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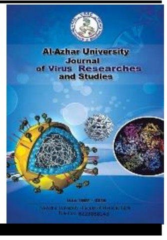

Automated Detection of Covid-19 Coronavirus Cases Using Deep Neural Networks with X-ray Images

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Abstract

Many health systems over the world have collapsed due to limited capacity and a dramatic increase of suspected COVID-19 cases. What has emerged is the need for finding an efficient, quick and accurate method to mitigate the overloading of radiologists' efforts to diagnose the suspected cases. In this paper, we propose a deep learning architecture to detect Covid-19 Coronavirus in chest radiographs. This architecture contains one network to classify images as either normal or Covid-19 Coronavirus. In this paper, we adopt ResNet-50 architecture in this blog as it has proven to be highly effective for various medical imaging applications. Those X-ray images database contain 147 images. The data divided into 73 samples for the normal X-ray images and 74 samples for Covid-19 Coronavirus X-ray images. The experiment results evaluated by three parameters including accuracy, sensitivity, and specificity. For the ResNet-50 deep learning, these outcomes refer to the maximum accuracy being 99.3% by the training dataset for the ResNet-50. ResNet-50 can be considered as a high sensitivity model to characterize and diagnose COVID-19 infections and can be used as an adjuvant tool in radiology departments.

Keywords: COVID-19, X-ray images, Deep learning, ResNet-50 architecture.

1. Introduction

Modern-day medical facilities are aiming to provide the human population with a safer living condition through the prevention of life-threatening diseases. Because of numerous unregulated and inevitable causes, chronic and communicable diseases are increasing globally in people. Most of these diseases, if diagnosed at their premature stage, can be managed and fully cured. The patient visits the hospital to diagnose the reason, the type and the seriousness of the disease in the event of an illness symptom. In contrast to other illness, the disease in internal body organs is very severe and therefore more diagnostics approaches for detecting the disease and its severity are advised and introduced to schedule a treatment regimen that is sufficient to handle the disease. The lung can cause adverse damage to the respiratory system and lung infection / illness can adversely damage the respiratory system and cause death from untreated lung disorder. Pneumonia, lung cancer and tuberculosis are major illness for lung defects [1,2]. In addition, microorganisms such as bacteria and viruses, and fungi can lead to mild and serious disease by infection in the lungs, which may require urgent medical aid in curing the illness. The pulmonologist will recommend a range of diagnostic methods to assess the origin, location and nature of the infection when a patient is admitted to the hospital because of respiratory diseases, ranging from non-laboratory testing to laboratory testing. Popular methods, including blood counting, blood gas analysis and plural fluid checks, are used in laboratory tests [3,4]. The non-laboratory examinations are primarily the picture-aided techniques for the recording or examination of lung regions by means of chest X-ray (CT) scans and bronchoscope. Chest X-rays and CT are needed to obtain digital lung images due to their non-invasive nature, which can be further examined by an experienced doctor or a computer-supported system to assess the extent of the infection. More than 3,000,000 cases of COVID-19 were diagnosed, and 200,000 deaths were registered by 1 May 2020, with COVID-19 having a major effect on public health and the economic. The primary test method developed for COVID-19 diagnosis is currently the reverse transcription polymerase chain reaction (RT-PCR). The early diagnoses and treatments of the disease are distinguished by the essential function of chest radiological pictures for example CT and X-Ray [5]. Even though negative outcomes are got, symptoms can be identified by analysing radiological images of patients due to the low RT-PCR sensitivity of 60 percent-70 percent [6,7]. CT is a reliable technique of detecting COVID-19 pneumonia and be capable of as a diagnosis instrument also as well as RT-PCR [8]. CT results are seen over a long period of time after symptoms begin, and patients typically have normal CT for the first 0–2 days [9]. The maximum severe lung illness is detected ten days after symptoms arise in a lung CT analysis of patients surviving COVID-19 pneumonia [10]. Chinese health centers had inadequate test kits at the start of the pandemic, which often produce a high rate of false-negative outcomes, so physicians are advised to diagnose only on the basis of clinical and chest CT findings [9,11]. Researchers also found out that it can help to early detect COVID-19 by integrating clinical image properties with laboratory findings [8,12-14]. Radiologic images collected from cases of COVID-19 provide valuable diagnostic information. A number of studies have seen variations in chest X-ray and CT images prior to the onset of COVID-19 symptoms [15]. Researchers in COVID-19 imaging studies have realized important discoveries. In a COVID-19 patient, Kong et al. [16] found accurate infra-hilar airspace opacities. Yoon et al. [17] recorded that, in the left lower lung area, one in three patients studied had a single nodular opacity. The other two, on the other hand, had four and five abnormal opacities in both lungs, the other two had four to five abnormal opacities. In maximum of the patients, Zhaoetal et al. [13] found not only ground-glass opacities or mixed floor-glass opacities, but also a consolidation of the lesion and vascular dilatation. Li and Xia [14] registered ground-glass opacities and consolidation, interlobular septal thickening and air bronchogram signs, with or without vascular expansion, as standard computed tomography features of COVID-19 patients. The use of machine learning methods for automated diagnosis in the medical field has recently gained prominence by being an adjunct tool for clinicians [18-22]. A popular artificial intelligence (AI) research area is a deep learning that allows the development of end-to-end models to accomplish assured results utilizing input data without the need for manual extraction of features [23,24]. In several issues, deep learning techniques such as rhythmic identification [25-27], classification of skin cancer [28,29], detection of breast cancer [30,31], classification of brain disease [32], chest X-ray pneumonia [33], fundus image segmentation [34], and lung segmentation [35,36] have been successfully implemented. The rapid growth of the

