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Deep Learning Techniques to Identify and Classify COVID-19 Abnormalities on Chest X-ray Images

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ABSTRACT

The new coronavirus disease (COVID-19) comprises the public health systems around the world. The number of infected people and deaths are escalating day-to-day, which puts enormous pressure on healthcare systems. COVID-19 symptoms include fatigue, cough, and fever. These symptoms are also diagnosed for other pneumonia, which creates complications in identifying COVID-19, especially throughout the influenza season. The rise of the COVID-19 pandemic among individuals has made it essential to improve medical image screening of this pneumonia. Rapid identification is a necessary step to stop the spread of this virus and plays a vital role in early detection. With this as a motivator, we applied deep learning techniques to diagnose the coronavirus using chest X-ray images and to implement a robust AI application to classify COVID-19 pneumonia from non-COVID-19 for the respiratory system in these images. This paper proposes different deep learning algorithms, including classification and segmentation methods. By taking advantage of convolutional neural network models, we exploited different pre-trained deep learning models such as (ResNet50, ResNet101, VGG-19, and U-Net architectures) to extract features from chest X-ray images. Four datasets of chest X-ray images have been employed to assess the performance of the proposed methods. These datasets have been split into 80% for training and 20% for validation of the architectures. The experimental results showed an overall accuracy of 99.42% for the classification and 93% for segmentation approaches. The proposed approaches can help radiologists and medical specialists to identify the insights of infected regions for the respiratory system in the early stages.

Keywords: COVID-19, chest x-ray images, deep learning, classification, segmentation

1. INTRODUCTION

The outbreak of the Coronavirus Disease 2019 (COVID-19) in the latter part of 2019 and the subsequent pandemic announced in March 2020 has changed the landscape of medical provision across the globe. At its peak in the EU, case numbers across the bloc were rising by over 300,000 per day [1], putting immense strain on healthcare systems trying to cope with large numbers of critically ill patients. Currently, the preferred method of diagnosis is by polymerase chain reaction (PCR) of a viral swab, a process that can take over 24 hours in a virology lab, the services of which are also inundated with a high-volume workload.

A faster method of screening is by plain x-ray of the patient's chest, which may show up features of Covid-19 infection [2]. These images would normally need to be reviewed by a radiologist for diagnosis, which is again constrained by workload capacity. An AI system, on the other hand, is able to screen images many times more efficiently and coupled with the fact that chest x-rays are a quick and non-invasive investigation, there exists a potential for a rapid screening test, which would allow medical practitioners the ability to more efficiently manage patient flow through hospitals and begin appropriate treatment sooner.

The main contribution of this work can be stated as the followings:

1. Create a feature extraction framework by deep learning models to identify COVID-19 on lungs and key-point features.

2. Deep learning techniques have been deployed to identify COVID-19 and non-COVID-19 on chest x-ray images.
3. Evaluation of the performance of various combinations has been applied to find the best feature extraction network algorithm and deep learning methods for identifying COVID-19 abnormalities on chest x-ray images.
4. Identification the infected regions on the lungs by U-Net model. Although the segmented chest x-ray images are not enough to train the model, the proposed approach showed promising results for replicating the segmented masks.

Here we present a deep learning system to reliably classify chest x-rays into one of three classes: normal, COVID-19 or non-COVID-19 pathology. We investigate three popular image classification models (ResNet50, ResNet101 [3] and VGG-19 [4]) and fine-tune them using chest x-ray images from four publicly available datasets. We also demonstrate lung-field segmentation using U-Net [5] as a method of preprocessing chest x-ray images. The rest of the paper is organized as the following: after the introduction in section 1, section 2 presents the related work. Section 3 describes the methodology. Section 4 shows the results, and finally, conclusions are withdrawn in Section 5.

2. RELATED WORK

Previous studies investigating COVID-19 detection on chest x-ray are presented below.

