The Impact of Super Resolution on detecting Covid-19 from CT Scans using VGG-16 Based Learning

N Aburaed[1]*, A Panthakkan[1], M Al-Saad[1], S Al Mansoori[2] and H Al Ahmad[1]

[1]College of Engineering and IT, University of Dubai, Dubai, UAE

[2]Mohammed Bin Rashid Space Centre (MBRSC), Dubai, UAE

*Email: noaburaed@ud.ac.ae

Abstract. With the recent outbreak of the novel Coronavirus (COVID-19), the importance of early and accurate diagnosis arises, as it directly affects mortality rates. Computed Tomography (CT) scans of the patients' lungs is one of the diagnosis methods utilized in some countries, such as China. Manual inspection of CT scans can be a lengthy process, and may lead to inaccurate diagnosis. In this paper, a Deep Learning strategy based on VGG-16 is utilized with Transfer Learning for the purpose of binary classification of CT scans; Covid and NonCovid. Additionally, it is hypothesized in this study that Single Image Super Resolution (SISR) can boost the accuracy of the networks' performance. This hypothesis is tested by following the training strategy with the original dataset as well as the same dataset scaled by a factor of ×2. Experimental results show that SISR has a positive effect on the overall training performance.

1. Introduction

The novel Coronavirus (COVID-19) has impacted the whole world with 37,801,975 confirmed infected cases and 1,074,817 deaths according to the World Health Organization (WHO) reports on October 13, 2020 [1]. The most common methods for detecting and diagnosing COVID-19 disease are Polymerase Chain Reaction (PCR) test, X-ray, and Computed Tomography (CT) scan [2,3]. Several research studies have been discussed applying the CT imaging technologies for the detection of COVID-19 infectious disease, however, the manual reading of these images is considered time consuming and subject to human error [4]. Nowadays, Artificial Intelligence (AI) techniques play a vital role in the analysis of CT scan images with less human intervention [5]. Hasan et al. [6] proposed feature extraction methodology that uses both Deep Learning and Q-deformed Entropy for the classification of CT scan images into three different types; COVID-19, pneumonia, and healthy lungs, with an overall accuracy of 99.86%. Another classification method is presented in [7], where the authors designed a Convolutional Neural Network (CNN) model for the classification of CT scan images into COVID-19 and non-COVID-19 types. This model outperforms other existing models in classification accuracy by 1.9789% and can be utilized for real time COVID-19 classification problems. Similarly, Babukarthik et al. [8] proposed a binary classification method for X-ray images using Genetic Deep Learning CNN (GDCNN). The classification accuracy of the proposed model is 98.84%, and it shows superior results compared to other well-known CNN models, such as ReseNet18, ReseNet50, Squeezenet, DenseNet-121, and VGG16. The researchers in [9] presented another binary classification model with Transfer Learning (TL) approach using pre-trained DenseNet201, in which a classification accuracy of 97% has been achieved. Wang et al. [10] developed semi-supervised Deep

Learning model for detecting and distinguishing COVID-19 from non COVID-19 cases using CT scan images. This methodology overcomes the lack of available labelled CT images.

This paper proposes a training strategy for binary classification of CT scans, Covid and NonCovid. Pre-trained VGG16 is utilized with TL technique in order to boost the accuracy of the network. The amount and variety of the dataset used in this study is boosted through data augmentation. Additionally, the effect of upscaling the dataset through Single Image Super Resolution (SISR) on the network accuracy is studied. The rest of the paper is organized as follows: Section 2 illustrates the methodology, which includes the dataset and the training strategy. Section 3 discusses the results. Finally, section 4 summarizes the paper and draws the future direction of this research.

2. Methodology
This section explains the dataset and its pre-processing steps, in addition to the Deep CNN (DCNN) used and the training strategy with SISR.

