CNR-IEMN: A DEEP LEARNING BASED APPROACH TO RECOGNISE COVID-19 FROM CT-SCAN

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ABSTRACT

The recognition of Covid-19 infection and distinguishing it from other Lung diseases from CT-scan is an emerging field in machine learning and computer vision community. In this paper, we proposed deep learning based approach to recognize the Covid-19 infection from the CT-scans. Our approach consists of two main stages. In the first stage, we trained deep learning architectures with Multi-task strategy for Slice-Level classification. In the second stage, we used the previous trained models with XG-boost classifier to classify the whole CT-scan into Normal, Covid-19 or Cap class. The evaluation of our approach achieved promising results on the validation data of SPGC-COVID dataset. In more details, our approach achieved 87.75% as overall accuracy and 96.36%, 52.63% and 95.83% sensitivities for Covid-19, Cap and Normal, respectively. From other hand, our approach achieved the fifth place on the three test datasets of SPGC on COVID-19 challenge where our approach achieved the best result for Covid-19 sensitivity.

Index Terms— Deep learning, Multi-task strategy, Slice-Level classification, Covid-19, CT-scans.

1. INTRODUCTION

Covid-19 is a respiratory infection caused by the virus named SARS-CoV-2 belonging to the coronavirus family. The virus mainly affects the respiratory tract, but can also cause symptoms affecting other organs [1]. In more than half of the cases the infection is asymptomatic and in about a third of the cases it presents flu-like symptoms [2]. Since the appearance of the Covid-19 in Whuan, China, in 2019, a lot of efforts have been made to fend off the spreading of the Covid-19 infection. The first stage, to prevent the spreading of this disease is the recognition and confinement of the infected persons. Different recognition methods have proved its efficiency including RT-PCR, X-ray scans and CT-scans [3]. These two last methods need an expert radiologist to identify the Covid-19 infection from the scans. Artificial Intelligence (AI) systems can provide an alternative solution for the automatic diagnosis of Covid-19 infections and them from other Lung diseases [3]. Many approaches related to CT-scan address the two-way classification task Covid-19/non-Covid-19 [4, 5, 6]. Other contributions are oriented to develop deep learning methods on CT-scan to predict severity with 11 severity scores without using slice level annotation [7], or to predict ICU admission, intubation, and mortality [8]. Better accuracy on classification can be reached by segmenting lung as in [9].

The objective of this work is to predict the health state of a patient using the CT-scans of the lungs as part of "COVID-19 Radiomics" challenge [10]. To evaluate the performance of our approach, we used SPGC-COVID dataset [11], which contains volumetric chest CT-scans of 171 patient positive for Covid-19, 60 Community Acquired Pneumonia (CAP), and 76 Normal cases. The SPGC-COVID dataset contains all slices in a CT scan provided with the Digital Imaging and Communications in Medicine (DICOM) format. Besides the patient-level labels, a subset of 55 Covid-19, and 25 CAP cases were analyzed by one radiologist to identify and label slices with evidence of infection.

To classify the CT-scans into Covid-19, CAP and Normal, we proposed an ensemble deep learning approach. Our CNR-IEMN approach consists of two stages. In the first stage, we train deep learning architectures using Multi-task strategy for Slice-Level classification. In the second stage, the entire volume of CT-scan is classified using the Slice-Level predictions and XG-boost classifier. As summary, the main contributions of this paper are:

- We propose to segment the lung nodules of the slice, then we stack the original slice channel with the segmented channels to have RGB like image.

- With the use of Multi-task strategy and data augmentation for Covid-19 and Cap slices, we trained four CNN architectures (ResneXt-50, Densenet-161, Inception-V3 and Wide-Resnet) for Slice-level classification.

- For Patient-Level CT-scans classification, we propose to divide the CT-scan slices into groups, then calculate

the percentage of each class within each group using all trained CNN models for the Slice-Level classification. At the end, we combined all grouping percentages from all trained CNN architectures then feed them into XG-boost classifier [12] to recognize the CT-scan category.

This paper is organized in following way: Section 2 contains the description of our approach. The experiments and results are described in Section 3. Finally, we concluded our paper in Section 4.

