# Automatic classification infectious disease X-ray images based on deep learning algorithms

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***Abstract*—Recent technological advancements allow deep learning to be employed in practically every aspect of life. Because deep learning techniques are so precise, they can be utilized in medicine to classify and detect various diseases. The coronavirus (SARSCoV2) epidemic has recently affected global health systems. SARSCoV2 may be diagnosed via PCR and medical imaging. A chest X-ray is used to diagnose SARSCoV2. This paper proposes a deep learning technique to distinguish SARSCoV2 positive and normal cases. X-rays are the traditional method for diagnosing SARSCoV2, and deep learning models have proven their superior ability to classify medical images, which will be the tool in the future for the classification of any other epidemics that may appear in the future. In this study, not only are the deep learning models fine-tuned, but also the hyperparameters are fine-tuned, which significantly improves the performance of the fine-tuned deep learning models. we developed a system based on deep learning algorithms to classify x-rays. We used five models: Xception, VGG19, ResNet50, DenseNet121, and Inception. We provide deep learning models and algorithms that were trained and evaluated to assist medical efforts and reduce medical staff workload in handling SARSCoV2. Further, the proposed classification model provides good results by leveraging accurate classification of SARSCoV2 disease based on medical images. Besides, the performance of our proposed CNN classification method for medical imaging has been assessed based on different edge-based neural networks. Whenever there is an increasing number of a class in the training network, the accuracy of tertiary classification with CNN will decrease. The proposed model has achieved a 0.9897 accuracy in tertiary classification that includes normal, SARSCoV2 positive, and normal. The proposed algorithm obtains good classification accuracy during the binary classification procedure with the DenseNet121 model by supervised contrastive learning loss function.***

***Keywords— Convolution Neural Network, Covid 19, Xception, vgg19, ResNet50, DenseNet121, Inception, X-ray Image Classification.***

## 1. INTRODUCTION

The first case of COVID-19 in the Chinese city of Wuhan was misdiagnosed. Whereas specialists initially believed that it was pneumonia, which led to the rapid spread of this epidemic and its spread throughout the country and the world [1-3]. The world health organization called that disease SARS-CoV-2. Covid 19 took thirty days to spread all over China [4]. On January 30, 2020, the world health organization declared the SARS-CoV-2 outbreak [5].

The first imaging tool to be used in the diagnosis of COVID-19 disease is the chest X-ray, which is the most commonly used. A negative chest X-ray is shown on the left in Figure 1, whereas a positive chest X-ray is shown on the right in Figure 1. for the purpose of automatically classifying digitized chest images A number of classical machine learning models have been used [6-7]. Using a Support Vector Machine (SVM) classifier, three statistical characteristics of lung texture were computed and classified as malignant or benign lung cancer [8]. in the case of images as normal or cancerous. With enough annotated images, deep learning approaches have outperformed classical machine learning approaches [9-10]. In medical imaging, the convolution neural network (CNN) architecture is a popular deep learning approach with high accuracy [11]. Deep learning models have great potential in assisting COVID-19 management efforts but require large amounts of training data. When training neural networks for image classification, images from different classes should only differ in the task specific characteristics; it is important, therefore, that all images are taken from the same machines. In this work, we designed the algorithm based on deep learning models to diagnose x-ray images of Covid-19 from Xception, vgg19, ResNet50, DenseNet121, and the Inception model. The results are highly accurate. In this paper, we used the new supervised contrastive learning loss function [14], and in this paper we are the first to use that technique in the classification of the SARS CoV 2 image.

