Lung disease prediction from X-ray images

Lorenzo Valentini‡

***Abstract*—COVID-19 is a highly contagious respiratory illness caused by the novel coronavirus SARS-CoV-2. It was first identified in Wuhan, China, in December 2019 and has since spread globally, leading to a worldwide pandemic.**

The principal detection tool for Covid-19 is an RT-PCR test, which has a good performance, but there can be significant challenges and problems when there are too many patients to test. These challenges can strain healthcare systems and testing infrastructure: laboratories may become overwhelmed, leading to delays in processing test samples. This backlog can result in delayed results and hinder the timely identification and isolation of infected individuals..

An alternative detection tool is chest X-rays. It is available in almost any hospital and it does not suffer shortages due to supply chain issues.

In this paper we propose a neural network architecture to detect covid and distinguish it from standard pneumonia. It obtains state of the art results, with an accuracy (97%) comparable with state of the art models and with the usual RT-PCR tests.

***Index Terms*—Deep Learning, Encoders, Neural Networks, Computer Vision, Lung Disease, Covid19**

I. Introduction

COVID-19 is the illness that results from infection with a coronavirus known as SARS-CoV-2. The World Health Organization's initial awareness of this virus occurred on December 31, 2019, subsequent to the reporting of a cluster of cases characterized as "viral pneumonia" in Wuhan, People's Republic of China [1]. Until February 2023, there has been 750 millions confirmed cases of COVID-19, including 6 millions deaths [2].

The rapid increase in the number of infected patients over a brief period led to deficiencies in medical resources, diagnostic tests, healthcare personnel, and ineffective screening and triage procedures, placing significant strain on public health systems during the peak of the outbreak. The limited resource availability poses challenges in effectively managing patients. Timely detection is essential for reducing virus transmission and plays a vital role in pandemic control. Research has demonstrated that a longer duration between the initial symptoms and a confirmed diagnosis is associated with a poorer prognosis for COVID-19 patients [3].

The conventional approach for COVID-19 detection relies on Real-Time Polymerase Chain Reaction (RT-PCR). However, this method is time-consuming and prone to high levels of false-negative results. To validate positive findings, alternative techniques like chest X-ray (CXR) and Computed Tomography (CT) are employed, either individually or in combination. Nevertheless, utilizing CT imaging comes with drawbacks, including the high radiation exposure to patients and the associated scan costs.

Indicators of COVID-19 can be detected using a traditional chest radiograph. Additionally, in instances of strong suspicion of infection, a positive chest X-ray (CXR) may obviate the necessity for Computed Tomography (CT). Furthermore, the use of CXR for early disease detection could be of significant importance in regions with limited access to dependable PCR testing [4], leaving CXR as the tool with more availability in developing countries.

In the initial stages of COVID-19, radiological assessments often reveal ground glass patterns near the pulmonary vessels, along with asymmetric, patchy, or widespread airspace opacities. Interpreting these abnormalities effectively requires the expertise of trained radiologists. Given the scarcity of such specialists, automated methods for identification can aid in the diagnostic process and enhance the early detection rate with remarkable accuracy. Artificial intelligence (AI) and machine learning solutions represent potent tools for addressing these challenges [5].

In this paper is proposed a neural network architecture to predict COVID-19 and pneumonia in CXR images. In particular a classifier is build on top of the encoder block taken from an autoencoder trained on X-rays of lungs in standard condition, affected by normal pneumonia and affected by COVID-19.

The report is organized as follows: section II provides an overview of prior research in COVID-19 prediction using AI/machine learning; sections III and IV describe the general idea of the architecture and the data preparation (dataset composition and preprocessing operations), while section V covers the Learning Framework in deeper detail; lastly, results are presented in VI.

II. Related Work

From the onset of the pandemic, researchers have been advocating for the application of Artificial Intelligence algorithms in the detection and diagnosis of COVID-19. During the initial stages, one of the primary challenges encountered was the scarcity of available data for training these models.

Some first attempts make use of basic machine learning techniques [8], obtaining accuracies of around 0.9. Similar results were obtained using some well extablished deep learning architectures [6]–[9]. The latest state of the art models obtain accuracies of circa 0.98, like Apostolopoulos in [10], using transfer learning with convolutional neural networks. The unsatisfactory performance of a discrete number of models was related to the initial poor quality and size of the datasets.

†Department of Physics and Astronomy, University of Padova, email: lorenzo.valentini.2@studenti.unipd.it

In the present work is used the database collected by Asraf and Islam [11] from different sources.

