

Neural network architecture for differentiating Covid19 and viral pneumonia

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ABSTRACT

Covid 19 has wreaked havoc on the world when in some countries had cases in ten thousand each day thus, leading to a load on the healthcare system. Meaning that doctors and nurses had to spend more time on diagnostics. Therefore, one of the methods for reducing this load was to use a neural network for differentiating between covid and pneumonia cases. This citation showcase how neural networks can be used to detect lung x-rays having covid and pneumonia. Recall, precision, and f1-score measures are utilized to optimize the adaptive brightness of the images, selection process, resizing, and tune the neural network architecture parameters or hyperparameters. Classification quality metrics values over 91% depicted a decisive difference between radiographic images of patients having COVID-19 and pneumonia. Making it possible to make a model with strong forecasting capacity without pre-training on data from the 3rd party or engaging ready-to-use complicated neural network models. It can be the next step for the advancement of reliable and sensitive COVID-19 diagnostics.

1. Introduction

The fast global spread of the SARS-CoV-2 coronavirus and the accompanying illness COVID-19 [1, 2] is partly attributed to a lack of operational diagnostics. Methods based on polymerase chain reaction offer the best dependability, however, the result is usually ready in a few hours while ensuring quite high standards for analysis technology compliance and medical personnel expertise. As a result, the development of quick and dependable COVID-19 detection methods is critical to preventing a pandemic of this illness.

COVID-19 has a tremendous impact on the lungs [3]. To identify pneumonia caused by diverse viruses, computed tomography with image analysis utilizing deep learning approaches is commonly employed [4, 5]. Although X-ray diagnosis has a lower resolution, it is more popular because of the availability of x-ray machines and exposes patients to less radiation. There are now research papers that suggest the use of neural networks (NN) to identify COVID-19 based on radiographic image analysis (RI)

[6–8]. In [9], an external ImageNet dataset to train a convolutional neural network, which was subsequently trained using 13,800 RIs, 183 of which were with COVID-19. To detect COVID-19 disorders, a NN was developed by decreasing the layers and filters of the previously existing DarkNet, and 127 radiographs with a COVID-19 diagnosis were utilized to generate a model in [10]. The ability to use ready-made NNs Alexnet, Googlenet, Resnet18, and Truncated Inception Net for diagnosing COVID-19 with just 307 RIs is demonstrated in [11] and [12], and the benefit of Googlenet in specific circumstances is underlined. These studies demonstrate the area's promise while emphasizing that its progress is hampered by a very small number of publicly available RI with COVID-19. Using pre-trained models, [13] shows that among VGG19, MobileNet v2 Inception, Xception, Inception, and ResNet v2, MobileNet v2 produces the best results, although stressing that classification performance is highly dependent on the quantity of data provided in each class. Special emphasis is placed in [14] on data preparation in order to increase

classification accuracy.

Objective is to create a RI classifier for patients with viral pneumonia and COVID-19 using the simplest NN, without using ready-made models from other developers or preparatory training on third-party data, and with only a limited collection of RI.

2. Image pre-processing and information flow

Fig. 1 depicts the main steps of data preparation and information flow movement. X-ray pictures were collected from the source [15], where they were in the public domain in the form of an archive including 219 RI in the PNG format for patients with COVID-19 and 1341 RI in the PNG format for patients with viral pneumonia, with a size of 1024 by 1024 pixels. The source of RI is indicated in the attached file: "Pictures taken from 43 different papers were used to create a database of COVID-19 x-ray images from the Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 DATABASE, Novel Corona Virus 2019 Dataset established by Joseph Paul Cohen, Paul Morrison, and Lan Dao in GitHub.". X-ray images of COVID-19 patients have been placed in the 'Covid All' folder, whereas X-ray images of pneumonia patients were placed in the 'Viral Pneumonia All' folder, and then they entered the preprocessing block (the PREPROCESSING block).

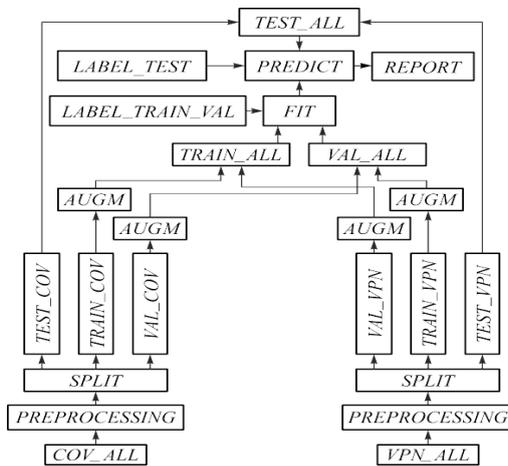


Fig. 1. Scheme of pre-processing of images and movement of information flows

A preliminary examination of the RI revealed that there are service symbols at the margins of certain pictures that, when encoded, can contain information about the image belonging to a specific class.

