUC
EfficientNet-B2	Normal	0.96	0.96	0.95	0.963	0.991
	Pneumonia		0.98	0.97	0.97	

Then confusion metrics are then plotted. In Fig.4, we can see that among 316 test images of the normal class, 300 images are predicted as normal. Again among 855 test images of pneumonia class, 828 images are predicted as pneumonia which is quite reliable.

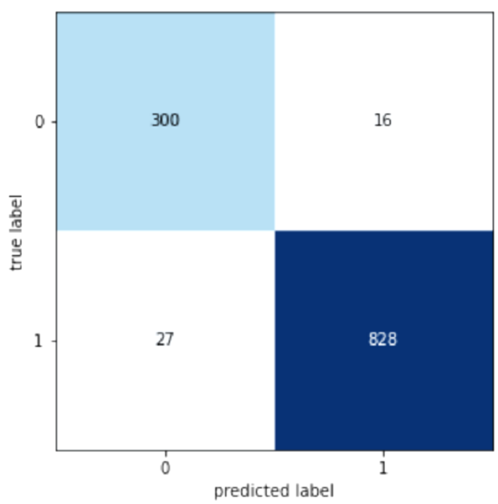

Fig. 4. Confusion matrix

In Fig. 5, the curves of validation accuracy and training accuracy are shown. The graphs of validation loss and training loss are presented in Fig. 6. We can observe that the accuracy is increasing with epoch and the loss is decreasing gradually.

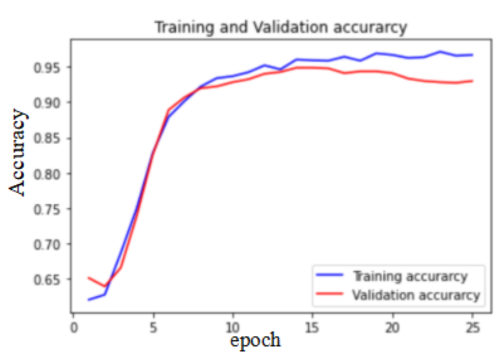

Fig. 5. Accuracy graph of EfficientNet-B2

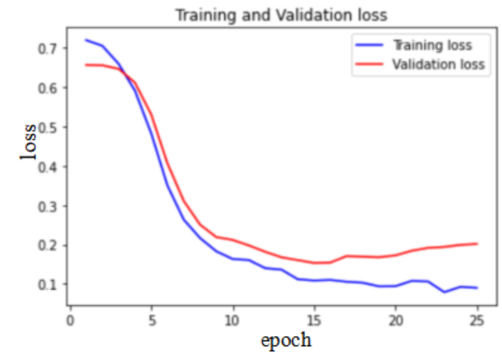

Fig. 6. loss graph of EfficientNet-B2

The ROC(Receiver Operating Characteristic) curve of the proposed work is demonstrated in Fig. 7 and the AUC (area under the curve) is calculated. We have got an AUC of 0.991 which is one of the best performances comparing with the other recent works. In Fig. 8, we have revealed our Precision-Recall curve.

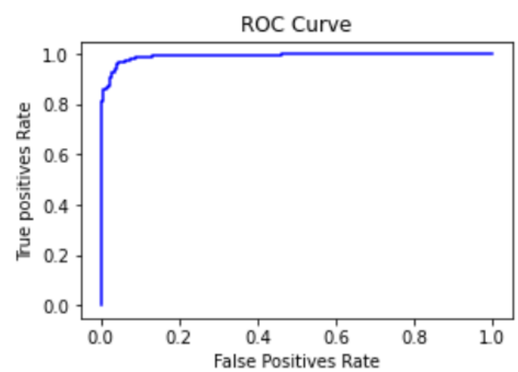

Fig. 7. ROC curve

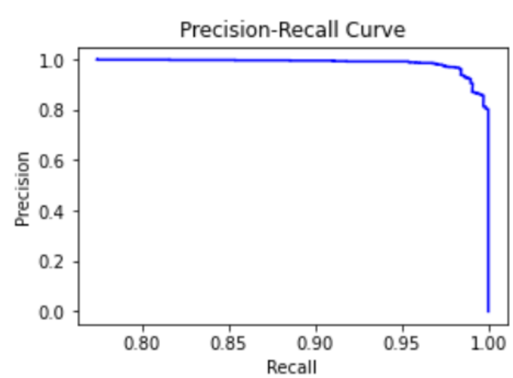

Fig. 8. Precision-recall curve

We have contrasted our work and some other latest examination works dependent on a similar chest x-ray dataset which is introduced in Table V.

TABLE V: Comparison with other recent works

Author	Accuracy	Precision	Recall	F1 score	AUC
G. Liang et al. (2019) [7]	0.905	-	0.967	-	0.953
O. Stephen et al. (2019) [9]	0.937	-	-	-	-
E. Ayan et al. (2019) [10]	0.87	0.91	0.82	0.90	-
A. Pant et al. (2020) [11]	0.90	0.87	0.99	0.92	-
R. Siddiqi (2020) [14]	0.958	0.952	0.985	0.967	0.990
Proposed work	0.96	0.98	0.97	0.97	0.991

V. Conclusion and Future Work

In our research, we have demonstrated an interactive form of treatment that categorizes chest x-ray objects into pneumonia and normal. We have applied a robust and recent transfer learning model EfficientNet-B2 with fine-tuning to train the model attaining 96.33% test accuracy, 98% precision, and 97% recall. Furthermore, our work has generated an F1 score of 0.97, an AUC score of 0.991 for the ROC curve. EfficientNet affords massive advances in parameter mitigation and loss of FLOPS(Floating Point Operations Per Second), together with tremendous accuracy gains by compound scaling scheme. It lowers the expense of computation and the use of batteries. Due to excessive transcription costs, the acquisition of broad training data is a demanding task. We have overcome this problem using transfer learning and data augmentation technique while avoiding over-fitting also. Moreover, we have diminished the issue of class awkwardness. While pneumonia is detected by a single physician or doctor, this transfer learning method can be considered as a mutual verification system reducing both computer and human error which is more reliable in diagnosing a patient. In the future, the performance of our work can be improved by increasing data size, image processing, and applying other transfer learning models to provide a more precise assessment of pneumonia.

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