COVID-19 epidemic has required the demand for skill or knowledge in this area. The development of automated detection systems based on AI methods has been a raised importance. Due to the small number of radiologists, it is a difficult challenge to give expert clinicians to each hospital. Easy, precise, and quick AI models can therefore be useful to overcome this issue and provide patients with timely assistance. While, due to their extensive expertise in this area, radiologists perform a significant responsibility, AI technologies in radiology can help to achieve accurate diagnosis [37]. In addition, AI methods can be useful in reducing drawbacks such as inadequate numbers of RT-PCR examination kits available, examination costs, and test results waiting time. Recently, several X-ray images have been commonly used for the detection of COVD-19. In order to diagnose COVID-19 in X-ray images, Hemdan et al. [38] utilized deep learning models and suggested a COVIDX-Net model containing seven convolutional neural network (CNN) models. A deep COVID19 detection model (COVID-Net) was proposed by Wang and Wong [39], which achieved 92.4 percent accuracy in classifying normal, non-COVID pneumonia and COVID-19 groups. A new deep neural network for the recognition of COVID-19 involving five elements is proposed by Jianping Zhang et al. [41], utilizing 100 X-Ray images as a Covid-19 of 70 patients and 1431 X-Ray pictures as a non-covid-19. The study found 96 percent for covid-19 detection and 70.65 percent for non-covid-19 detection. Wang et al. [42] suggested a recent COVID-Net design for CNN. The COVIDx dataset is created by joining and adapting two separate datasets, the "covid-19 image data collection" and the "RSNA Pneumonia Detection Challenge" dataset, containing 16,756 chest radiographs from the two dissimilar datasets listed above over 13,645 patient cases. The COVIDx testing accuracy is 92.4 percent. The main objective of above study is to provide accurate measures for the identification of X-rays images patients with COVID-19 via CNN. Chest X-rays is preferred over CT scan. The reason behind this is that X-rays machines are available in most of the hospitals. X-rays machines are cheaper than the CT scan machine. Besides this, X-rays has low ionizing radiations than CT scan. In the field of many computer visions tasks. We utilized a relatively recent methodology, CNN, where the learning methodology is developed to classify persons with COVID-19 with a Resnet50. We follow the ResNet-50 architecture as it has proven to be very successful for different medical imaging applications.