III. Processing Pipeline

In the training process two main architectures are used. The initial architecture employed is a conventional autoencoder, consisting of two essential components: the Encoder and the Decoder. Its primary function is to efficiently encode data through a sequence of 2D convolutions that reshape the data before decoding it to reconstruct the original image. The second architecture utilized is the actual classifier, constructed using the same encoder as the autoencoder, but followed by some fully connected layers, that give in output the predicted class of the input image.

The full processing pipeline consists of: data preprocessing (original, smoothed and sharpened dataset), training of the autoencoder, training of the classifier's fully connected layers, training of the full classifier.

The idea is to first train the autoencoder as a whole. It is trained on the simple task of decomposing and reconstructing the original image. This in order to obtain a decider that creates a meaningful representation of the original image. Upon achieving this intermediate objective, the decoder is substituted with a set of fully connected layers, which are subsequently trained to predict the image's class (healthy, pneumonia, or COVID-19). In the initial stages of classifier training, only the fully connected layers are marked as trainable. This step is essential because it is necessary to bring the parameters of the fully connected layers closer to their optimal values before permitting any modifications to the encoder layers. After successfully training the fully connected layers, the classifier undergoes a subsequent training phase, with all layers marked as trainable, in order to arrive at the model's final parameterization.

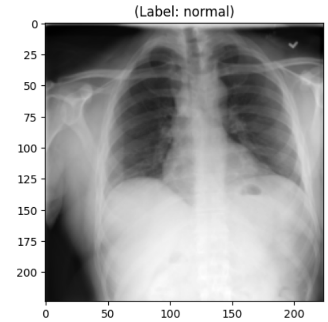
This process is repeated for the three preprocessing options, choosing as final model the one with the preprocessing that performs better.

IV. Data Preparation

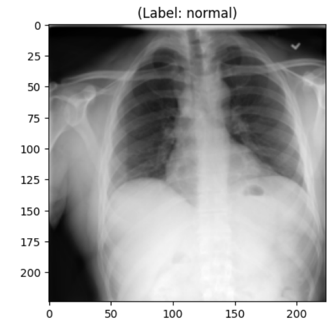
Images from the Asraf and Islam dataset [11] are used for traing, validation and test sets, using about 3700, 680 and 230 images. In all of them, images belonging to the three classes (healthy, pneumonia, or COVID-19) are equally represented. All of these images are transformed into grayscale and resized to dimensions of 224x224 before being input into the neural network. Furthermore, the grayscale values are adjusted to ensure they span the entire range from 0 to 1.

After this, the preprocessing happens, as shown in figure 1. Three strategies are used:

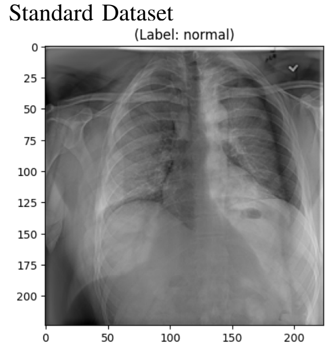
- **Normal Dataset**: The dataset is used as is.
- **Smoothing**: The dataset is processed using a gaussian filter, cancelling the high frequency features.
- **Sharpening**: The dataset is the dofference between the Standard Dataset and the Smoothed Dataset, so that the high frequency features are enhanced.



Standard Dataset



Smoothed Dataset



Sharpened Dataset

Fig. 1: Images preprocessed using the different techniques

V. Learning Framework

As previously mentioned, the learning framework commences with the training of the Autoencoder (figure 2), which comprises four convolutional encoding layers and three convolutional decoding layers. All layers employ ReLU activation, padding to preserve the desired output size, and a 3x3 kernel. Beginning with the encoder, each layer consists of two consecutive convolution operations, with batch normalization applied after each. Subsequently, the first two layers are followed by Max pooling operations. Ultimately, this information is relayed to the Decoder, which incorporates two convolutional layers, each followed by an Upsampling operation and another convolutional layer along with its corresponding Upsampling. The final step involves a convolutional layer with sigmoid activation, restoring the image to its original dimensions of 224x224x1.

Thanks to the padding technique, the original and generated images are comparable, allowing the autoencoder to learn the reconstruction of the provided images.

The model is compiled with a mean squared error loss function and RMSprop optimizer, running for 100 epochs with a batch size of 32.

