Covid-19 X-ray Image Classification

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ABSTRACT

As part of CS598 Deep Learning for Healthcare course, we have decided to reproduce and improve FLANNEL model for COVID-19 classification using X-ray images.

1. INTRODUCTION

COVID-19 pandemic has ravaged the world on an unprecedented scale. It has caused loss of millions of lives and long lasting damages on surviving patients. X-ray imaging is very important part of diagnosis of Covid-19 and other pneumonia and is often the first-line diagnosis in many cases. Using deep learning for X-ray classification is an ongoing research area.

We have taken this paper to strengthen our understanding of deep learning models and improve the current research.

Specifically we would work to reproduce and improve FLANNEL model for classification of COVID-19 X-ray images from other pneumonia and normal images.

2. LITERATURE SURVEY

We studied a lot of papers and found the following literature to be related To our task in hand i.e. to identify X-ray images for COVID-19 with imbalanced dataset.

2.1 FLANNEL for COVID-19 detection

This is the main paper[5] that we are trying to reproduce and improve. In this paper, Zhi Qiao *et al.* has shown that with ensemble learning FLANNEL can detect and diagnose COVID-19 from pneumonia x-ray images with high accuracy, even when trained on only 100 available COVID-19 x-ray images.

COVID-19 classification requires three main Tasks 1. CNN for image classification 2. Ensemble for poor/varied classification 3.

The main idea in the paper is 1. Ensemble to handle poor classification 2. FOCAL Loss for loss optimization 3. Use state of arts models in stage-1

2.2 COVID-19 classification using chest CT

X. Bai and Wang [1] were able to create an AI system that could differentiate COVID-19 and other pneumonia using a chest CT scan. They approached this as a classification problem and used the EfficientNet B4 architecture which was a CNN based network. They were able to achieve results of 96% accuracy, 95% sensitivity , 96% specificity, and an area under receiver operating characteristic curve of 0.95 and an area under the precision recall curve of 0.90. When compared with radiologists on the same test dataset, the AI system performed better. This study concluded that the AI can support radiologists in detection of COVID-19 in Chest CT images.

2.3 Focal loss for dense object detection

Lin T, Goyal P, Girshick R propose Focal loss [3], a modification to the standard cross entropy criterion that focuses weights for loss on hard examples versus well classified examples. This is accomplished by adding a factor $(1-p_t)^\gamma$ to the standard cross entropy criterion where setting $\gamma > 0$ reduces the relative loss for well-classified examples ($p_t > .5$). This results in achieving higher accuracy than using the standard cross entropy loss and surpassed speed and accuracy when compared with state of the art two stage detectors; Faster R CNN Variants.

2.4 Towards contactless patient positioning

This paper [2] discussed about patient positioning routine that comprised a novel robust dynamic fusion (RDF) algorithm for accurate 3D patient body modeling. With 'multi-modal' inference capability, RDF can be trained once and used across different applications (without re-training). They have used multiple CNN branches o learn the joint feature representation and a fully-connected parameter regressor module to estimate the 3D mesh parameters.

2.5 Deep learning COVID-19 features on CXR using limited training data sets

The authors of this paper[4], proposed a patch-based convolutional neural network approach with a relatively small number of trainable parameters for Covid-19 diagnosis. The architecture contains first pre-processed data that are fed into a segmentation network [FC-DenseNet] to extract lung areas. From this segmented lung area, classification network is used to classify the corresponding diseases using a patch-by-patch training and inferences [ResNet-18 (pre-trained) and many ResNet-18 models are used for K patches], final decision is made based on the majority voting from previous layers. A Grad-CAM saliency map is calculated to provide an interpretable result. This method has an accuracy of 91.9%, compared to that of 92.4% for COVID-Net.

2.6 COVID19-Net Deep Convolutional Neural Network

This is the first open source network design for COVID-19 detection from CXR images, our final research paper also considers this as its baseline for experiments. This paper considered COVIDx dataset which contains 13,975 CXR images for training and experiments. COVID-Net architecture makes heavy use of a lightweight residual 'projection expansion projection extension' (PPEX) design pattern that contains multiple levels of convolution layers with fully connected layers and a softmax at the end. COVID-Net achieved higher test accuracy than other architectures such as VGG-19 and ResNet-50.