2. PROPOSED APPROACH

The overall structure of our approach is summarized in Figure 1. In summary, our proposed approach consists of two main stages. The main focus of the first stage is to classify the slices into one of the three classes (Normal, Covid-19 and Cap). To this end, we used the CT-scans that have the slice-level labels for both Covid-19 and Cap classes. Furthermore, we selected the first 30 Normal CT-scans and labelled all their slices as Normal class. Since these CT-scans are labelled as Normal class, so no slice within these CT-scan contains Covid-19 or Cap infection. In total, we have 30, 55 and 24 CT-scans for Normal, Covid-19 and Cap, respectively, which were used to train and test Deep learning architectures for slice-level classification. Among these CT-scans, we have 9, 17 and 8 validation CT-scans that have the slice level labelling. In the second stage, we predicted the slices label for the whole CT-scan using trained CNN architectures. Since the number of slices of the CT-scans varies from one CT-scan to another, we propose to divide the slices into 20 equal groups. For each group, we calculate the slice prediction percentage of each class. By concatenating the percentages of all CT-scan groups, we create a feature vector, which will be fed into XG-boost classifier [12] to predict the class of the CT-scan.

2.1. Slice-Level Classification Stage

The aim of this stage is to train CNN architectures to classify the CT-scans slices into Normal, Covid-19 or Cap class. For deep learning training, we used the Pytorch [13] library with NVIDIA GPU Device Geforce TITAN RTX 24 GB.

2.1.1. Preprocessing

In the preprocessing phase, we read the Slice images from the ".dcm" files format which gives one channel image (Grayscale). Since most of computer vision architectures were designed for color images, we propose to stack the gray image, the segmented lung nodules image using the proposed method in [14] and the multiplication of the gray-scale image with the binary lung nodules mask. Figure 2 shows an example of the original image, the segmentation result and the result of stacking the three channels. In addition of having three channels as input to the CNN architectures, the segmentation guides

the slices classification by concentrating on the lung nodules features and remove non-relevant ones.

2.1.2. Slice classification using CNN architectures

To train the slice-based classification, we have 10.294, 2.482 and 742 slices for Normal, Covid-19 and Cap classes, respectively. From the number of slices of each class, we notice that they are not balanced. To deal with this issue, we used data augmentation techniques for the Covid-19 and Cap slices. The used data augmentation techniques are:

- Color Jitter with brightness = 0.2, contrast = 0.2 and applying probability = 0.2.
- Random Horizontal flip with applying probability = 0.2.
- Random Perspective with distortion scale = 0.5.
- Random Rotation from -30 to 30 degree.
- Random Cropping.

For Covid-19 class, we generated 3 augmented images from each slice. From other hand, we generated 10 augmented images for each Cap slice. In total, we obtained 9.928 and 8.162 for Covid-19 and Cap, respectively.

Figure 3 shows an example of how we trained the four backbone CNN architectures which are: ResneXt-50 [15], Densenet-161 [16], Inception-V3 [17] and Wide-Resnet [18]. For each CNN architecture, we trained multi-task classification where the first task is the classification of the input image into Normal, Covid-19 and Cap classes. Since the size and the shape of the Lungs changes from the first, middle and last slices of the CT-scan, we divide each CT-scan into equalized five regions. The slices within the same region in the CT-scan will have the same label. In addition to the main task (to classify the slices into Normal, Covid-19 and Cap), the second task classifies the slice into one of the region classes. For the same purpose, we add the total number of slices of the CT-scan and the slice location in the CT-scan into the deep features (FC layer) as shown in Figure 3.