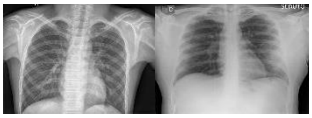

Fig. 1. Normal and covid 19 chest X-ray images

## 2. DATASET

The datasets were obtained from Kaggle [12], while the code was obtained from GitHub [13]. Chest imaging is commonly used in medicine, and it plays an important role in the detection of SARSCoV2. Through the diagnosis of chest imaging, medical staff can more accurately grasp the imaging modal characteristics of SARSCoV2 cases, such as multiple small patchy shadows and interstitial changes in the early stages, which are obvious outside the lungs. It then develops into multiple ground glass and infiltration shadows in both lungs. In severe cases, lung consolidation and pleural effusion are rare. It has important guiding value for accurately judging the condition and its development, formulating treatment plans, and evaluating prognoses. There are many SARSCoV2 datasets, but the number of samples is small. The experiment collected 2295 SARSCoV2 chest X rays on Kaggle, consisting of 1811 in a training set and 484 in a validation (test) set [12].

## 3. Proposed method

Our proposed method is based on the well-established deep learning model Xception, vgg19, ResNet50, DenseNet121, Inception models. We prefer to use the DenseNet121 model (see detailed description in Table because , it extracts the features at low-level by using its smaller kernel size, which is appropriate for COVID-19 images with a lower number of layers compared to its others counterpart models. Schema of the algorithm in Figure 2.Our algorithm works on the first input x-ray image, and then it works automatically for all five models: Xception, vgg19, ResNet50, DenseNet121, and Inception. The second step is a comparison of different architectures, and the third step is hyperparameter tuning. The fourth step is a comparison of the results, and finally, the best convolution neural network (CNN) model is selected automatically.

Table 2. The comparison study of DenseNet121 with other existing methods

| Methods | ***Sensitivity*** | ***Specificity*** | ***Accuracy*** | ***F-measure*** |
|---|---|---|---|---|
| Xception | 0.9837 | 0.9850 | 0.9793 | 0.9840 |
| vgg19 | 0.8992 | 0.9946 | 0.9215 | 0.9430 |
| ResNet50 | 0.7692 | 1.0000 | 0.8099 | 0.8670 |
| DenseNet121 | 0.9882 | 0.9972 | 0.9897 | 0.9925 |
| Inception | 0.8837 | 0.7850 | 0.8793 | 0.8840 |

Table 1 provide an elaborate comparative results analysis of the DenseNet121model with other existing techniques. On examining the predictive outcome in terms of sensitivity, the ResNet50 and Inception models have achieved minimal sensitivity values.

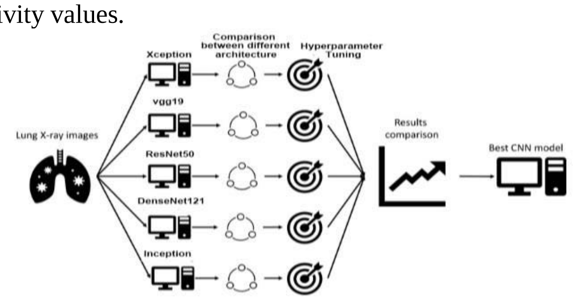


Fig. 2. Proposed method

## 4. Conclusion and further research

The proposed method has major limitations. The experiment only applies to X-ray images and not CT images, because X-ray images are RGB and CT images are grayscale. This experiment can only be used to classify SARSCoV2 patients and healthy people, and it cannot classify SARSCoV2 and general pneumonia. We will next focus on the classification of SARSCoV2, bacterial pneumonia, and viral pneumonia. This paper has developed a novel algorithm for SARSCoV2 detection and classification. The DenseNet121 model performs well. We evaluated our method on SARSCoV2 image datasets. The evaluation results indicate that our method is not only efficient in terms of classification accuracy but also training parameters. From this result, we can conclude that our proposed method is more appropriate for SARSCoV2 image classification. However, the performance of our proposed method could be further improved by the following two techniques: First, our method does not utilize offline data augmentation techniques in the experiment. Thus, the use of extensive augmentation techniques such as GAN or Convolution Auto-encoder before training could improve the performance further. This also helps to increase the number of SARSCoV2 images, which results in mitigating the overfitting problem during the training step. Second, the use of other pre-trained deep learning models having a smaller filter size could improve the performance of SARSCoV2 images. This is because a smaller filter size helps extract more discriminating ROIs from SARSCoV2 images

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