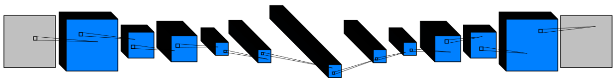


Fig. 2: Autoencoder: it is composed by encoder and decoder.

Preprocessing	Training Loss	Validation Loss
Standard	8.54e-04	6.09e-04
Smoothing	6.86e-04	4.76e-04
Sharpening	2.19e-04	2.27e-04

TABLE 1: Autoencoder Training Results

Following the completion of the first training, the encoder component of the autoencoder is detached, and an additional classifier layer is appended to the end, as shown in figure 3. This classifier layer involves a flattening operation followed by two dense layers, ultimately yielding a 1x3 matrix as output. This matrix assigns probabilities ranging from 0 to 1 to indicate the likelihood of the image belonging to a specific class. To facilitate successful comparison, labels are transformed into a 1x3 matrix with a ”1” placed at the index corresponding to the label (0, 1, or 2). Additionally, all layers of the original autoencoder are designated as non-trainable at this stage, as the primary focus is on training the final classifier layer. Over the course of 100 epochs with a batch size of 32, the classifier is trained.

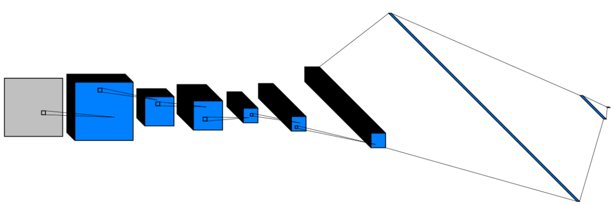


Fig. 3: Classifier: it is composed by encoder and dense layers.

Once this step is accomplished, a classifier is now in place. The final phase involves designating the original encoder as trainable and training the entire model together. Over the course of 200 epochs with a batch size of 32, the classifier is trained.

VI. Results

In this section, the results are be presented. Each training phase has its interim findings, ultimately leading to the selection of the optimal preprocessing method and the presentation of the final results, complete with their respective confusion matrices.

Beginning with the autoencoder phase, the primary focus was on loss minimization and the development of an architecture capable of fully reconstructing images from the information generated by the encoder, thereby enabling its use for classification. The results from the initial training of the autoencoder are shown in table 1. As evident from the table, the training of the autoencoder demonstrated success in all three cases, with minimal differences observed.

Preprocessing	Training Accuracy	Validation Accuracy
Standard	0.95	0.93
Smoothing	0.99	0.93
Sharpening	0.98	0.89

TABLE 2: Fully Connected Layers Training Results

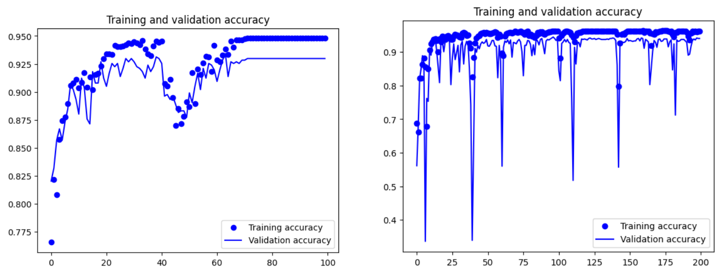
Subsequently, the encoder was detached and trained as a classifier, yielding the results shown in table 2 for the first training (with the fully connected layers being the only trainable layyers) and the results shown in table 3 for the final training of the full classifier:

As shown in table 3, the best performance corrsponds to the sharpened dataset. While during the first step of the training of the classifier the performance of the sharpened preprocessing is by far the worse, it acquires a significant advantage during the final step. As can also be seen in the training histories of figure 4, the smoothed dataset encounters overfitting problems, while the standard dataset doesn’t manage to significantly improve its performance from the previous step.

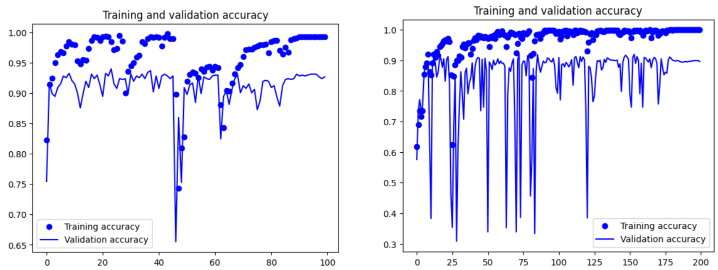
Given the great level of accuracy achieved, there are relatively few conclusions to be drawn from an analysis of the test results. Nonetheless, it is intriguing to observe in the confusion matrices of figure 5 that the majority of misclassifications occur between healthy individuals and either COVID-19 or pneumonia, whereas misclassifications between COVID-19 and pneumonia appear to be comparatively less frequent.