Apostolopoulos and Mpesiana [6] employ transfer learning techniques to several pre-trained networks with weights learned from the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [7]. They use VGG-19, MobileNet-v2 [8], Inception [9], Xception [10] and Inception ResNet v2 [9] models, with a custom densely-connected classifier at the top to predict on the extracted features. The parameters of the convolutional base of the models are fixed during training, updating only the latter weights as well as the custom dense network. They use a chest x-ray dataset comprising 224 images with confirmed Covid-19, 700 images with confirmed common bacterial pneumonia, and 504 normal images and present a 3-class accuracy of 94.72% with their adjustment of the MobileNet-v2 model.

Brunese et al. [11] adopt a 2-step approach to Covid-19 detection. First, they train a model to perform a binary prediction of normal vs abnormal chest x-ray. Secondly, the abnormal x-rays are further classified with a second model as COVID-19 vs other pulmonary diseases. They also choose to use transfer learning using a VGG-16 model with pre-trained ImageNet weights and append a small projection head classifier. They fix all the VGG-16 weights during training and only train the projection head, using a dataset comprising 250 COVID-19 images, 3,520 normal images and 2,753 images showing other pulmonary diseases. They present accuracy of 96% and 98% (F1-score 0.94 and 0.89) for their first and second models, respectively. Ozturk et al. [12] modify the DarkNet [13] architecture to create their DarkCovidNet, which they train end-to-end using a dataset comprising 127 COVID-19 images, 500 normal images and 500 pneumonia images on both binary classification (COVID-19 vs Normal) and multiclass classification (COVID-19 vs Normal vs Pneumonia). They present accuracies of 98.08% and 87.02% (F1-score 0.9651 and 0.8737), respectively, for these two tasks.
Khan et al. [14] present CoroNet, a transfer learning approach using Xception as a base model, initialized with pre-trained weights, and a custom, densely connected classifier network appended to the end. All weights, including the convolutional kernels, were then fine-tuned during training, using a dataset comprising 290 COVID-19 images, 660 images of bacterial pneumonia, 931 images of viral pneumonia and 1203 normal x-rays. They performed 4-class classification, along with 3-class (COVID-19 vs Normal vs Pneumonia) and binary (COVID-19 vs Normal) classifications. They present accuracies of 89.6%, 95.0% and 99.0% for these different tasks, respectively. Ucar and Korkmaz [15] present COVIDiagnosis-Net, a modification of SqueezeNet [16] that uses Bayesian optimization to tune the model's hyperparameters. They train this model end-to-end using a dataset comprising 1,583 normal chest x-rays, 4,290 x-rays showing non-COVID pneumonia, and 76 COVID-19 images. They use offline data augmentation to balance the classes prior to training and present a 3-class accuracy of 98.3%.

Wang and colleagues [17] present COVID-Net, a completely novel CNN architecture tailored for COVID-19 detection on plain chest x-ray. The model was pretrained on the ImageNet database [18] before being fully fine-tuned on a chest x-ray dataset comprising 358 COVID-19 images, 8,066 normal images and 5,538 images showing non-COVID pneumonia. They obtain a 3-class accuracy of 93.3% (F1-score 0.94).

Waheed et al. [19] produced CovidGAN, a VGG-16-based CNN with an auxiliary classifier generative adversarial network (ACGAN) that enhanced training with synthetic images to improve performance. Their initial dataset comprised 403 COVID-19 images and 721 normal chest x-rays. Using a VGG-16 model with fixed weights, they trained a small projection head using their data and obtained an accuracy of 85%. They then used CovidGAN to generate 1399 synthetic normal chest x-rays and 1669 synthetic COVID-19 x-rays. Using this enhanced dataset, they achieved an accuracy of 95% (F1-score 0.95). Teixeira et al. [20] use image semantic segmentation approaches to isolate the lung fields of chest x-rays prior to performing classification. They employ a U-Net CNN to segment the lung fields and discard the background image. They show that in all models tested, this approach improves the F1-score compared with using raw chest x-ray images.

