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Efficient deep learning based data augmentation techniques for enhanced learning on inadequate medical imaging data

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ABSTRACT
The world has come to a standstill with the Coronavirus taking over. In these dire times, there are fewer doctors and more patients and hence, treatment is becoming more and more difficult and expensive. In recent times, Computer Science, Machine Intelligence, measurement technology has made a lot of progress in the field of Medical Science hence aiding the automation of a lot of medical activities. One area of progress in this regard is the automation of the process of detection of respiratory diseases (such as COVID-19). There have been many Convolutional Neural Network (CNN) architectures and approaches that have been proposed for Chest X-Ray Classification. But a big problem still remains and that is the minimal availability of Medical X-Ray Images due to improper measurements. Due to this minimal availability of Chest X-Ray data, most CNN classifiers do not get trained to an optimal level and the required standards for automating the process are not met. In order to overcome this problem, we propose a new deep learning based approach for accurate measurements of physiological data.

Section: RESEARCH PAPER

Keywords: CNN; COVID-19; GAN; transfer learning; X-ray images

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1. INTRODUCTION

COVID-19 has reached at least 200 countries worldwide and is overwhelming the healthcare infrastructures like any other emerging pandemic [1]. This pandemic has made everyone realize the importance of hygiene and preventive measures of contracting a virus. When trying to help potential COVID-19 patients, allocating clinical resources to the most probable cases can improve the flow of treating patients. To identify the potential cases among all the cases in a hospital, an automated system that can detect the disease can provide immense help to the hospital staff. Although the method provided in this work cannot be implemented in a standalone fashion, it can be implemented with minimal interaction. Automating the recognition of the virus through the X-ray images can be done through teaching the computer to recognize patterns in the X-ray images [2]. To teach a computer to recognize the patterns in an image, computer vision technique such as Convolutional Neural Networks (CNNs) are required. A CNN can classify given images based on training data, which is not abundantly available in the medical field. Even though the available data is increasing at a steady rate, external factors such as human errors and incorrect data can decrease the accuracy with which the CNN can classify an image. So, to prevent these problems, more data is generated using GANs on some accurate and curated data. This work will implement Computer Vision techniques such as Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to classify the X-Ray images. The mechanism also uses a number of Conventional Data Augmentation techniques such as changing the axis of the image, rotating the image, changing the brightness and other factors of the image corresponding to the RGB values.

Generative Adversarial Networks (GANs) is a class of Deep Learning and Image Processing models/architectures which are used to generate new images similar to an already existing image dataset. The two sections of a GAN are: Generator and Discriminator. The Discriminator tries to classify the input images as Real or Fake with high accuracy. The Generator's aim is to generate new images which can trick the Discriminator into believing that these newly generated images are also Real. If the Generator is successful in doing so, then the GAN is able to

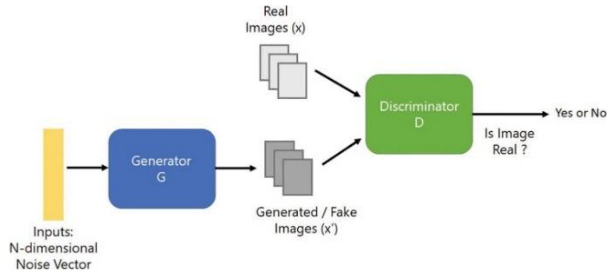

Figure 1. Flowchart for working of a GAN [3].

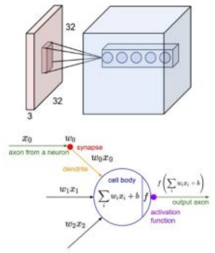

Figure 2. Working of a CNN [5].

generate images which are very similar to the original images and its flow chart is shown in Figure 1.

Computer Vision is a branch of computer science that deals with giving a computer (or a machine) the ability to read and analyse images and videos in digital format. Although it seems trivial and very easy for people to see and perceive the visual stimuli offered by the surrounding, replicating the same for a computer is a complex task which requires a deep understanding of the biological vision and digital conversion of vision perception in the dynamic and ever-changing physical world [4], [5]. Computer Vision has come a long way from concept to application in the past few years. Computer Vision is being used in various sectors such as Healthcare, Robotics, Astrophysics, Manufacturing, Transportation, Agriculture, etc. Applications such as Self-Driving Cars, Artificial-Intelligence powered Robots, Defect Detection in Manufacturing, Intrusion Detection, and Optical Character Recognition are possible only because of the advancement of Computer Vision.