2.1. Dataset
For this study, the dataset provided by Zhao et al. is used [11]. This dataset contains lung CT scans of two classes; 349 COVID-19 CT images from 216 patients, and 463 non-COVID-19. The dataset was collected from several research papers and preprints such as medRxiv and bioRxiv. According to the authors, the utility of the dataset was confirmed by a senior radiologist who has been treating COVID-19 patients. Additionally, the authors confirm that CT scans have been vital in diagnosing and treating COVID-19 patients during the outbreak time. For these reasons, this dataset is utilized in this research for training and testing purposes. Furthermore, data augmentation was applied to this dataset in order to boost the variety of images and to make the training more resilient. The applied augmentation techniques include horizontal flip, vertical flip, brightness and contrast adjustment, scaling, cropping, and combinations of them. It is important to ensure a balanced amount of both Covid and NonCovid classes in the dataset to avoid potential learning bias and overfitting. The final size of the dataset is shown in Figure 1, which demonstrates balanced counts of both classes.
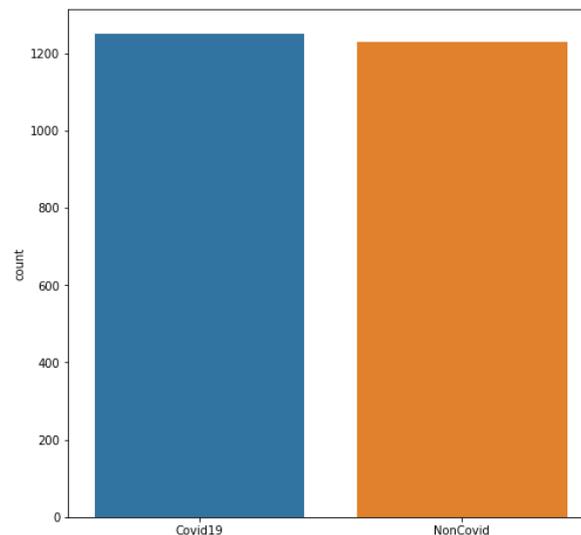
Figure 1. Covid and NonCovid counts show balance in the dataset

2.2. VGG16

VGG16 [12] is a DCNN initially proposed by K. Simonyan and A. Zisserman. It was one of the most powerful models that contributed to Large Scale Visual Recognition Challenge (ILSVRC) 2014 challenge [13], in which it was trained on ImageNet dataset. This dataset contains 14 million images and 1000 classes. In this study, pre-trained VGG16 on ImageNet dataset is utilized with TL technique. That is, pre-trained VGG16 layers are frozen except for the final densely connected layer and the output layer. The dataset described in Section 2.1 is used to train the remaining unfrozen layers. The output layer produces a binary result, either Covid or NonCovid. The general architecture of VGG16 is shown in Figure 2.
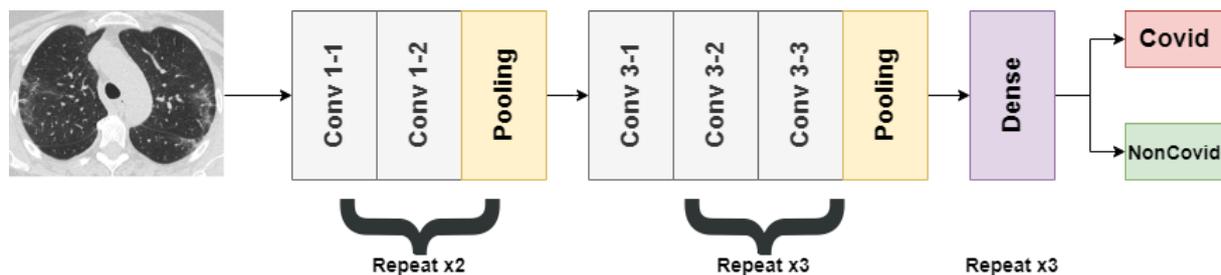

Figure 2. VGG16 general architecture [12].

2.3. SISR

This research hypothesizes that using SISR can enhance the overall classification accuracy of the network. The SISR technique used in this paper in Residual Dense Network (RDN) devised by [14]. This network is chosen for several reasons; it achieves high PSNR and SSIM compared to other state-of-the-art methods, it converges relatively faster, and it can be extended to be deeper and wider to enhance the performance further. RDN is used to enlarge the dataset by a scaling factor ×2. The general architecture of RDN is shown in Figure 3.
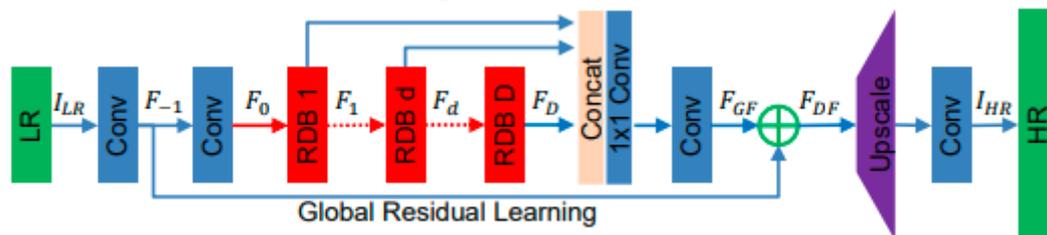

Figure 3. RDN general architecture [14].

2.4. Network Training

In order to test the hypothesis of this study, two experiments are conducted. In the first experiment, pre-trained VGG16 with TL is trained over the original dataset described in Section 2.1. In the second experiment, pre-trained VGG16 with TL is trained over the same dataset enlarged by a factor of x2. The accuracy and loss of both experiments are compared to verify this hypothesis. The network parameters summarized in Table 1 were used for all training experiments to guarantee consistency and fair reporting of results.