2. MATERIALS AND METHODS

We use a publicly accessible dataset [43] [44] that includes COVID x-ray images and normal x-ray images. collects this data. The dataset contains 147 images. The data divided into 73 samples for the normal X-ray images and 74 samples for Covid-19 Coronavirus X-ray images. Figure 1 represents certain sample images marked as normal by an expert reader. Figure 2 represents certain sample images marked as COVID-19 cases by an expert reader.

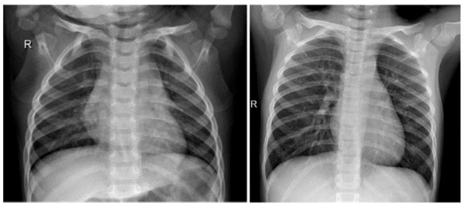

Figure 1. Sample images annotated as 'Normal' by Expert Readers

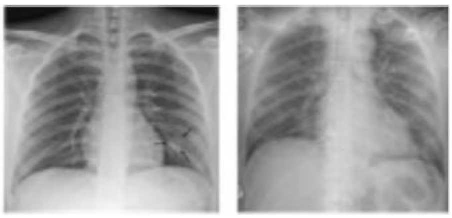

Figure 2. A few COVID-19 cases.

2.1 Covid-19 Coronavirus Detection Architecture

The transfer learning-based CNN model approved for the classification of images as normal or COVID-19 is described in this portion. At first, in conjunction with the used architecture, we re-sample all images to 224 × 224. We used well-established networks such as ResNet-50 for transition learning purposes, as described above. The use of these well-established networks allows us to maintain a riches of knowledge for classifying various artefacts from previous training. Both weights and layers are maintained awaiting the final fully linked layer. Based on our data we will update ResNet-50. Since 1000 classes are trained in ResNet-50 million photos. In our case we have 147 images with 2 classes. With our own completely linked and softmax our last three layers are replaced. Particularly for image-based classification issues, these approaches have proven to be highly effective. The block diagram of the transfer learning method applied in this paper is presented in figure 3. Cross-validation is a model assessment technique that used to evaluate a deep learning algorithm's performance in making predictions on new datasets that it has not been trained on. This is done by partitioning the known dataset, using a subset to train the algorithm and the remaining data for testing. Each round of cross-validation involves randomly partitioning the original dataset into a training set and a testing set. The training set is then used to train a supervised learning algorithm and the testing set is used to evaluate its performance. This process is repeated several times and the average cross-validation error is used as a performance indicator. We split the dataset into 10-folds for analysis i.e. 10 different algorithms would be trained using different set of images from the dataset. The 10 different algorithms contain set of training images and set of testing images from the dataset. This type of validation study would provide us a better estimate of our performance in comparison to typical hold-out validation method.

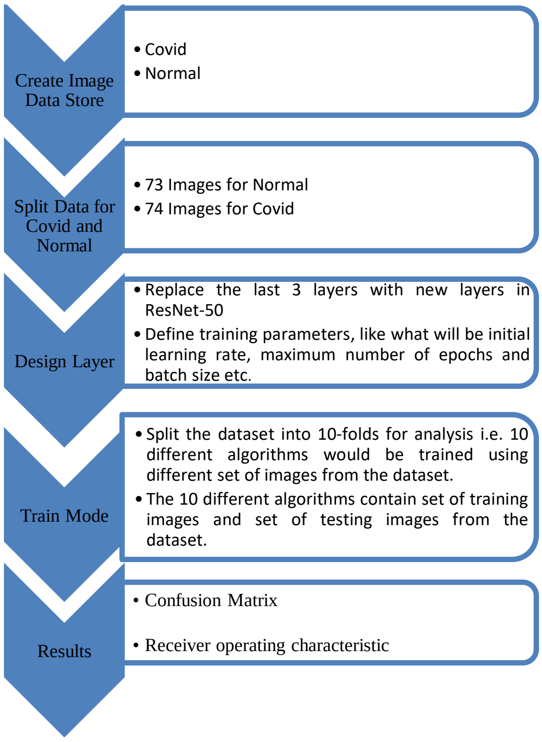

Figure 3. Block diagram of our algorithm.