Convolutional Neural Network is a neural network with neurons having learnable weights and biases performing dot products and following non-linearity [6]. It is specifically designed for image processing, segmentation, and classification with convolutional layers. The Convolutional neural networks have neurons arranged in three dimensions and multiple layers, , its working flow is shown in Figure 2. Each layer of the CNN has a simple task of creating a 3D output from a 3D input with a differential function [7]. There are three major layers in the CNN Convolutional Layer, Pooling Layer, and Fully-Connected Layer. Each of these three layers has a particular function; the Convolutional Layer performs a series of operations on the input matrix/array using filters of the same dimension, the Pooling layer decreases the length and width of the input array while increasing the depth/height which is followed by a Flatten layer that transforms the 3-Dimensional Matrix into a 1-Dimensional Array which is then fed to a Fully Connected layer (an Artificial Neural Network).

Tang and Tang provided an end-to-end process of creating a Generative Adversarial Classifier that can find anomalies in Chest X-ray images which is trained on Normal Chest X-ray images [8]. The architecture proposed in the model is composed three Deep Neural Networks. The entire model is trained on the correct or normal images. So when the model encounter a normal image then the model categorizes it as a normal image but if the image the model encounters is a an abnormal image which the model did not recognize in the training data it is categorized as an abnormal image. This model is trained on normal Chest X-Ray Images numbering 6000, 1025 normal one-class Chest X-Ray Images, 1025 Chest X-Ray Images with lung opacities and 1000 images with lung opacities [9]. From this paper the whole process of creating a GAN which is used in this research paper is described in detail will be used.

Wong and Lam have researched upon the possible findings from the Chest X-Ray Images of potential COVID-19 patients. The study of findings of chest radiographies in patients of bilateral lower zone consolidation showed that the frequency of findings in the chest radiographies peaked at 10-12 days after the symptoms' onset [10]-[15]. The paper also discusses matters regarding the usage of CT scans which are more sensitive to infection in the body. The paper suggests the usage of RTPCR, and chest radiography testing for generating the required images. This paper gives an understanding of selection of images that are best for analysis and testing.

Zhang and Miao have observed that obtaining pixel wise labels for creation of a model is not possible due to anatomy overlaps in the images and texture which cannot accurately reveal information about the patient. In this paper the authors proposed an Image-to-Image model that can segment multiple organs in a 3D CT scan. The model was trained with digitally reconstructed radiographs formed over CT volumes. The paper implements a Task Driven Generative Adversarial Network that can create the X-ray images according to real images and achieve synthesis between the model and generated images [16]-[20]. Through this work, the implementation and symbiotic relation between the model and GAN is observed and modified to an extent.

Ke, Zhang, and Wei give a background to a neuro-heuristic approach to the classification of respiratory diseases using X-Ray images. This paper [21] proposes a Machine Learning architecture/methodology that can be used to assist doctors in making their decisions thus speeding up the process. The authors use a spatial analysis methodology with the main focus being on Hue, Saturation, and Brightness. The method proposes in this paper involves the use of Neural Networks in collaboration with heuristic search algorithms to detect degenerated lung tissues in X-Ray images. First, the Neural Network predicts the probability of a possible respiratory disease; if this probability is significantly high, then the heuristic algorithm scans and identifies the degenerated tissues in the X-Ray images based on the fitness function of the algorithm. The paper [22] presents promising results with an accuracy of over 79 % and a misclassification error of 3.23 % for False Positive predictions and 3.76 % for False Negative predictions.

In their paper, Chouhan and Singh present a Transfer Learning based approach to the classification of Pneumonia-based chest X-Rays. In this approach [23], the features of the X-Ray images are extracted using Neural Network models pretrained on ImageNet architecture and then these features are given as input to a classifier to classify the X-Ray as Pneumonia positive or Pneumonia Negative. The paper [24] analysed the performance of five measurement models. These models provide better measurement capability of X-ray data. The proposed deep learning-based approaches are well suited for measuring the medical image and as well analysis. The authors