2.7 Noise-robust segmentation of COVID-19 from CT images

This is a CNN model [6] developed to be effective with detection of COVID-19 lesions from CT images that have a lot of noise. This paper discusses how Wang et al developed a novel noise-robust learning framework based on self-ensembling of CNNs. To better deal with the complex lesions, a novel COVID-19 Pneumonia Lesion segmentation network (COPLE-Net) was proposed that uses a combination of max-pooling and average pooling to reduce information loss during downsampling, and employs bridge layers to alleviate the semantic gap between features in the encoder and decoder. Experimental results with CT images of 558 COVID-19 patients showed the effectiveness of the noise-robust Dice loss function, COPLE-Net and adaptive self-ensembling in learning from noisy labels for COVID-19 pneumonia lesion segmentation. To make the training process robust against noisy labels, a novel noise-robust Dice loss function was proposed and integrated into a self-ensembling framework, where an adaptive teacher and an adaptive student are introduced to further improve the performance in dealing with noisy labels. The experiments used 2D CNNs for slice-by-slice segmentation, and implemented COPLE-Net, 1 LNR-Dice and the adaptive self-ensembling framework in Pytorch with the PyMIC 3 library on a Ubuntu desktop with an NVIDIA GTX 1080 Ti GPU. The proposed COPLE-Net was compared with four state-of-the-art networks for semantic or medical image segmentation

1. 3D nnU-Net that is extended from 3D U-Net
2. Attention U-Net 3) ScSE U-Net
3. ESPNetv2 and proven to be most effective with noisy images.

In addition, COPLE-Net was compared with three variants: COPLE-Net (-A), COPLE-Net (-D) and COPLE-Net (-B)

3. DATA

For the purpose of reproduction and show comparable improvement, we have decided to use the same datasets that are used in the FLANNEL paper.

1. Covid Chest X-ray (CCX) dataset: This dataset contains COVID-19 pneumonia images as well few X-ray images from other classes. The dataset can be obtained from github at this link https://github.com/ieee8023/covid-chestxray-dataset
2. Kaggle Chest X-ray (KCX) dataset: This dataset contains normal, bacterial pneumonia, and nov-COVID-19 viral pneumonia. The dataset can be obtained from Kaggle at this link https://www.kaggle.com/paultimothymooney/che xray-pneumonia

In the FLANNEL paper, 5508 chest x-ray images across 2874 independent patient cases. Both dataset contains anteroposterior (AP) and posteroanterior (PA) view.
As done in the research paper, we will include both AP and PA views. Due to AP and PA views being different types of X-ray images, horizontal flips and random noise will be used to convert PA into AP view.

4. APPROACH

4.1 Tasks

It is a Classification problem. Classes: COVID, Pneumonia virus, Pneumonia bacteria, Normal

4.1.1 Stage-1

Use a basis model and get predictions for four clases. Use pretrained model using imagenet, because 5000 images is not sufficient

1. InceptionV3
2. Vgg19_bn
3. ResNeXt101
4. Resnet152
5. Densenet161

4.1.2 Stage-2

Ensemble model learning Introducing a Neural weight module to assign weights for all five predictions in Stage-1. Combine the prediction and compare against the actual classification using Focal Loss (New loss function)
Use Focal loss learning (FLANNEL Training algorithm)
Neural Weight Module Concat all predictions in a long vector (called f) Take the outer product over f. f*f Flatten the prediction in a long matrix Pass to dense neural network TanH activation Assign Learner weights
Focal Loss Cross Entropy Loss Assign uniform weight for all predictions TODO -¿ Latex formula
Focal Loss Introduces alpha and gamma parameter which generalizes to Cross Entropy loss when gamma = 0 and alpha = 1
Alpha -¿ higher weight of poorly/Rare classified/specific classification Gamma -¿ Downvote the well classified glass TODO: Latex formula