3. METHODOLOGY

Medical images provide detailed images of bones, organs, blood vessels, and soft tissues. X-ray images allow radiologists and doctors to identify the internal structure shape size and see their texture. Computer vision assisted significantly in resolving the issues in the medical imaging field. On the images understanding front, deep learning models have made a big leap to help classify, identify, and locate patterns in medical images. In this research, we used different types of deep learning techniques for COVID-19 identification on Chest-X-ray images. Using recent strategies in AI methodologies shows that current deep gaining knowledge of structures to locate COVID-19 from chest radiographs depends upon confounding elements instead of scientific pathology, growing an alarming scenario wherein the structures seem accurate. We looked at the method to gain the statistics for those AI structures that introduce an almost perfect state of affairs for AI to study spurious results. The deep learning approach has also been used to detect and classify COVID-19 in X-ray images, which are associated with other diseases. In this regard, we proposed two approaches that include classification and segmentation for screening COVID-19 based on the chest-x-ray images. The experiments of this work take place at NVIDIA Tesla K80 GPU under the Google Colab operating system and its support packages.

3.1 Classification

Chest x-ray image-based diseases classification methods are employed as an alternative to assist the medical diagnoses. Classification techniques are powered by deep learning algorithms, which learn from medical images and classify the presence of COVID-19 from the other diseases to improve the current diagnosis process. Recent research explored abnormalities in chest x-ray images of COVID-19 patients that could be beneficial for disease identification. However, manual recognition of COVID-19 in a set of chest x-ray images compromising COVID-19 and other types of pneumonia diseases are prone to doctors' and radiologist error. Towards this purpose, we exploited three widely used CNN architectures that have been shown to be successful in computer vision and medical diagnosis. In this paper, we have implemented various deep learning models such as VGG19, ResNet50, and Resnet101 in conjunction with the developed computer vision AI-based system on convolutional neural network models (CNN) for classification of COVID-19 in chest x-ray images. The trade-off between classification performance and computational costs determines the model versions. We chose these architectures to verify the model's efficiency and the number of learning parameters. The convolutional neural network is the main approach for classifying and predicting COVID-19 in the images. Figure 1 shows a deep learning-based classification workflow to predict whether the chest x-ray images have COVID-19 or are normal.

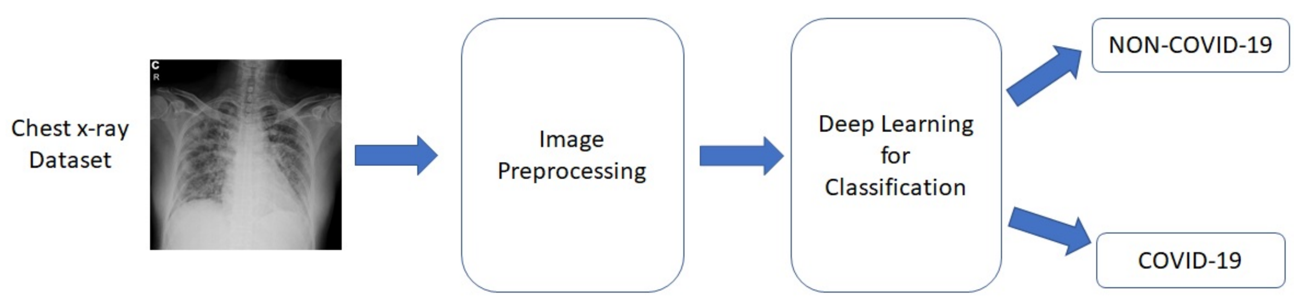

Figure 1: Deep learning-based classification workflow for COVID-19 detection

3.1.1 Dataset description

We utilized a combination of three datasets [29], [30], [31], which consists of COVID-19 and normal, to perform the experiments with ResNet50, ResNet101, and VGG19 models. These datasets are obtained from the Kaggle website. The chest x-ray images have two classes that include COVID-19, and normal, respectively. We used in total 1699 chest x-ray images (357 images with COVID-19 and 1342 images with normal cases). In collaboration with doctors and radiologists, the researchers have prepared these databases of chest x-ray images with positive cases and normal conditions. The images of these datasets don't follow any standard regarding the image size and contrast quality.