In order for the NN to seek informative characteristics, especially on lung pictures, 10% of the image's periphery portion was eliminated using the

CROP procedure on all initial images. Because the picture is a mathematical matrix, the chopped image is created by replicating the matrix and skipping 10% of the start and end rows, as well as 10% of the left and right columns of the images. This mathematical procedure is stated in Python as follows:

```
im_crop = im[102:922,102:922],
```

Where:

- im – original image matrix,
- im_crop – cropped image matrix.

A closer look at the Ri revealed that their brightness is exceedingly inhomogeneous. Excessive darkening or lightening was detected in informationally essential portions of the lungs, i.e. pixel values were constrained to a tiny range, resulting in a narrow peak in the brightness histogram. Simply expanding the histogram over the full image might result in unintended brightness fluctuations. Thus, the adaptive histogram equalization was applied to the X-ray using the CLAHE function of the OpenCV computer vision library to improve the manifestation of information characteristics.

Images are segmented into rectangular portions in this approach, and the distribution function of pixel brightness is determined as a function of the relative number of pixels from specified brightness values for each. The converted picture is created by converting the brightness of each pixel R_j in the input image into the brightness value S_k of the corresponding pixel in the output image using the formula [16]:

$$S_k = \sum_{j=0}^k \frac{n_j}{n}$$

Where;

- k – pixel number, varying from 0 to $L-1$,
- L – the maximum number of gradations of brightness, and j varies from 0 to k ;
- n_j – number of pixels with brightness R_j ,
- n – total number of image pixels.

Then, to remove checkerboard artifacts at the section borders, bilinear interpolation is used, which involves computing the weighted average of the brightness of the pixels using linear interpolation first in one diagonal direction and then in the other.

The cv2.imresize() method was used using the cv2.INTER_AREA interpolation technique to get pictures of the desired size, as recommended by the OpenCV library's creators because using this approach prevents the occurrence of moiré-type distortions.

Furthermore, samples of the NN's training (train), verification (val), and testing (test) were created for each class (Split block). To do this, the Python3 random.shuffle() method was used to randomly shuffle all RI. The random module creates random integers in this scenario, while the shuffle() extension enables random image shuffling.

Then, in each class, 10% of the RI were chosen at random and placed in test samples (blocks TEST COV and TEST VPN).s

The remaining data for each class were randomly divided into two separate sets, 90 percent for training (Train Covid, Train Viral Pneumonia blocks) and 10% for validation (Value Covid and Value Viral Pneumonia blocks). Following that, all data were standardized. In all computations thus, random mixing was conducted 50 times for each image to fall into the test sample.

To avoid overfitting and partially compensate for the imbalance, the training sample's number of pictures in each class was raised to 10000 by including modified photos (AUGM block). The following parameters were changed in random order: rotation in the range of +15 to -15 degrees, shift to the left and right in the range of 1 to 15 pixels, change in scale and brightness in the range of 0 to 10%, rotation around the horizontal axis in the range of 1 to 180 degrees, which was provided by the ImageDataGenerator function, which is part of the Keras library.

Furthermore, by combining the two classes' respective samples, full training, verification, and testing samples were created (TRAIN ALL, VAL ALL, and TEST ALL blocks).

The neural network (FIT block) is trained by feeding it the whole training and test data, as well as the class labels of these examples (LABEL TRAIN and LABEL VAL blocks). The NN model is the learning outcome.

To put this model to the test, it is sent to the PREDICT block, which also gets the whole test sample (TEST ALL) and the appropriate set of class labels (LABEL TEST block).

The REPORT block displays the model's output on test data. The primary classification criteria are shown for each class: precision, recall, and f1-score. There is also a count of the number of RIs in each class.

Precision = $TP / (TP + FP)$ denotes how many of the projected good outcomes occur.

Recall = $TP / (TP + FN)$ reveals how many positives were predicted out of the total number of positives.

The balanced average result is calculated using the F1-score, which is the harmonic mean of

accuracy and recall.

Where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

The report was created using the scikit-learn machine learning library's classification report function.

3. Structure of a convolutional neural network

A convolutional NN with RI as input was utilized to construct the RI classifier. The trained NN's work yields a label that categorizes the image. Cross-validation and lattice search methods revealed that the NN, which comprises five consecutive convolutional layers, produces the best results (Fig. 2). The first and subsequent convolutional layers, these layers contained 32, 64, 128, 192, and 256 filters, as well as the same kernel sizes (3 3). [17] provides a full overview of the additional strata.