4.2 Performance Analysis

Use below measures to calculate the accuracy of Ensemble model for verification

1. Precision-Recall curve
2. ROC curve
3. Confusion Matrix
4. F1 score comparison accuracy of all methods

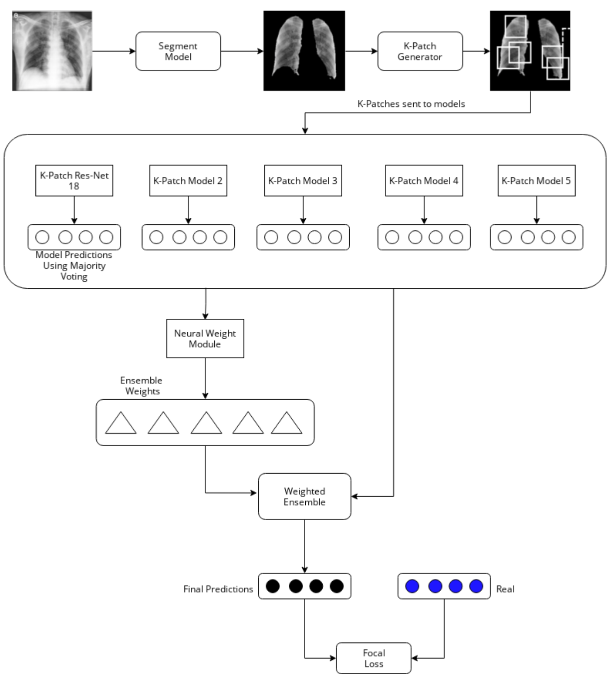
Table 1: Experimental data description

Source		Total	COVID-19	Viral	Bacterial	Normal
Original data	CCX data					
	KCX data					
View Distribution	AP view					
	PA view					
Training/test splits	Training					
	Testing					
	Total					

4.3 Improvement Discussion

Based on the performance of the novel FLANNEL architecture, our team is motivated to improve the performance further. With inspiration from the approach of Oh Y., and Park S., a primary improvement that we are proposing is to extract the lung contours from the CXR images prior to classification. The motivation behind this is to have the classifier focus on the specific lung regions versus the whole CXR image. In addition, another improvement we propose is to modify each base model in the ensemble to process the segmented CXR image in K patches.
To accomplish this, the steps we will follow are

1. Extract the lung contours from the CXR images using Segment Model.
2. Train k-patch classifiers.
   - (a) Start with pre-trained model from Image Net
   - (b) Divide extracted lung contours into k-patches
   - (c) Run each patch through model to generate classification, prediction is calculated based on majority voting
   - (d) Update shared weights for each of the k models
3. Construct improved FLANNEL architecture by using extracted lung contours as input and k-patch classifiers used as the base models.
4. Train Improved FLANNEL architecture
   - (a) Input is CXR image
   - (b) Extract lung contours using Segment Model
   - (c) Create k-patches of segmented CXR
   - (d) Each k-patch classifier processes k-patches and produces predictions
   - (e) Calculate weighted ensemble through neural weighting module
   - (f) Compute prediction based on k-patch model predictions and weights
   - (g) Compute focal loss and update neural weighting module weights
   - (h) Continuously calculate metrics to measure performance such as but not limited to: accuracy, precision, F1 and ROAUC.
5. Perform ensemble (combining multiple K patch classifiers) to calculate the weighted ensemble.
6. Get the prediction and compare with the ground truth.
7. Apply Focal Loss to train the model (improve weights).
8. Test the model on the 'test' dataset to calculate accuracy, precision, F1 measure, ROAUC and other metrics.



5. EXPERIMENTAL SETUP

TODO We are planning to use AWS for the training and evaluation.

6. TIMELINE

Table 2: Project Timeline

Task	Planned Due Date
Research, Planning and proposal	03/28/2021
Data Cleaning and Preprocessing	04/02/2021
Extract the lung contours	04/09/2021
Apply classifier on each patch	04/09/2021
Ensemble the results from each classifier	04/16/2021
Calculate weights	04/23/2021
Run the training data to get the prediction	04/23/2021
Apply Focal Loss	04/23/2021
Model Training	04/23/2021
Performance Evaluation	04/23/2021
Documentation and Video presentation	05/07/2021
Code and Report Submission	05/08/2021

7. ADDITIONAL AUTHORS

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8. REFERENCES

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