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Data Augmentation of Medical X-Rays in Deep Learning

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ABSTRACT: As a result of the expansion of dynamic strategies influencing the health sector on a large scale, interest in computer science techniques is steadily increasing. Data is being created in massive amounts at a rate of petabytes per second in every little corner of the globe. Data allows the organizations to measure the effectiveness of a given strategy, when these strategies are put into place to overcome a challenge, collecting the results from the strategy will allow us to determine how well the solution is performing, and whether the approach needs to be modified for a short term or long term. The right application of this information will enable us to reach new heights in any field.

This paper is based on two types of data, one of which is x-rays and the other is patient information. To lessen the data imbalance, the two data sets are exposed to various pre-processing procedures. To execute augmentation procedures, the X-rays are transformed to matrices. The features retrieved using a pretrained image model called ImageNet are mapped using the dense Net algorithm which is an advanced convolution neural network algorithm.

KEYWORDS: Data Augmentation, Dense Net, Convolution Neural Networks, Deep Learning, Augmentation of Medical Images

I. INTRODUCTION

Many picture diagnosis tasks necessitate a preliminary search to locate problems, quantify measurements, and track changes over time. Automated image analysis tools based on machine learning are significant enablers for improving image diagnostic and interpretation quality by promoting quick finding identification. Deep learning is one of the most widely used strategies for achieving state-of-the-art accuracy. Deep learning applications in healthcare encompass a wide range of issues, from cancer screening and disease monitoring to individualised treatment recommendations.

Deep learning approaches have made significant progress in medical image diagnosis, and most deep learning models have made huge progress in medical image categorization. Because deep learning models require a big data set for training, the key issue is obtaining enough data for training. Data augmentation is one of the methods for increasing data variability and, as a result, training data with greater generalization. Geometric transformations (e.g., random horizontal flip, translation, rotation, scaling, crop), and colour space augmentations are common DA (Data Augmentation) methods used in deep neural network training. Data augmentation allows us to create new data by changing existing data, which permits us to train the model for large amounts of data and improves its accuracy. As a result, numerous augmentation approaches might be used to attain the desired effects.

II. RELATED WORK

Rama et al in their research paper depicted that pre-processing of medical images for classification using deep learning techniques has used superimposing of images, various superimposing techniques as the strategy to increase the data set.

Using label-maintained modifications, the data augmentation technique of superimposing the original image with the appropriate augmented images aids in generation of addition fresh samples, but it has failed in oversight and management of the data set. [1]

In research manuscript, Jason Wong and Luiz Prez, gave an essence of effectiveness of data augmentation in image classification using deep learning that has used generative adversarial networks algorithm to reduce the overfitting of data also proposed a new technique for information enlargement that uses Generative Adversarial Networks to create new images (GANs). By implementing standard data growth procedures, the number of images has increased, but it has consumed thrice the amount of time. It promises to increase the accuracy and the time in future. [2]

Muhammad Imran Razzak et al in their research work described about deep learning for medical image processing that has used style transfer for data augmentation for less complexity in data, but this method is vulnerable to data stealing.[3]

During this investigation Kaiming H et al depicted that deep residual learning for image recognition has used reinforcement learning algorithms to address the overfitting of the data but it has failed to overcome all the test cases in the dataset. [4]

Gao H in their exploration portrayed that when densely connected convolution networks, used CNN (convolution neural network) based image segmentation to decrease the complexity of layers, but the channels have increased with respect to data set. [5]

III. METHODOLOGY

The most typical application of data augmentation is on medical scans. Data augmentation can be divided in two categories. The first is picture alteration, while the second is the fabrication of synthetic images. Focused mostly on image transformation with a medical imaging application in python for this project. Part of the code in this demonstration were adapted from deep learning's AI for medical Diagnosis. PIL and Augmenter are two libraries that can operate on scan directly. Augmenter also has a pipelining feature that allows you to work on many photos at once. Apart from keras pre-processing, ImageDataGenerator is used for this purpose.

The scarcity of required data sets for medical image diagnosis is addressed by implementing various augmentation techniques such as horizontal rotation right, horizontal rotation left, cropping, scaling, flipping, shearing, adding noise. This approach necessitates the use of several library modules, including pandas, NumPy, keras and tensor flow. Multiple pre-processing procedures are applied to the obtained data set of patient information in order to replace null data values with the column's mean or mode value. In their pixel ratio, the scans are transformed into matrices. Following that, the data sets are merged based on image ids.

Once the data has been pre-processed the augmentation is followed. The model has been categorised into three forms of augmentation to justify the precision of augmented images:

- ☒ No augmentation
- ☒ Primary augmentation
- ☒ Advanced augmentation

The resulting images are trained using a pre-extracted feature dataset, ImageNet. The Dense Net method connects the channels by mapping the characteristics. It searches for a low-resolution image of the augmented image and compares the features and map to the patient's information.