3.1.2 Image pre-processing

Pre-processing is a vital process for deep learning applications. Pre-process step is beneficial for eliminating unwanted noise and distortion. The chest-x-ray images have been pre-processed for training and validating the proposed models. It emphasizes the aspects of the images, which can help the classification task and optimize the training phase for the architectures. The input images for the convolutional neural network are resized to account for the compatibility of the neural network models. In our experiments, we swapped the colour channels, resized all images to 224 x 224 pixels, and ignored the aspect ratio. We converted the data and labels to NumPy while scaling the pixels' intensity to the range [0, 1]. We also applied label binarize in the one-vs-all scheme for all images. It is a simple way to extend deep learning algorithms to convert class labels to binary labels, which makes this process easy with the transform method.

3.1.3 Classifiers training and validation

We split these datasets into 80% for training and 20% for validation of the architectures. During the experiments, the proposed models were set to be hyper-parameters fine-tuned with different settings during the training phase, see Table 1. The number of epochs was set to 80. These epochs define the number of times that the learning algorithm will perform through the training dataset. We used a learning rate parameter in the training option to control the model change in response to the error [24]. We trained the network with stochastic gradient descent (sdgm) [25]. Based on the results, the training loss has been improved with pretrained architectures VGG19, and Resnet101 in comparison to the Resnet50 architecture. Both Resnet101, and VGG19 show promising results for the loss curve. Throughout the training process of Resnet50, we discovered an over-fitting problem, as evidenced by the divergence of training. Along with the training, the gradients in the top four blocks of Resnet50 were very small. That is due to the few learnable parameters in the model. Figure 1 shows the loose curve for Resnet50, Resnet101, and VGG19 models.

TABLE 1: Training Hyper-Parameters for the deep learning models (Resnet50, Resnet101, and VGG19)

Parameter	Method
Training options	sdgm
L2 Regularization	0.06
Number of Epochs	80
Verbose Frequency	50
Mini-batch size	64
Learning rate	0.001

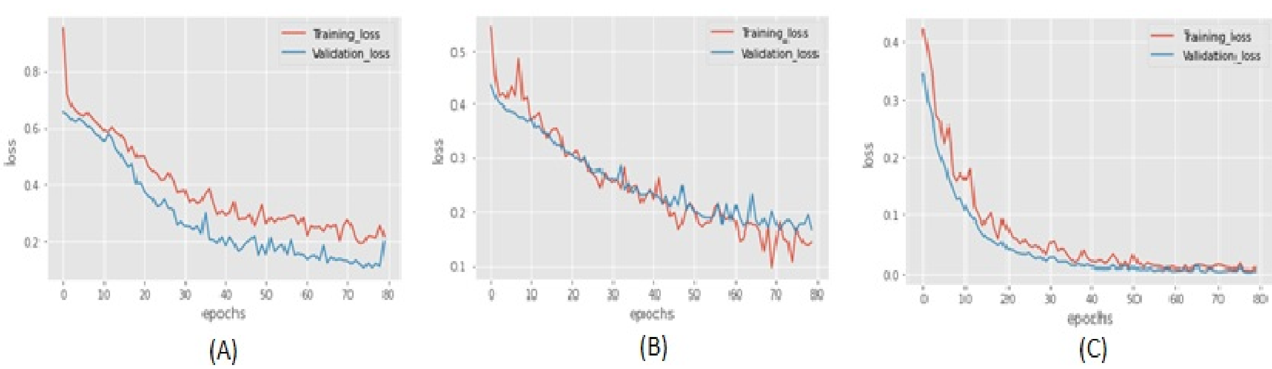

Figure 2: Training and validation loose curves A) Loose curve for Resnet50 B) Loose curve for Resnet101 C) Loose curve for VGG19

3.2 Segmentation

The overall methodology of segmentation is to create a structure that extracts features through successive convolutional neural networks and utilizes that information to design a segmented map as an output. By locating the Region of Interest (ROI), such as the lung field, segmentation improves the efficacy of COVID-19 detection. Our proposed lung segmentation model in this project is based on U-Net architecture [5]. The proposed approach is shown in Figure 3. The U-Net model, which is based on Convolutional Neural Networks (CNN), was designed to achieve high segmentation efficacy in this project. The main advantage of the U-Net is that the information from the down-sampling path and the information from the up-sampling path are combined to predict a better segmentation. U-Net model is mainly developed for medical images understanding and segmentation. It has been a key model in medical imaging, which is deployed in many applications. The algorithm of this architecture consists of two main parts: contractive and expensive. The contractive part consists of various convolutions with filters of size 3 x 3 and strides in both directions connected by ReLU functions. The contractive path extracts the input features and generates a feature vector of a particular length. The computationally expensive part is to pull the features from the contractive path by copying and cropping features from a feature vector by up-convolutions, and produces an output segmentation map by consecutive operations. The main operation of this model is the linking process between the first and the second part together. This combination allows the architecture to attain precise information from the contractive side, thus producing the segmentation masks as accurate as possible to the intended output.