3. Experimental Results

The results achieved for the method mentioned in sections 2 are discussed in this partition. The COVID-19 identification is determined on the basis of the datasets that composed of 147 images and the data divided into73 samples for the normal X-ray images and 74 samples for Covid-19 Coronavirus X-ray images. First, the ResNet-50 model is trained to detect two classes: COVID-19 and Normal categories. The performance of the proposed model is evaluated using the 10-fold cross-validation procedure for the binary classification problem. Approximately ninety percent of X-ray images are used for training and approximately 10% for testing. The experiments are repeated ten times. We have trained ResNet-50 for 30 epochs. In Fig. 8 the training of the binary class classification graph is shown for the Fold-

1. The overlapped as well as each separate confusion matrix (CM) are shown in Fig. 4, Fig. 5, and Fig. 6. The overlapped CM is created using the sum of CMs obtained in all folds. Thus, it is aimed to obtain an idea about the general perforations of the model. The ResNet-50 model achieved an average classification accuracy of 99.33% to classify: Normal and COVID-19. Sensitivity, specificity, precision, F1-score, and accuracy values are shown in Table 1 for the detail analysis of the model for the 2-class problem. It can be noted from the overlapped confusion matrix of the binary-class classification task that the deep learning model classified COVID- 19 with sensitivity, specificity, and accuracy values are 100%, 98.65%, and 99.32%, respectively. It can be noted from Table 3 that the proposed model has achieved an average accuracy of 98.08% in detecting COVID-19 and the obtained average sensitivity, specificity, and F1-score values of 100%, 98.65%, 99.32% and 99.32%, respectively. In the COVID-19 epidemic, radiological imaging plays an important role in addition to the diagnostic tests performed for the early diagnosis, treatment, and isolation stages of the disease. Chest radiography can detect a few characteristic findings in the lung associated with COVID-19. Deep learning models are sensitive in detecting COVID-19 lung involvement and hence the diagnostic accuracy rate is high. During the evaluation of the model, X-ray radiographs of COVID-19 patients confirmed positive by the PCR Test are used. The model can easily detect GGO, consolidation areas, and nodular opacities, which are the pathognomic findings of patients for COVID-19 on X-ray radiography. In COVID-19, bilateral, lower lobe, and peripheral involvement is observed, and the proposed model can detect localization of the lesion. These models are particularly important in identifying early stages of COVID-19 patients. Early diagnosis of the disease is important to provide immediate treatment and to prevent disease transmission. The models can also play an indispensable role in patients lacking early symptoms. There is a margin of error in patients with diffuse late lung parenchyma and in patients with significantly reduced lung ventilation due to poor quality X-ray images. X-rays that are not of optimal quality are difficult to evaluate by radiologists. The clinical and radiological images of later stage patients are well established, and it is easier to detect the findings by experts. The role of deep learning models is more prominent in screening and diagnosis when the infection is at its early stages time can be significantly reduced, and it will alleviate clinician workload.

4. Conclusion

In order to get an early detection of COVID-19 from x-ray images with the assistance of a computer-aided automated method, the contribution of this research is explained. The epidemic status scheme requires the correct x-ray reader for COVID-19 via deep learning algorithms to minimize the prevalence of the virus, especially in low-income countries. Moreover, the usefulness of a CAD system is supported by the vision of x-ray images of COVID-19. The satisfactory results were declared by the CNN classifier with high accuracy of 99.3%. Lastly, this type of architecture would be highly essential for COVID-19 detection and its diagnosis and would enhance the workflow of radiologists.