2.2. Patient-Level Classification Stage

Since the CT-scans have different number of slices, we propose to divide the CT-scan into 20 groups where each group contains the same number of slices. After that, we applied our trained Slice-Level architectures on the slices of each group, then we calculate the percentage of slices of each class within the group. This produces $20 \times 3 = 60$ features for each CT-scan using one of the train CNN architectures. For classifying the CT-scans, we feed the combination of all trained CNN architectures features, by concatenating them along side each other, into XG-boost classier [12]. In our experimental part, we trained the XG-boost with the training CT-scans features, then we evaluate the performance of our approach using the validation CT-scans features.
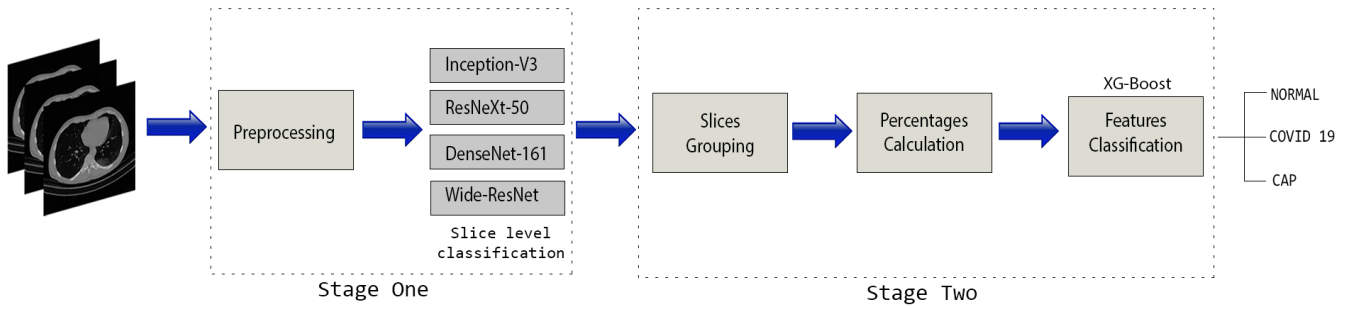
Fig. 1: The overall structure of our proposed CNR-IEMN approach.

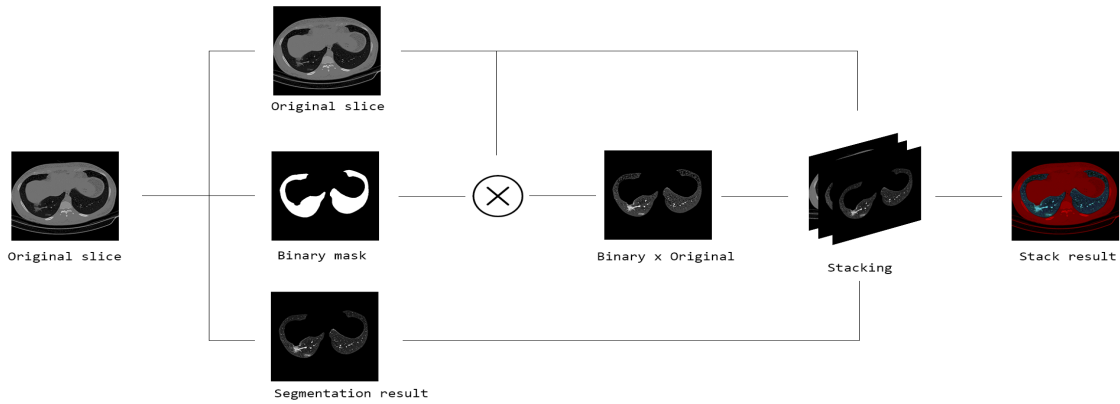**Fig. 2**: Prepocessing phase.

3. EXPERIMENTS AND RESULTS

3.1. Validation Data:

3.1.1. Slice based classification

In this section, we trained four CNN architectures which are ResneXt-50, Densenet-161, Inception-V3 and Wide-Resenet using Multi-task classification strategy. Each CNN architecture was trained for 10 epochs with Adam optimizer [19]. The initial learning rate is 0.0001 which decay by 0.1 after 3 epochs, then another decay of 0.1 after 6 epochs. The used batch size is 64 images and as loss function we used Focal loss function [20] with gamma equals 1.5.

The obtained results are summarized in Table 1. From these results, we notice that the architectures achieved close result on classifying the slices with slightly better performance by ResneXt-50 architecture.

Table 1: Validation Slice-level classification results using Multi-task learning with four backbone CNN architectures (ResneXt-50, Densenet-161, Inception-V3 and Wide-Resenet).

