Pneumonia Detection Using Computer Vision

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ABSTRACT

Pneumonia is one of the top most reported diseases in many countries. It can be caused by bacterial infection of internal tissues of one or both lungs. It is in turn difficult to say just by looking at x-ray scans of chest of a patient that if he is suffering from pneumonia. Using Computer Vision reduces the burden on the shoulders of doctors. Timely diagnosis of diseases is pretty essential. Computer vision allows us to create artificial intelligence to automate techniques for analysis of numerous X-Ray images of chests. Features from images are extracted using different neural networks. These features are fed into a classifier for prediction.

1. **INTRODUCTION**

Deep learning methods reach human-level accuracy in predicting pneumonia by scanning X-Ray images of chest. In the medical industry, computer vision plays a major role in detecting major diseases, especially imaging. With all the advancements in deep learning, it is now a prominent part of the medical industry.

X-Rays are highly effective in diagnostic tools for detecting pathological alterations. Chest images using X-Rays are shown as cavitations, infiltrates, consolidates, blunted costophrenic angles and broadly distributed nodules. The appearance of pneumonia in X-Ray images is often unclear and is mistaken for other diseases. Due to these inconsistencies, there is need for computerized support system for detecting pneumonia from chest X-Ray images. Using Convolutional Neural Networks (CNNs) for image classification shows great success. Popularity of CNNs is because using CNNs, one can extract more significant features than other hand-crafted methods. Various CNN based networks are developed to find the prediction in form of classification, segmentation, object detection and localization using computer vision. CNNs are very successful in predicting medical problems including breast cancer detection, alzheimer disease diagnosis and brain tumor classification.

Based on prior experiments using CNN for pneumonia detection from X-Ray images, we propose to build a model of our own for detecting pneumonia cases from X-Ray images of chest using Convolutional Neural Networks.

1. **METHODOLOGY**

**2.1 Data**

For our training and validation, we choose the dataset provided by Kermany and others. This dataset contains thousands of validated Chest X-Ray images described and analyzed. The images are further split into a set for training and a set for testing of independent patients. There are a total of 5856 images in the dataset. The resolution of the images can vary from 712x439 to 2338x2025. Normal case image are total of 1583 and pneumonia case image are total of 4273. These images are used for training, validation and testing of our proposed model. 1349 images are used for training of normal cases and 3883 images are used for training of Pneumonia cases, resulting in a total of 5232 images. For validating our model, we use total of 624 images of which 234 are normal images and 390 are pneumonia images. Finally for testing our model, we use 234 normal X-Ray images and 390 pneumonia X-Ray Images, with a total of 624 images. This proposed distribution is shown in the table 1.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Training | Validation | Testing |
| Normal | 1349 | 234 | 234 |
| Pneumonia | 3883 | 390 | 390 |
| Total | 5232 | 624 | 624 |

Table 1. Distribution of images in the current dataset

**2.2 Data Pre-Processing And Augmentation**

All the pre-trained models are quite large to hold out dataset and models could be over-fitted easily. In order to prevent this, we add some noise to the data set. This helps in significantly generalizing the dataset and acts as some sort of data augmentation. Since all augmentation techniques are not suited for X-Ray images, we process the images in four step.

* Resize the images to 224x224x3.
* Random Horizontal Flip to deal with pneumonia symptoms on both sides of the chest.
* Random resize crop to get deeper relation to pixels.
* Augmenting images with a variable intensity.

**2.3 Convolutional Neural Network**

Modern Deep Learning models in computer vision use Convolutional Neural Networks (CNNs). Unlike the early convolutional networks, which were only able to detect low-level features in images like edges, with our model we can successfully capture the spatial and temporal dependencies in any image with the help of filters.

For our model, we use pre-trained models, instead of meticulously training the models from scratch. The method of transferring the learning from one predefined model to a new model by reusing the network layer weights is called transfer learning. This is a very useful technique in computer vision and produces significant results. We propose to use transfer learning in our model for pneumonia detection.

**2.4 Pretrained Neural Networks**

In our model, we use AlexNet, ResNet, Inceptionv3, DenseNet121 and GoogLeNet which are pretrained on the ImageNet dataset and use them on our dataset of chest X-Ray images dataset.

**2.4.1 AlexNet Architecture**

AlexNet is a Convolutional Neural Network which uses Rectified Linear Unit (ReLU) to add non-linearity to our model. It uses dropout layers to deal with over-fitting. Overlapping pooling is also used to reduce the size of network. We propose to use the pre-trained AlexNet as the first model and train the classifier only by freezing the convolutional layer via transfer learning.

**2.4.2 ResNet18 Architecture**

With a residual learning framework, ResNet architecture simplifies the training of deeper networks. The depth of the network is 8 times deeper than VGG nets, with a lower complexity.

**2.4.3 Inceptionv3 Architecture**

Maintaining the computational cost constant, Inceptionv3 architecture allows for increasing the width and depth of the deep learning networks. It generates multi-level feature by computing convolutions of 1x1, 3x3 and 5x5. This architecture also allows for use of all kinds of kernels.This model achieves top performance for computer vision tasks.

**2.4.4 DenseNet121 Architecture**

Unlike a traditional CNN architecture, the DenseNet architecture requires a fewer parameters. With a small set of new feature maps, DenseNet uses only 12 filters. Also the training time is more for DenseNet as every layer takes its input from previous layers. However we can get access to the gradient values from the loss function and the input image. This reduces the computation cost and makes this architecture a better choice.

**2.4.5 GoogLeNet Architecture**

GoogLeNet Architecture uses global average pooling. Also it includes inception modules. This allows for convolution of different types using different kernels on the same image, finally stacking the output of that layer.

**2.5 Ensemble Classification**

Finally we combine the output of all the architectures. Each layer gives a prediction of 0 or 1. 0 corresponds to chest X-Ray image of a normal person and 1 correspond to chest X-Ray image of a pneumonia patient. The output of each pre-trained network is then fed into a prediction vector. We propose majority voting to come to a final prediction. Figure 1 below shows the ensemble classification approach that we propose to take for our model.

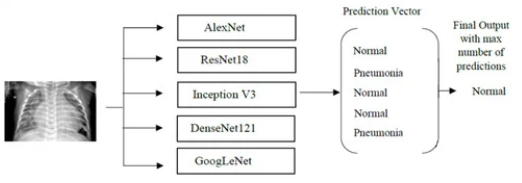


Figure 1. Proposed model using 5 pretrained models with ensemble classifier using majority voting.

ACKNOWLEDGMENTS

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Conference Name:ACM Woodstock conference

Conference Short Name:WOODSTOCK’18

Conference Location:El Paso, Texas USA

ISBN:978-1-4503-0000-0/18/06

Year:2018

Date:June

Copyright Year:2018

Copyright Statement:rightsretained

DOI:10.1145/1234567890

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Price:$15.00