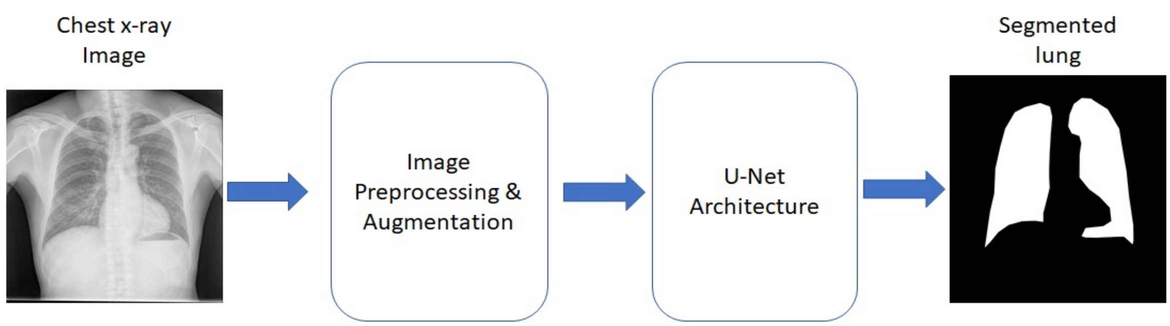

Figure 3: Framework for lung segmentation

3.2.1 COVID-19 Segmentation dataset

Images of the dataset used in this research are collected from two different sources, which are Shenzhen and Montgomery datasets. The dataset is made up of images and segmented masks from chest x-ray images. There is a slight abnormality in the naming convention of masks. Chest x-ray images are made a total of 704 images [26]. This dataset offers an image mask to segment the regions of the lungs. By visualization of the images of these datasets, we noticed that the infected regions of the lungs are localized in a specific area. To demonstrate the correlation between the infected area and its relative location, all the masks of this dataset are plotted with a colourmap. Some parts of the lungs are prone to infection more than others. The generation of accurate segmented masks for the lungs are a key feature of this research.

3.2.2 Experiments

Each X-ray image was resized to 512 x 512 before feeding to the U-Net architecture for segmentation. The left and right masks for each dataset are combined and processed the Morphological transformation on the masks. All chest x-ray images of both datasets are combined to create our input dataset. The training dataset consisted of 80% of the data, and 20% were used for the test dataset. We train the architecture by using an Adam optimizer with a learning rate of 0.001, 50 epochs, and a batch size of 16, see Table 2. We augmented the data by adjusting the zoom range to 0.05 width shift, height shift, and horizontal. Figure 4 illustrates the training and testing loose curve for the U-Net model.

TABLE 2: Training Hyper-Parameters for the U-Net model

Parameter	Method
Training options	ADAM15
Number of Epochs	50
Mini-batch size	16
Learning rate	0.001

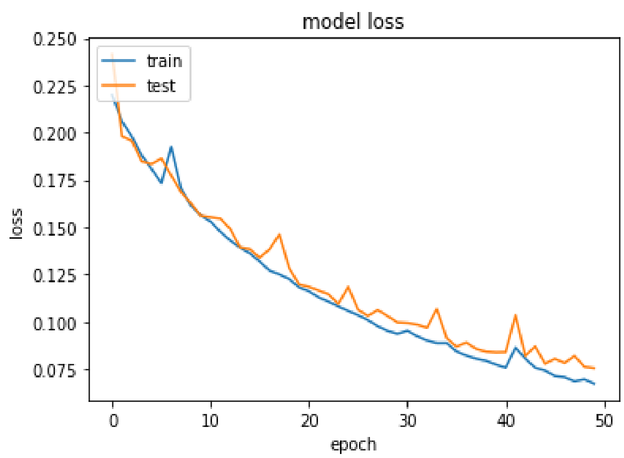

Figure 4: Training and Testing loose curve for U-Net architecture.