Existing System

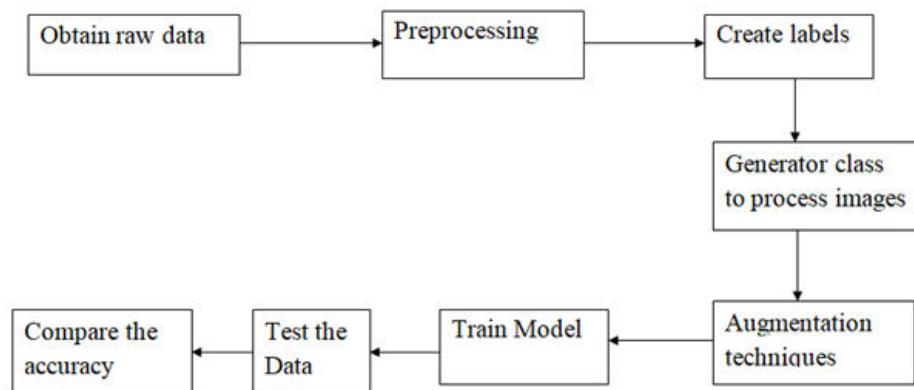
- ☒ Only uncomplicated augmentation methods were performed.
- ☒ This model is only used for one segment of images in prediction.
- ☒ Very few systems use the available clinical data for prediction purposes and even if they do, they are restricted by the large number of association rules that apply.

✎ Merging of two images randomly but it has acquired an error rate of 11 percent

Proposed System

- ✎ Complex Augmentation systems like zooming, cropping, adding noise, colour space transformations (RGB), random erasing.
- ✎ STN (Spatial Transformer Network) can perform more adaptive transformations than image processing functions.
- ✎ Compared the mean value to find the difference in accuracies.
- ✎ This issue can be resolved by adopting various data augmentation methods

System Architecture



IV. EXPERIMENTAL RESULTS

Experimental results are shown in the below figures. Figure 1 depicts the frequency of the diseases in data set. Figure 2 depicts the AUC values of each value of the disease. Figure 3 depicts the values of the ROC curve values for no augmentation. Figure 4 depicts the values of ROC curve after applying primary augmentation techniques such as rotation, they are used for posteroanterior and anteroposterior view of the scans. Figure 5 depicts the values of ROC curve after applying advanced augmentation techniques such as cropping, shearing, translation and noise, they are used for oblique view of the scans. Figure 6 are the observed mean values of the AUC curves of three different augmentations.

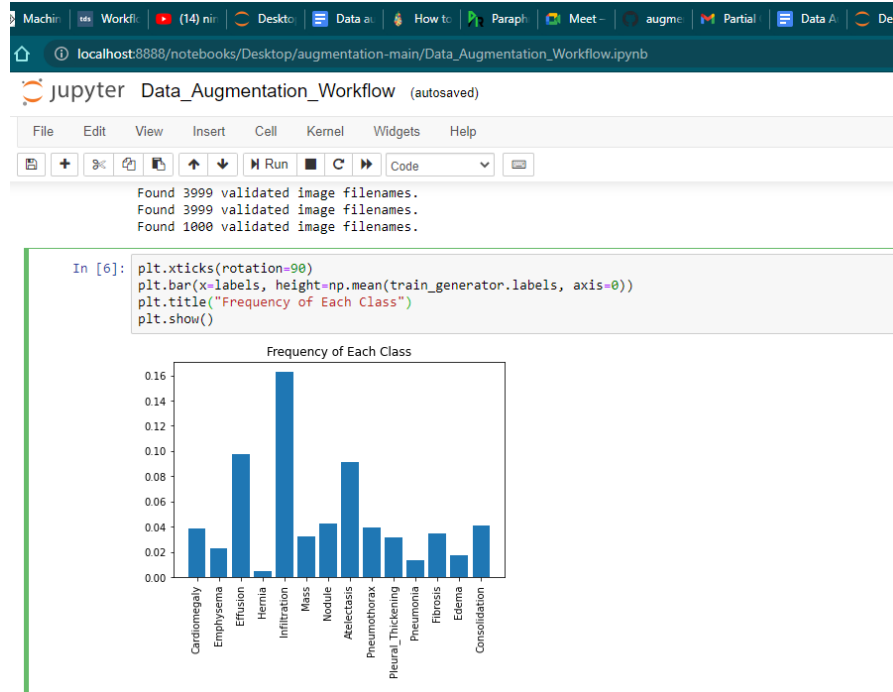


Figure 1 Frequency of Diseases

Condition	No Augmentation	Basic Augmentation	Complex Augmentation
Cardiomegaly	0.502	0.529	0.500
Emphysema	0.513	0.498	0.545
Effusion	0.457	0.546	0.564
Hernia	0.597	0.598	0.329
Infiltration	0.480	0.536	0.503
Mass	0.526	0.439	0.567
Nodule	0.464	0.446	0.513
Atelectasis	0.488	0.550	0.531
Pneumothorax	0.530	0.541	0.592
Pleural Thinkeng	0.472	0.589	0.470
Pneumonia	0.641	0.288	0.489
Fibrosis	0.491	0.494	0.498
Edema	0.546	0.450	0.597
Consolidation	0.457	0.521	0.489