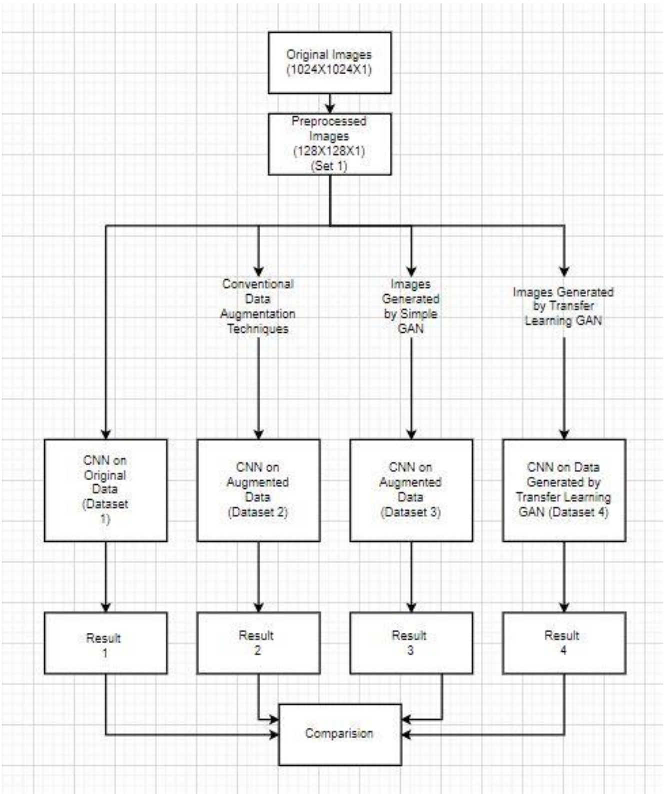

Figure 3. Procedure.

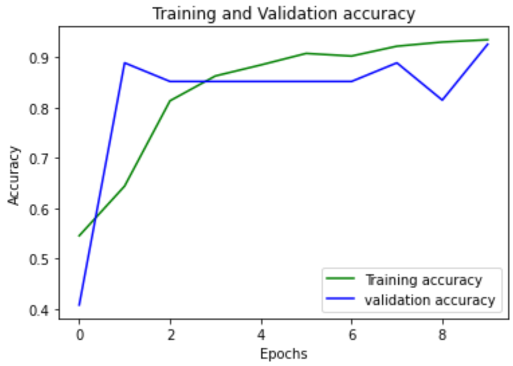

Figure 4. Training and Validation Accuracy of CNN on Original Dataset.

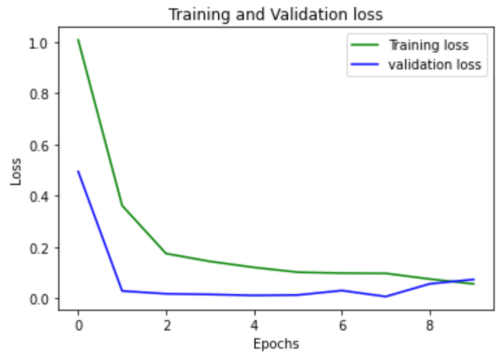

Figure 5. Training and Validation Loss of CNN on Original Dataset.

also proposed an ensemble model which was able to achieve a state-of-the-art accuracy of 96.4 % in classifying Pneumonia with a recall of 99.2 %.

2. METHOD

2.1. Data Pre-processing

i. Pre-processing the dataset [25] as per the needs of the problem was the first step. We had 1340 images of Normal X-Ray and 1340 images of Viral-Pneumonia X-Ray each of size $1024 \times 1024 \times 1$.

ii. To reduce the time and computation power needed for training, we reduced the size of the images from $1024 \times 1024 \times 1$ to $128 \times 128 \times 1$.

iii. To ensure that there was minimal information loss, we trained 1 CNN on the original data and another CNN on the minimized image data. The accuracy of both these CNNs was almost the same. So, we used the minimized image dataset for the purpose of this experiment and is shown in Figure 3.

2.2. Training GANs

iv. After minimizing the data, we trained 2 simple GANs (one on each class of images) for 200 epochs. Then, we generated 1000 images for each class and then saved the GAN models.

v. For transfer learning, we first trained a GAN on 7,864 face images [26] of size $128 \times 128 \times 1$ for 200 epochs. After training, we saved this Faces GAN model.

vi. Then, we trained the Faces GAN model on the Normal X-Ray images for 75 epochs. Then we generated 1000 images from this GAN and saved the model.

vii. Then we also trained the Faces GAN model separately on the Viral Pneumonia X-Ray images for 75 epochs. Then, we generated 1000 images from this GAN and saved the model.