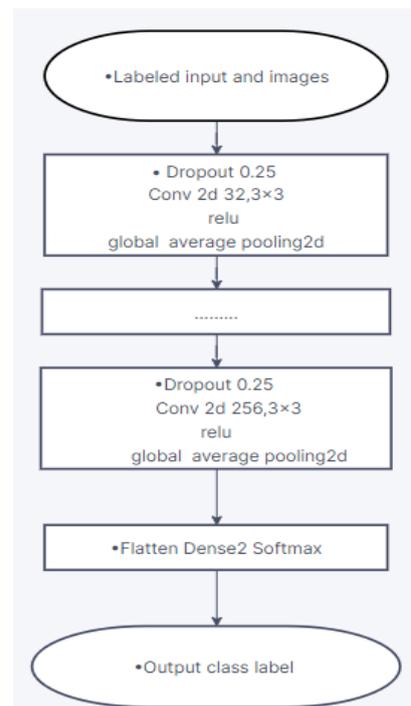


Fig. 2. Architecture and main parameters of the convolutional neural network

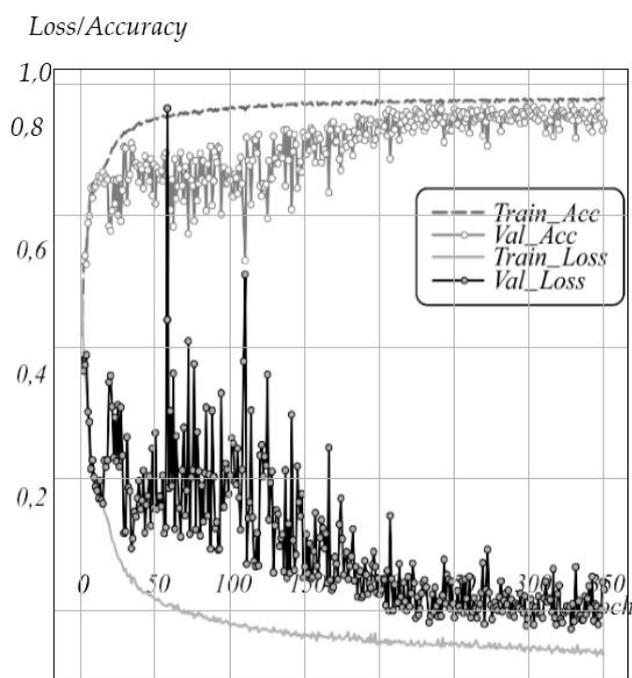
The Adam optimizer was used for training ($\text{lr} = 0.001, \text{beta}_1 = 0.9, \text{beta}_2 = 0.999$). In our situation, using categorical cross-entropy as the loss function rather than binary cross-entropy yielded the greatest results. The training was carried out across 350 epochs. To avoid overfitting, regularization was applied.

The measure for deciding on the architecture and hyperparameters of the NN was utilized.

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$
,
representing the total number of properly categorized results divided by the total number of correctly classified outcomes [18].

The absence of retraining of the NN model is shown by the type of the change in the values of accuracy and loss functions for the Train and Val samples (Fig. 3)

The classifier's performance was assessed on a test set using the most generally used metrics Precision, Recall, and F1-score [18, 19].



The values of the quality metrics of this classifier for patients with pneumonia and COVID-19 are shown in table 1 for the test sample.

Table 1. Classifier accuracy metrics

	precision	recall	f1-score	Num of RI
Pneumonia	0,99	0,99	0,99	134
COVID-19	0,91	0,95	0,93	21

The high classification values (> 0.91) provided persuasive confirmation of the filter's accuracy, on the dependable difference between X-ray images of pneumonia and X-ray images of COVID-19 cases.

The high precision values in Table 1 (0.99 for pneumonia and 0.91 for COVID-19) indicate a low number of false-positive detections of these diseases, and the high recall values (0.99 for pneumonia and 0.95 for COVID-19) demonstrate that the classifier gives an incorrect result in less than 5% of cases with COVID-19.

The higher pneumonia measures may be related to a much larger number of RIs suffering from this condition.

All the markers in Table 1 suggest that the classification is of excellent quality, implying that NS may be used to detect COVID-19 instances by chest X-ray.

4. Conclusion

An evaluation of the predictive ability of the presented NN revealed that with suitable sample preparation, architecture selection, and hyperparameter selection, it was possible to create a RI classifier for patients with viral pneumonia and COVID-19 without involving ready-made complex models or preliminary training on third-party data.

An increase in the number of RIs for patients with COVID-19 was estimated to improve the classifier's prediction power and lead to the development of sensitive and reliable express diagnostic procedures, reducing the load on the healthcare system.

Recognizing the urgent need to develop high-precision and practical solutions for the quick detection of COVID-19, the authors are willing to share all of the information collected during this study with the National Assembly, the scientific community, and interested developers.

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