Table 1: Sensitivity, specificity, precision, F1-score, and accuracy values for Normal and COVID-19 classes of the proposed model.

Folds	Sensitivity	Specificity	Precision	F1-score	Accuracy
1	1	1	1	1	1
2	1	1	1	1	1
3	1	1	1	1	1
4	1	1	1	1	1
5	1	1	1	1	1
6	1	0.8750	0.8750	0.9333	0.9333
7	1	1	1	1	1
8	1	1	1	1	1
9	1	1	1	1	1
10	1	1	1	1	1
Overlapped	1	0.9865	0.9865	0.9932	0.9932

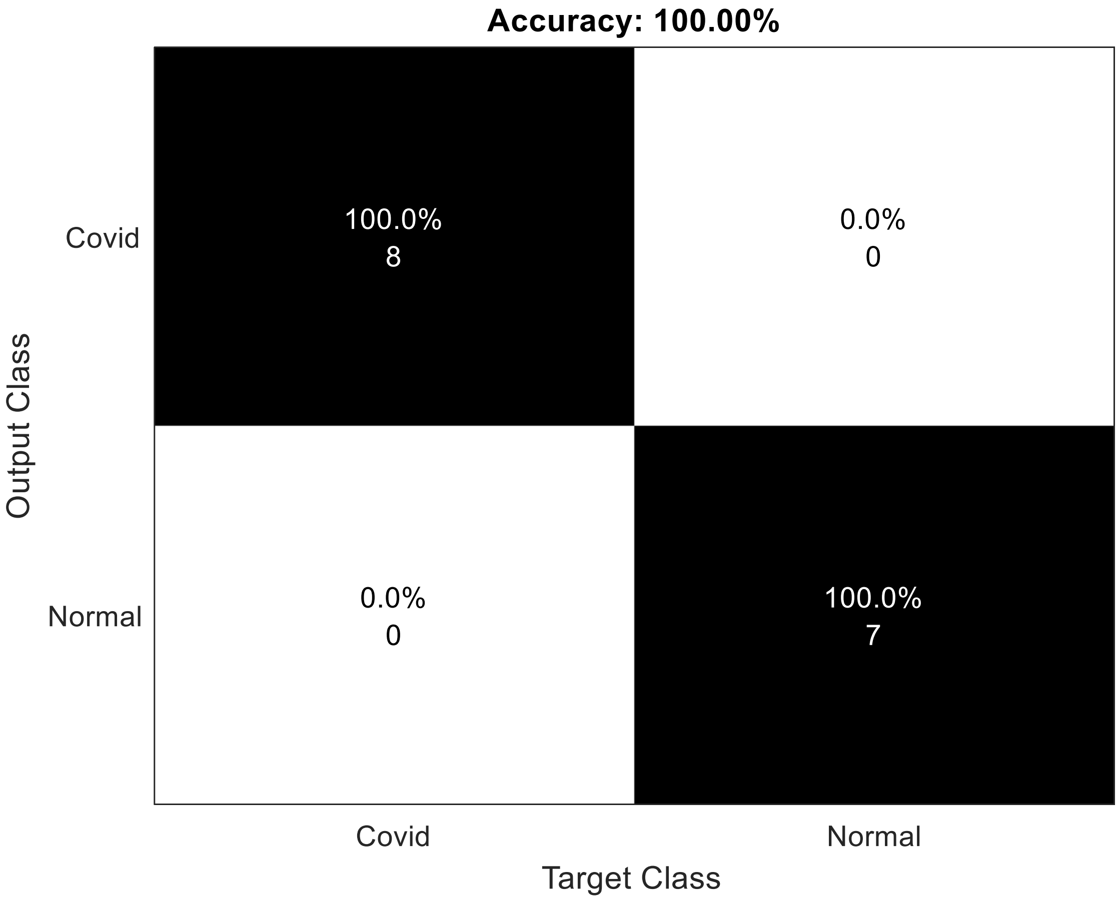

Fig. 4. The 3-folds confusion matrix (CM) results of the binary classification task: Fold-1 CM, Fold-2 CM, and Fold-3 CM.