2.3. Training CNNs

viii. Our next step was to train 1 CNN each on each of the following:

1. The Original Data
2. Data Generated by Conventional Data Augmentation Techniques
3. Data formed by combining the Original Data with the Data Generated by Simple GAN
4. Data formed by combining the Original Data with the Data Generated by Transfer Learning GAN

ix. Since one CNN was already trained on the original data, we then trained a second CNN on the data generated by using Conventional Data Augmentation Techniques (by using ImageDataGenerator()).

x. Then, we trained a third CNN on the data formed by combining the Original Data with the data generated by Simple GAN.

xi. As the last step, we trained a fourth CNN on the data formed by combining the Original Data with the data generated by Transfer Learning GAN.

xii. The accuracies of all the models were computed and its output is shown in Figure 4.

Note: The architecture and parameters used to train each CNN and GAN were the same.

3. RESULTS

We performed training of CNNs on 4 different datasets and the results are as follows:

1. Dataset 1 - *Original Data*

The plot for training and validation accuracy for the CNN trained on the original data is below.

Final Training Accuracy: 0.9348
Final Validation Accuracy: 0.9259

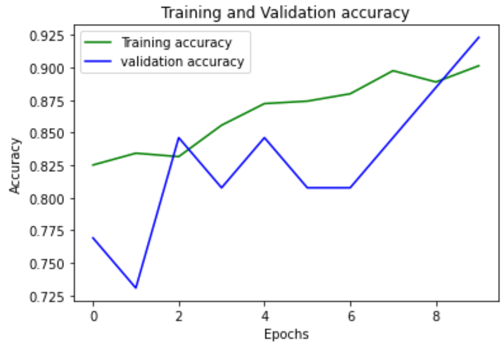

Figure 6. Training and Validation Accuracy of CNN on Second Dataset.

Figure 7. Training and Validation Loss of CNN on Second Dataset.

The plot for training and validation loss for the CNN trained on the original data is below.

Final Training Loss:	0.1595
Final Validation Loss:	0.3016

The CNN achieved a Training accuracy of 93.5 % on the original data as shown in Figure 5. This suggests that the model achieves a high accuracy without any data augmentation techniques but an accuracy of 93.5 % is not enough when classifying X-Ray images in a real-time scenario.

2. Dataset 2 - *Data Generated by Conventional Data Augmentation Techniques*

The plot for training and validation accuracy for the CNN trained on the second dataset is shown in Figure 6.

Final Training Accuracy:	0.9013
Final Validation Accuracy:	0.9231

The plot for training and validation loss for the CNN trained on the second data is shown in Figure 7.

Final Training Loss:	0.2587
Final Validation Loss:	0.2919

The values of accuracy and loss for this model are similar to the model trained on the original dataset. There is not a big difference. This means that conventional data augmentation techniques might not be a feasible option for data augmentation in medical image classification.

3. Dataset 3 - *Data formed by combining the Original Data with the Data Generated by Simple GAN*

The plot for training and validation accuracy for the CNN trained on the third dataset is shown in Figure 8.

Final Training Accuracy:	0.9771
Final Validation Accuracy:	1.0000

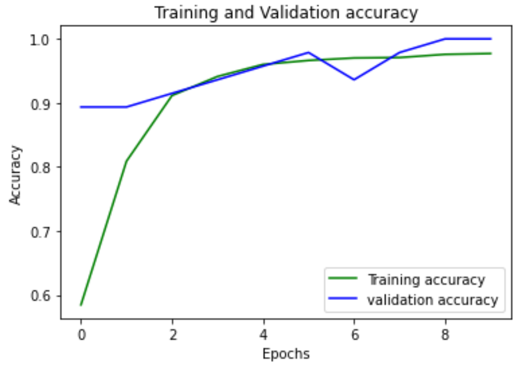

Figure 8. Training and Validation Accuracy of CNN on Third Dataset.

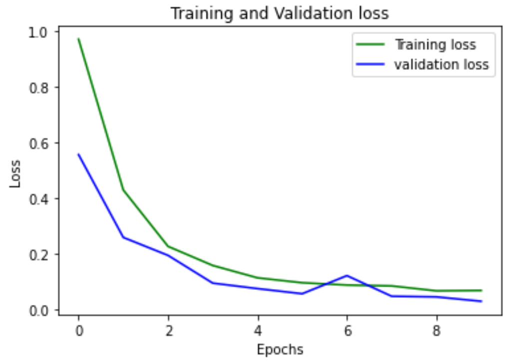

Figure 9. Training and Validation Loss of CNN on Third Dataset.