**Table 1.** VGG-16 with TL training parameters.

| Network Parameter	VALUE
Optimizer	RMSprop
Batch	50
Epochs	200
Pre-train weights	ImageNet
Learning rate	0.001
Data shuffle	True

3. Results and Discussion

The results of training VGG-16 with TL for the original dataset and the one scaled by ×2 are summarized in Table 2. All the qualitative metrics during training and testing indicate that the upscaled dataset has superior performance. Moreover, the confusion matrix, loss progression, and accuracy progression for the original dataset are shown in Figures 4, 5, and 6, respectively. The same assessment is performed for the dataset scaled by ×2 in Figures 7, 8, and 9, respectively, for comparison purposes. It can be noticed that applying SISR to the dataset enhanced the accuracy. Moreover, the loss progression graphs seen in Figures 5 and 8 show that the loss stabilized faster for the dataset scaled by ×2. A similar observation can be drawn from the accuracy progression graphs seen in Figures 6 and 9. Therefore, it can be concluded that SISR boosts the classification of CT scans and enhances the overall performance of the training.
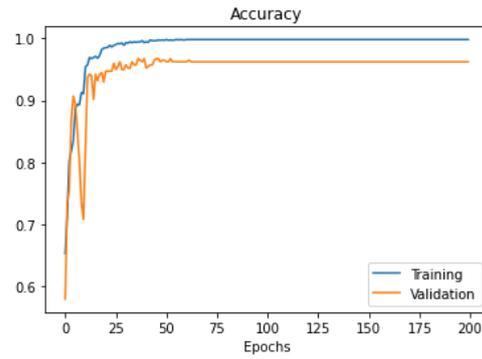
Table 2. Results Summary.

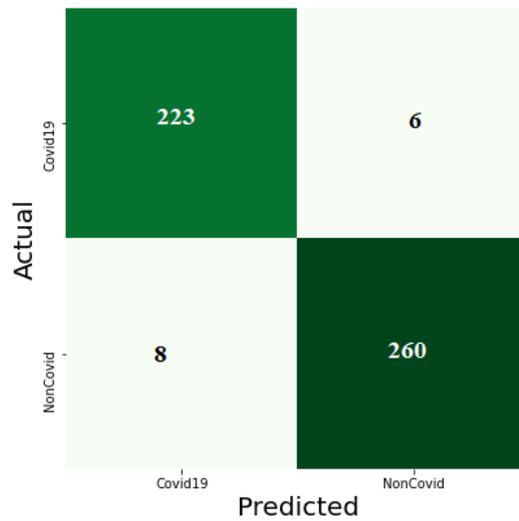|	Training accuracy	Training loss	Testing accuracy	Testing precision	Testing recall	Testing f1-score
Original Dataset	99.0%	0.041	95.0%	95.0%	95.0%	95.0%
×2	100.0%	0.0002	97.0%	97.5%	97.0%	97.0%
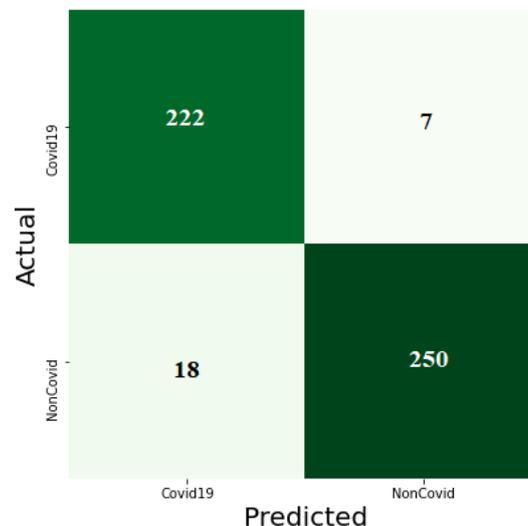
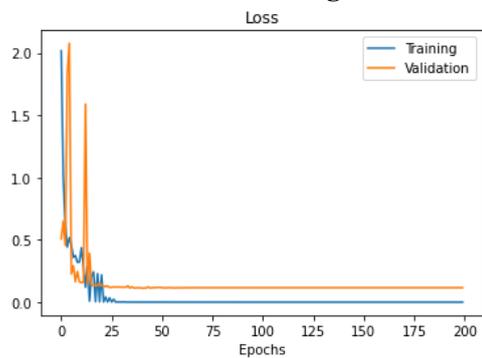**Figure 4.** Confusion matrix (original dataset)
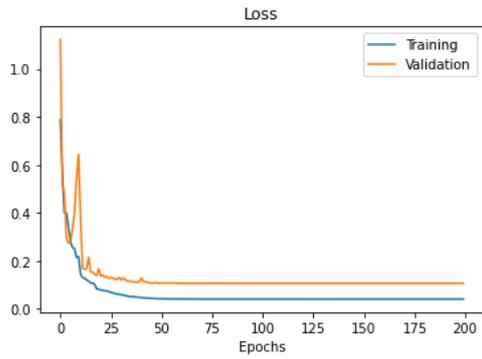
Figure 5. Loss progression throughout the training (original dataset)
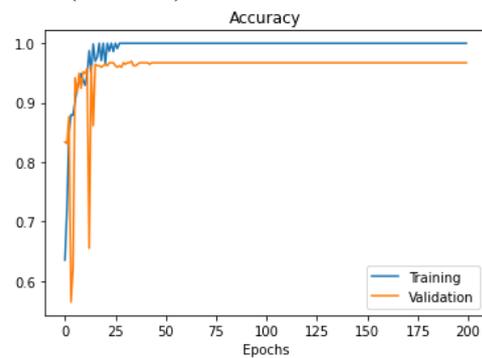