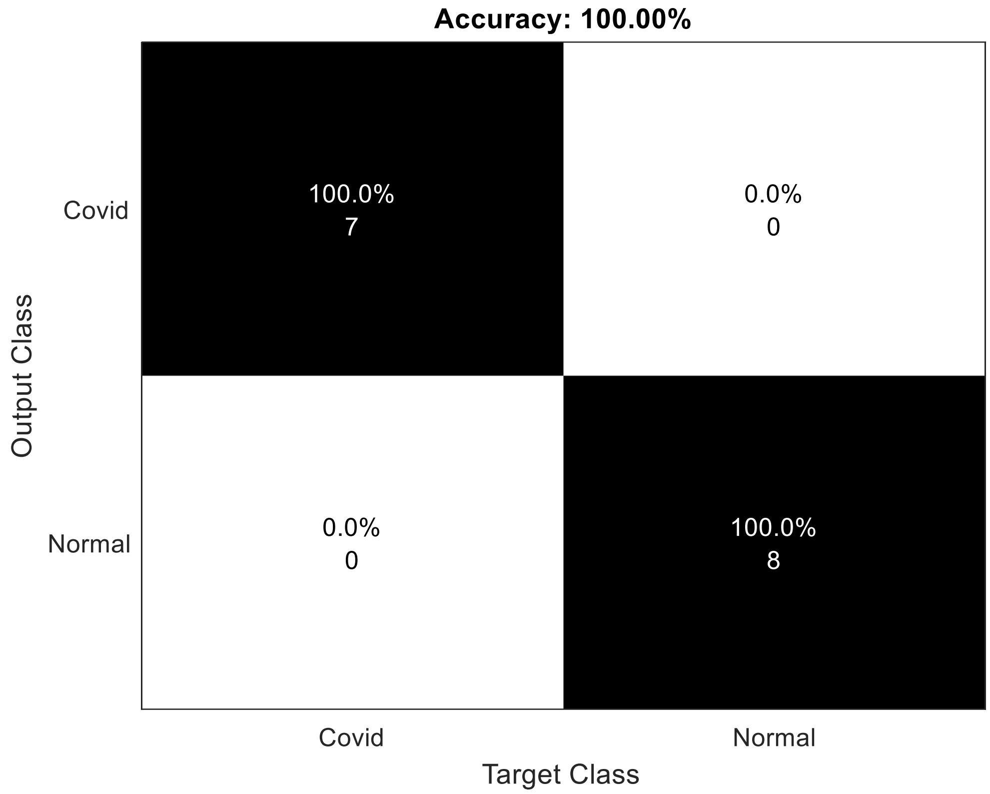

Fig. 5. The 6-folds confusion matrix (CM) results of the binary classification task: Fold-4 CM, Fold-5 CM, Fold-7 CM, Fold-8 CM, Fold-9 CM and Fold-10 CM.