4. RESULTS

4.1 Evaluation matrices

In this research, we used confusion matrix criteria to analyze different matrices in terms of (Recall, precision, F-score, and Accuracy). This is to evaluate the performance of deep learning models.

4.1.1 Accuracy

Accuracy is measuring the number of correct instances predicted over the total number, as shown in Eq 1.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}$$

4.1.2 Precision

Precision estimates the ratio number of instances predicted correctly as positive to the total number of instances as predicted positive, as shown in Eq 2.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

4.1.3 Recall

Recall estimates the ratio of number of instances predicted correctly as positive to the total number of instances available in that specific class as shown in Eq 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

where TP is the true positive, TN is the true negative, FN is the false negative, and FP is the false positive.

4.2 Classification results

According to the results on the testing datasets, VGG19 achieved promising results and overcame Resnet101, and Resnet50 architectures with the accuracy of 99.42%, 91%, and 85%, respectively, see Table 3 and Figure 5. The VGG19 model showed the best results for COVID-19 detection and improved the classification performance, and in addition to that, it reduced the over-fitting problem. The outputs of the VGG19 model are processed by a pointwise convolution block, which is designed to reduce channel dimensionality while keeping the outputs of different layers summable. This is to note that the test images have never been used to train or fine-tune the hyperparameters for the classification models. Furthermore, we compared the VGG19 versus the other methodologies, see Table 4. VGG19 showed the best performance in comparison to the state-of-the-art methods.

TABLE 3: Performance of the proposed deep learning models

	Precision %	**Recall %**	**Accuracy %**
VGG19	98.87	98	99.42
ResNet101	94	90	91
ResNet50	85	83	85

TABLE 4: Performance of VGG19 vs other methodologies.

Method	**Accuracy %**
VGG19	99.42
Jaiswal et al [27]	96
Ismael et al [28]	94
Gomez et al [29]	89