Model	Slice-level Classification (%)
ResneXt-50	88.91
Densenet-161	88.61
Inception-v3	88.74
Wide-Resnext	88.37

3.1.2. Patient-Level Classification

In this section, we evaluate the performance of each CNN architecture percentage features and the obtained results are summarized in Table 2. From these results, we notice that Inception-v3 features achieved the best performance compared with the other architectures features. From other hand, combining all of the four models features achieved the best performance. From the confusion matrix in Figure 4, we
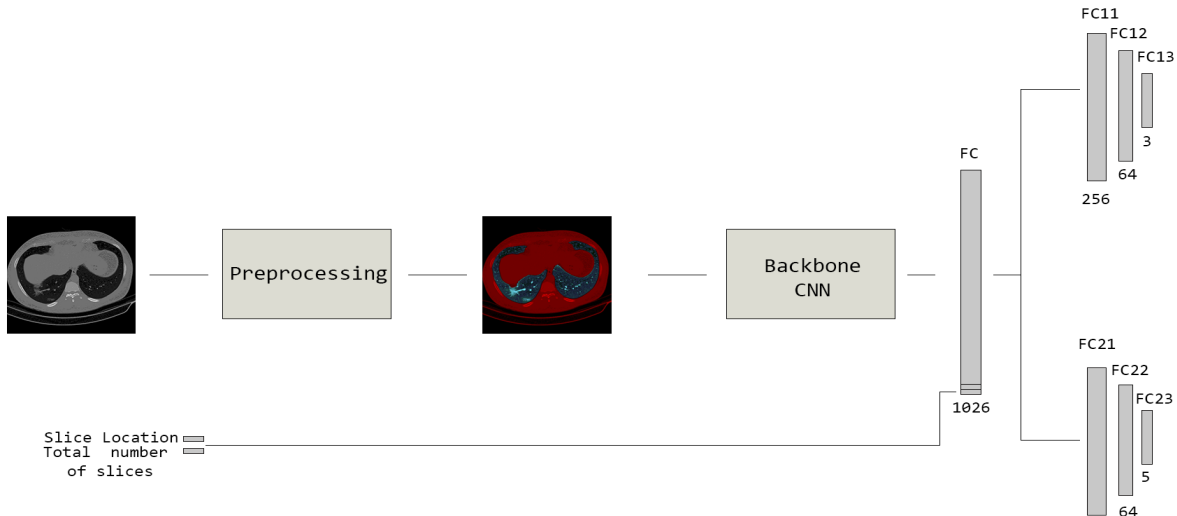
Fig. 3: Multi-task Slice-Level training using CNN architectures.

Table 2: Validation CT-scans classification results using XG-boost with different grouping percentages features (ResneXt-50, Densenet-161, Inception-V3 and Wide-Resenet grouping percentages features) and their combination.

Model	CT-scans classification (%)
ResneXt-50 features	79.59
Densenet-161 features	82.65
Inception-v3 features	85.71
Wide-Resnext features	80.61
CNR-IEMN	87.75

Fig. 4: The Confusion Matrix of the validation data CT-scan classification.

notice that our approach achieved high accuracy in the recognition of Normal and Covid-19 CT-scans, where it achieved 95.83% and 96.36%, respectively. On the other hand, our approach achieved 52.63% for the recognition of Cap CT-scans and this because the Cap class has less training data for both Slice-Level and Patient-level stages than the Normal and Covid-19 classes.

3.2. Testing Data:

The testing data of SPGC on COVID-19 challenge consists of three sets. The testing data labels are not known for all challenge participants. Our approach achieved the fifth place on SPGC on COVID-19 challenge. In more details, our approach achieved 81.11% as overall accuracy and 91.43%, 45.0% and 91.43% sensitivities for Covid-19, Cap and Normal, respectively. Comparing with other participants, our approach achieved the best sensitivity of Covid-19 class.

4. CONCLUSION

In this paper, we proposed a fully automatic approach to classify the CT-scans into three distinct classes (Normal, Covid-19 and Cap). Our approach consists of two stages: Slice-level and Patient-Level classifications. Our approach achieved promising results, where the overall accuracy is 87.75% and 95.83%, 96.36% and 52.63% sensitivities for Normal, Covid-19 and Cap, respectively. To improve the results, specially for the Cap class, we suggest to use more Cap CT-scans for the Slice-Level and Patient-level classification.

5. ACKNOWLEDGMENTS

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