Figure 2 AUC values of each disease

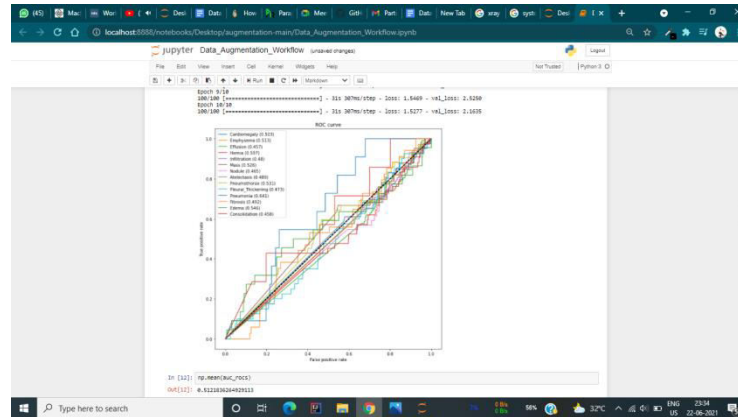


Figure 3 Values of no augmentation

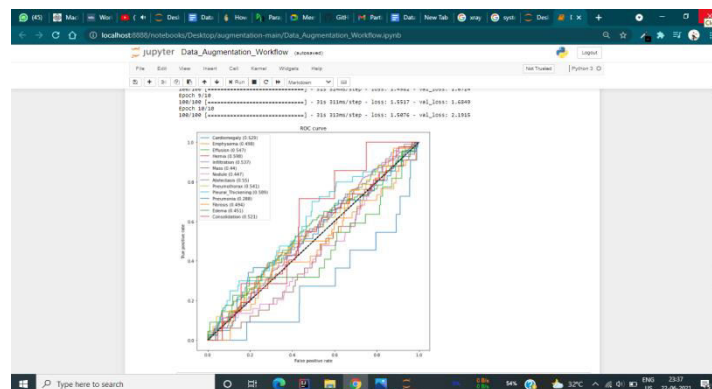


Figure 4 Values of primary augmentation

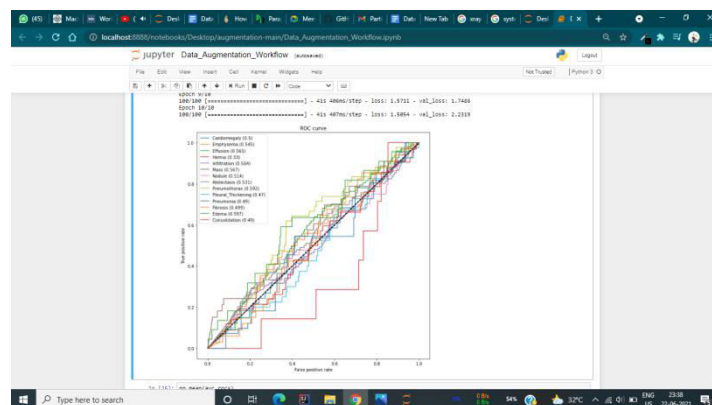


Figure 5 Values of advanced augmentation

```

In [29]: df_results.mean()

Out[29]: No Augmented Images      0.512184
         Basic_Augmentation      0.502272
         Multiple_Augmentations  0.517904
         dtype: float64

In [36]: df_results['No_aug'] = np.where(df_results['No Augmentation']>=0.5,1,0)
         df_results['B_aug'] = np.where(df_results['Basic Augmentation']>=0.5,1,0)
         df_results['C_aug'] = np.where(df_results['Complex Augmentation']>=0.5,1,0)

In [38]: df_results.sum()

Out[38]: No Augmentation      7.170571
         Basic Augmentation    7.031813
         Complex Augmentation  7.244658
         dtype: float64

```

Figure 6 Mean values of AUC curve

V. CONCLUSION

The shortage of medical images is addressed in this approach utilising deep learning. Using label-maintained transformations, a data augmentation technique using the original image with the matching augmented images aids in the generation of additional new samples. Geometric transformations, such as Random horizontal flip, rotation, crop, and colour space augmentations, are commonly used in training deep neural networks using DA approaches. DA helps to create new augmented data by changing existing data, which in turn trains the model to handle large amounts of data and improves accuracy. To achieve more accurate medical images, sophisticated augmentation procedures such as cropping, zooming, adding noise, and colour space augmentations are applied. To achieve more accurate medical images, sophisticated augmentation procedures such as cropping, zooming, adding noise, and colour space augmentations are applied.

The notion of data augmentation is introduced, and its relative performance enhancement is proved in a modest multiclass recognition job. Data augmentation is a useful method for expanding the amount of labelled data available to deep learning models. Some methods of data augmentation were outlined, as well as the dangers of augmenting without taking the classification orientation into consideration. The accuracy has been enhanced to 7% of the original model's accuracy.

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