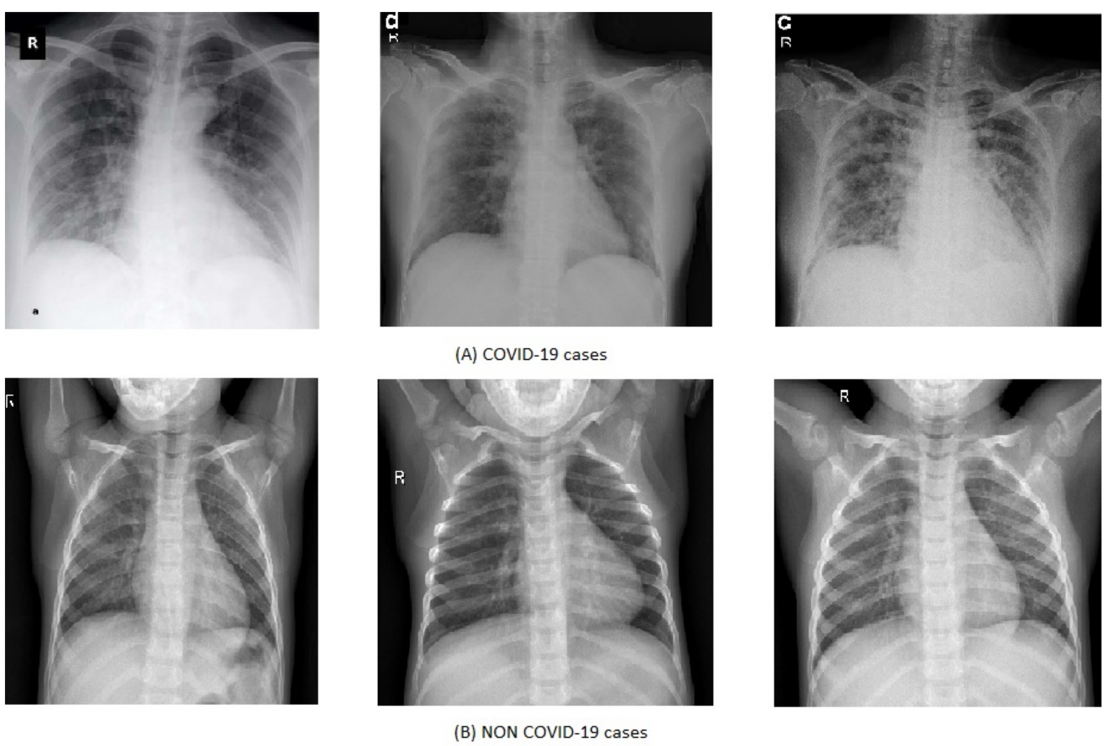

Figure 5: Classification results for COVID-19 and non-COVID-19 for chest x-rays images.

4.3 Segmentation results

The quality of the results for the proposed method is shown in Figure 6. According to the experiments, the results are promising where the lung region is visible, integrating the segmented patches can produce excellent segmentation results with the minimal error between the ground truth masks and the output masks from U-Net segmentation. The segmentation results achieved accuracy with 93 %, and overcame the other methodologies, see Table 5. Thus, the results illustrate that U-Net model has the best results for lung segmentation of COVID-19.

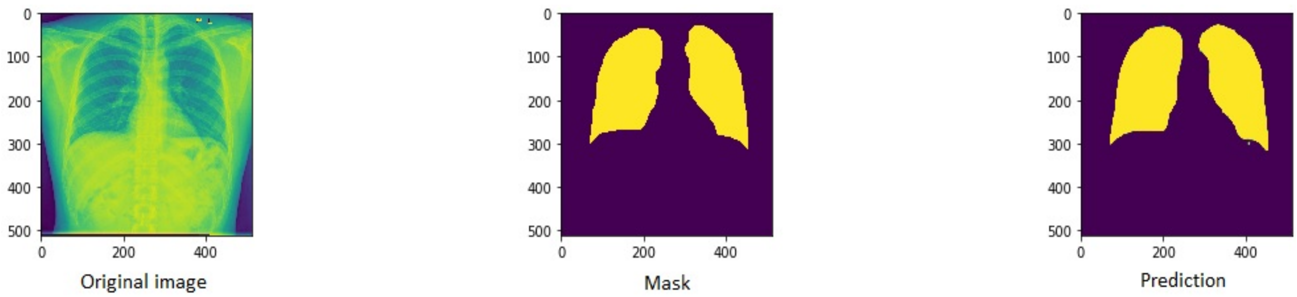

Figure 6: Experiment results for replicating the masks for lungs on Chest-X-ray images

TABLE 5: Performance of U-Net vs other methodologies.

Method	**Accuracy %**
U-Net	93
Xux et al [30]	86
Chen et al [31]	79
Hassantabar [32]	70

4.4 Limitation

There are few segmented mask x-ray images available to train U-Net architecture effectively. To achieve better performance, we applied data augmentation to enrich the dataset. This paper has obtained ideal results for lung segmentation. Datasets are scarce, so having more images can improve further the performance of deep learning model.

5. CONCLUSIONS

In this research, we exploited two different deep learning techniques, including classification and segmentation, for identifying COVID-19 diseases on the Chest X-ray images. Three architectures have been investigated on the usage of the classification method. The consequences are analyzed through accuracy, precision, and robustness metrics. The utilization of the VGG19 model demonstrates exceptional category overall performance in our comparative study compared to ResNet50 and ResNet101, which illustrated its capability to be carried out in medical settings for computer-aided analysis of COVID-19 effective cases. Considering a real application, segmentation is critical because it gets key features of heritage information, reduces the threat of information leak, and forces the model to recognize the critical regions on the lungs. The segmentation approach enhanced the class performance. It focused on developing an effective segmentation replication, which is able to produce a binary lung mask for CXR images from the proposed COVID-19 database. In the future, we aim to develop and use different object detection models for location and identifying the targeted classes on the chest x-ray images with better performance. In addition to that, we will enrich the current available public datasets and enable further refinements to the systems employing them.

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