Preprocessing	Training Accuracy	Validation Accuracy
Standard	0.96	0.94
Smoothing	0.999	0.9
Sharpening	0.99	0.97

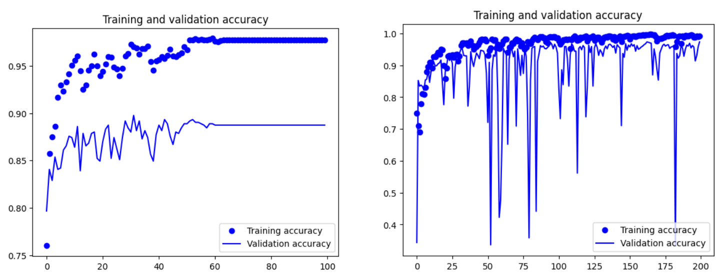
TABLE 3: Full Classifier Training Results



Standard Dataset: partial training anf final training

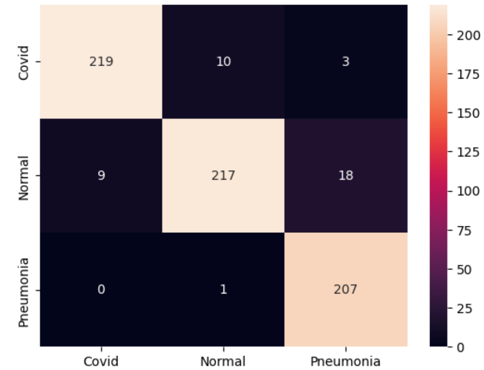


Smoothed Dataset: partial training anf final training

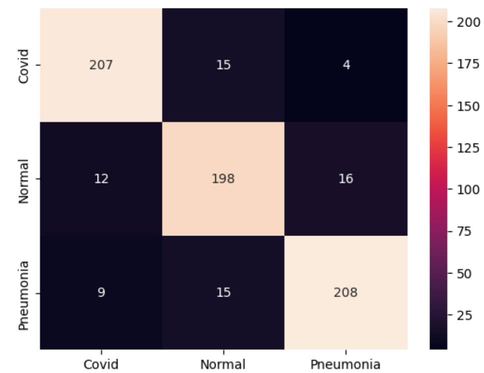


Sharpened Dataset: partial training anf final training

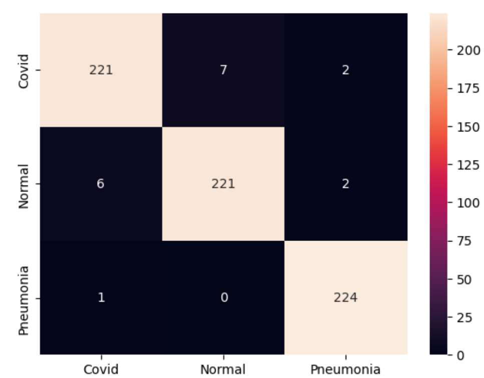
Fig. 4: Training of the Classifier using the three different preprocessing techniques



Standard Dataset



Smoothed Dataset



Sharpened Dataset

Fig. 5: Confusion matrices of the disease classification

VII. Concluding Remarks

In conclusion, a classifier was implemented starting from an encoder trained within an autoencoder.

This research highlights the efficacy and efficiency of employing autoencoders for image classification tasks. It demonstrates the capacity to achieve respectable accuracy levels even with a relatively simple architecture, with potential for further improvements through more complex networks, possibly reaching levels akin to state-of-the-art BotNet architectures.

A serious obstacle was the computational demands imposed by testing various solutions. At first an Nvidia Tesla P100 GPU was used, however, due to performance problems probably related to the hardware, it was necessary to downgrade to a Tesla T4, requiring approximatively 5 hours for completing the whole training pipeline. Future steps in this study involve augmenting the dataset size, given the network's demonstrated ability to generalize with larger datasets, compatibly with the computational resources available.

Moreover, notable success was observed when employing a sharpened dataset, highlighting the critical role of preprocessing in achieving higher accuracy. Strong sharpening or presegmentation techniques may also warrant exploration in subsequent research endeavors.

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