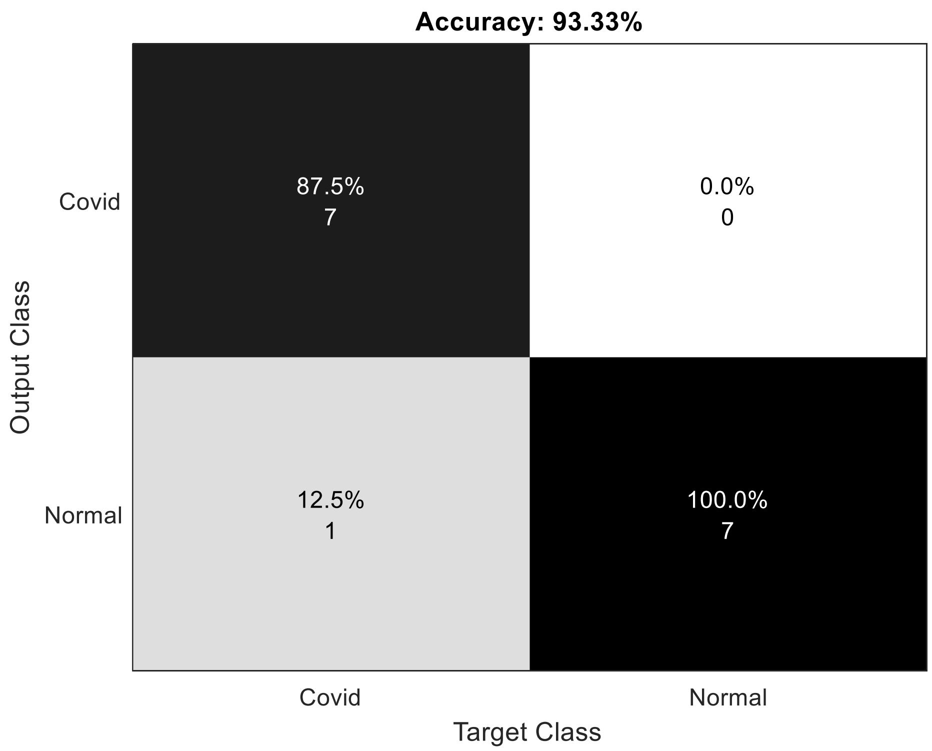

Fig. 6. The 1-fold confusion matrix (CM) results of the binary classification task: Fold-6 CM.

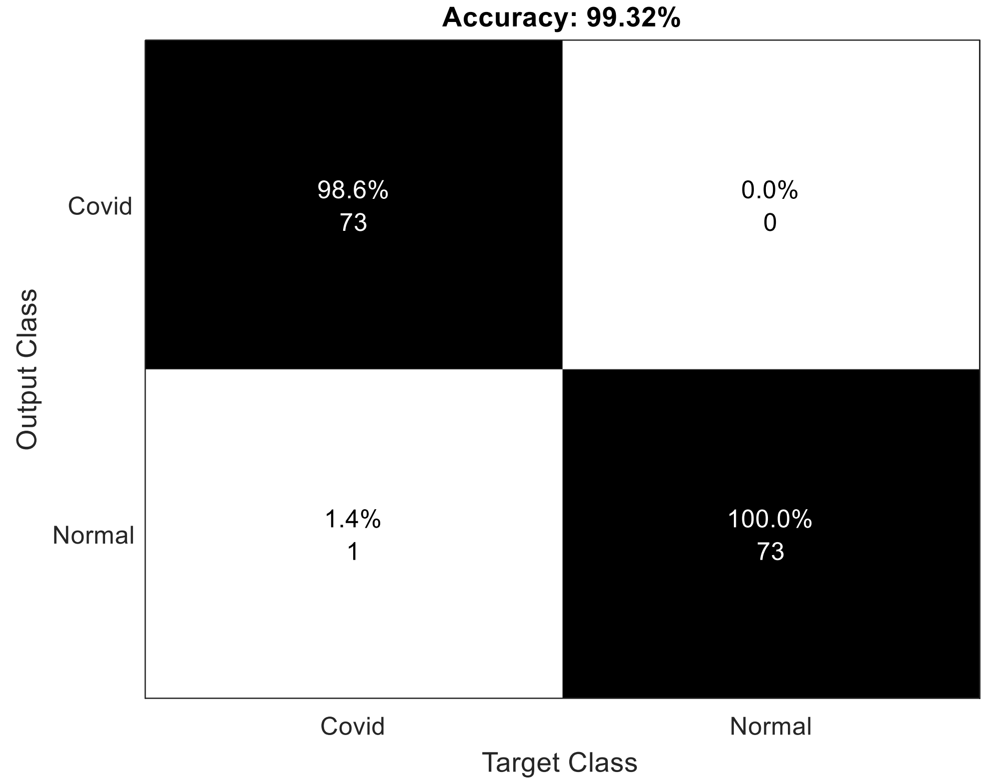

Fig. 7. The overlapped confusion matrix (CM) results of the binary classification task.