The plot for training and validation loss for the CNN trained on the third data is shown in Figure 9.

Final Training Loss:	0.0670
Final Validation Loss:	0.0281

There is a huge improvement the images generated by a Simple GAN along with the original images are used to train a CNN. The training accuracy goes up to 97.71 % and the validation accuracy is a perfect 100 %

4. Dataset 4 - *Data formed by combining the Original Data with the Data Generated by Transfer Learning GAN*

The plot for training and validation accuracy for the CNN trained on the fourth dataset is shown in Figure 10.

Final Training Accuracy:	0.9786
Final Validation Accuracy:	0.9574

The plot for training and validation loss for the CNN trained on the fourth data is shown in Figure 11.

Final Training Loss:	0.0566
Final Validation Loss:	0.0739

There is a small improvement in the training accuracy of this CNN. However, there is a dip in the validation accuracy. This model maintained an accuracy of 100 % from epoch 1 to epoch 7 but after that, there was a dip. This might be due to overfitting of the model on the data.

4. DISCUSSIONS

Based on the results, it can clearly be seen that when data is generated through a GAN (normal or Transfer Learning), there is a huge improvement in the accuracy of the classifier when it is trained on an ensemble of generated images and original images.

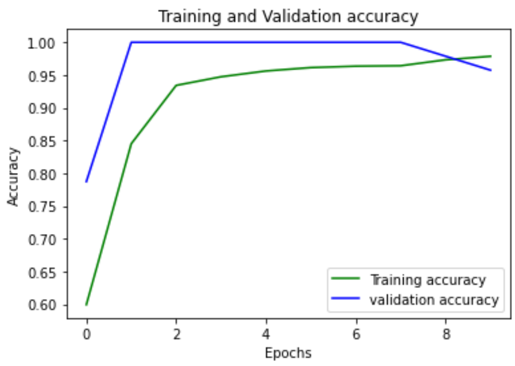

Figure 10. Training and Validation Accuracy of CNN on Fourth Dataset.

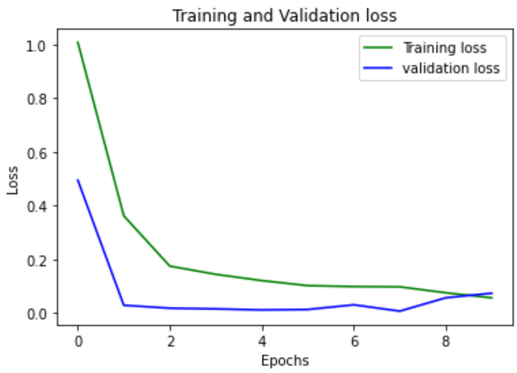

Figure 11. Training and Validation Loss of CNN on Fourth Dataset.

Table 1. Accuracies and losses of each dataset.

	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Dataset 1*	93.48 %	92.59 %	0.1595	0.3016
Dataset 2*	90.13 %	92.31 %	0.2587	0.2919
Dataset 3*	97.71 %	100.0 %	0.6700	0.0281
Dataset 4*	97.86 %	95.74 %	0.0566	0.0739

* Dataset 1 - Original Data
* Dataset 2- Data Generated by Conventional Data Augmentation Techniques
* Dataset 3 - Data formed by combining the Original Data with the Data Generated by Simple GAN
* Dataset 4 - Data formed by combining the Original Data with the Data Generated by Transfer Learning GAN

The accuracy achieved by the model on the original data is pretty high but not good enough to be used in a real-time medical scenario. But with an accuracy of 98 %, a model can be fabricated from the GAN generated data to automate the process of Chest X-Ray classification and is shown in Table 1. There is also scope to improve upon the said method in future research with better GAN architectures to generate new images.

5. CONCLUSION

In this work, a novel approach of data augmentation for medical images was proposed which could eradicate the problem of minimal availability of Chest X-Ray data up to some extent.

A pre-processing step was done on the original data to decrease the image size from 1024 × 1024 × 1 to 128 × 128 × 1. It was verified that there was no loss of data during this step. After the pre-processing step, 4 datasets were generated as mentioned above and a CNN was trained on each of the datasets to analyse which dataset the model was learning best from.

The CNN learned much faster and got better accuracy from the datasets generated by a Simple GAN and a Transfer Learning GAN and this could be a one-stop solution for the minimal availability of Chest X-Ray data.

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