Figure 6. Accuracy progression throughout the training (original dataset)

Figure 7. Confusion matrix (scale ×2)

Figure 8. Loss progression throughout the training (scale ×2)

Figure 9. Accuracy progression throughout the training (scale ×2)

4. Conclusion

In this research, a publically available CT scans dataset was used to test a training strategy for binary classification of Covid and NonCovid. A pre-trained VGG16 over ImageNet dataset was utilized with TL in order to enhance the training performance. Additionally, RDN was used for the purpose of SISR to test the effect of scaling the dataset on the overall performance. The testing results show that the dataset scaled by ×2 shows better accuracy overall. The network stabilized faster for that dataset as well. In the future, more detailed analysis will be conducted on various scaling factors and the testing will be done across various CNN models.

5. References

[1] World Health Organization, 2020. WHO Coronavirus Disease (COVID-19) Dashboard. [Online]. Available: https://covid19.who.int/

[2] Kumar R, Nagpal S, Kaushik S and Mendiratta S 2020 COVID-19 diagnostic approaches: different roads to the same destination *VirusDis.* **31** pp 97–105

[3] Pan Y, Guan H, Zhou S, Wang Y, Li Q, Zhu T, Hu Q and Xia L 2020 Initial CT findings and temporal changes in patients with the novel coronavirus pneumonia (2019-nCoV): a study of 63 patients in Wuhan, China *Eur. Radiol.* **30** pp 3306–3309

[4] Perumal V, Narayanan V and Rajasekar S Detection of COVID-19 using CXR and CT images using Transfer Learning and Haralick features 2020 *APPL INTELL*

[5] Shi F, Wang J, Shi J, Wu Z, Wang Q, Tang Z, He K, Shi Y and Shen D 2020 Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19 *IEEE Reviews in Biomedical Engineering* pp 1-1

[6] Hasan A, AL-Jawad M, Jalab H, Shaiba H, Ibrahim R and AL-Shamasneh A 2020 Classification of Covid-19 Coronavirus, Pneumonia and Healthy Lungs in CT Scans Using Q-Deformed Entropy and Deep Learning Features *Entropy* **22** p 517

[7] Singh D, Kumar V, Vaishali and Kaur M 2020 Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks *Eur. J. Clin. Microbiol. Infect. Dis* **39** pp 1379–1389

[8] Babukarthik R, Adiga V, Sambasivam G, Chandramohan D and Amudhavel J, 2020 Prediction of COVID-19 Using Genetic Deep Learning Convolutional Neural Network (GDCNN) *IEEE Access* **8** pp 177647 – 177666.

[9] Jaiswal A, Gianchandani N, Singh D, Kumar V and Kaur M 2020 Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning J. *Biomol. Struct. Dyn* pp 1-8

[10] Wang X, Deng X, Fu Q, Zhou Q, Feng J, Ma H, Liu W and Zheng C 2020 A weakly-supervised framework for covid-19 classification and lesion localization from chest Ct *IEEE Transactions on Medical Imaging* **39** pp 2615 - 2625

[11] Zhao J, Zhang Y, He X and Xie P 2020 COVID-CT-Dataset: a CT scan dataset about COVID-19 *arXiv preprint* arXiv:2003.13865

[12] Simonyan K and Zisserman A 2015 Very Deep Convolutional Networks for Large-Scale Image Recognition *arXiv preprint* arXiv:1409.1556v6

[13] Russakovsky O et al. 2014 *International Journal of Computer Vision* **115** pp 211-252

[14] Zhang Y, Tian Y, Kong Y, Zhong B and Fu Y 2018 *arXiv preprint* arXiv:1802.08797v2