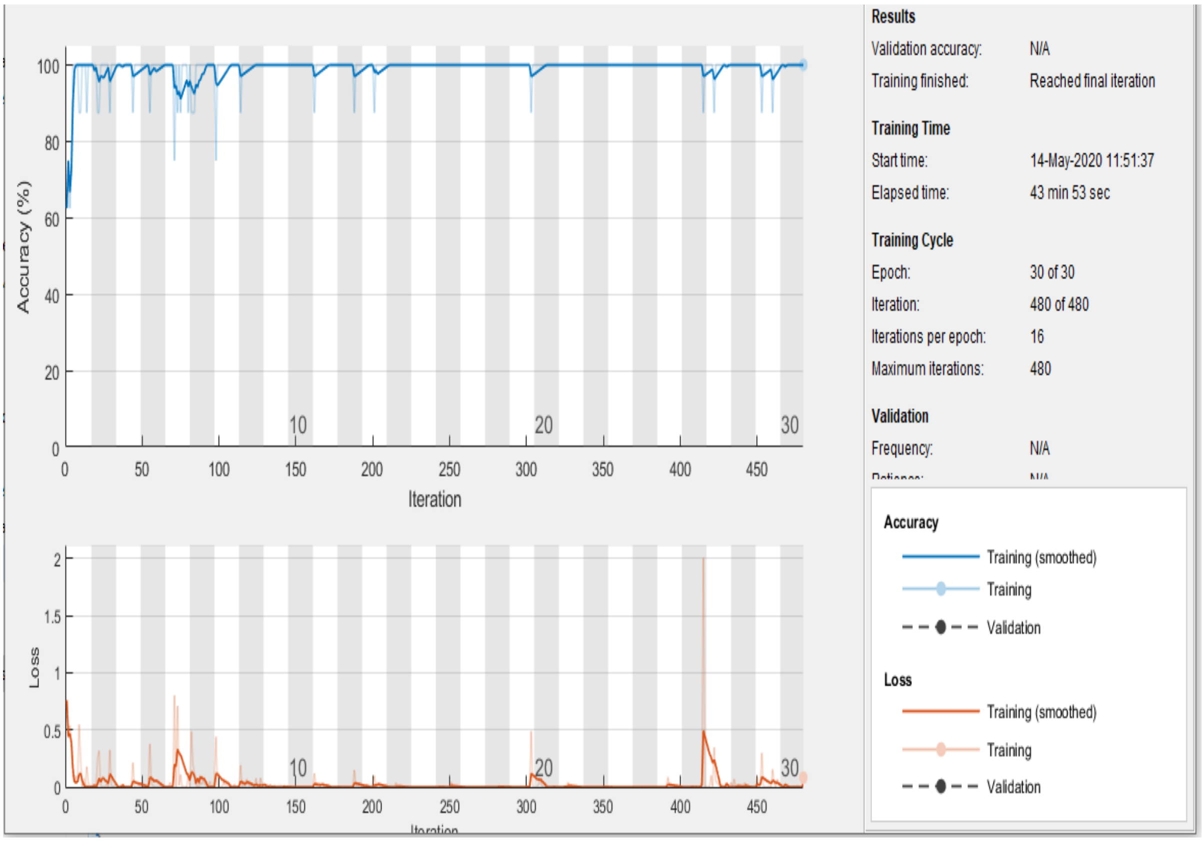

Fig 8: Training progress for ResNet-50 architecture on the dataset.

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