Efficacy Analysis in Different Architectures of Convolutional Neural Networks for COVID-19 Diagnosis Based on X-ray Images

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***Abstract*—The Covid-19 pandemic has caused numerous infections and deaths worldwide since 2019 due to its high transmission and respiratory contagion capacity, reaching over 535.1 million confirmed cases. Nowadays, there are different types of tests to diagnose Covid-19, such as PCR or antigen tests. However, radiographs are characterized by being fast, efficient, and low-cost, being a key factor in the diagnosis of Covid-19. Deep learning can be added to this through convolutional neural networks that use convolution operations to classify data. This could mean a great advantage when diagnosing people who have the disease compared to healthy people, in order to support medical specialists and not overload the healthcare system. This article analyzes the efficacy of image classification through deep learning of three convolutional neural network architectures: standard, VGG16, and NASNet. The database was collected from different repositories such as GitHub, Radiopaedia, the Italian Society of Radiology (SIRM), and others, gathering a total of 10,000 X-ray images between healthy patients and patients with Covid-19. The Matlab software was used for image preprocessing and the Google Colaboratory web application for deep learning training. The proposed convolutional neural networks achieved an accuracy of 97%, 94.5%, and 93.3%, respectively, which shows high effectiveness in classifying X-ray images with Covid-19 from healthy patients**

Keywords— COVID-19, Chest X-ray, NASNet, VGG16, Standard, CNN.

I. Introduction

COVID-19 has been a pandemic of unprecedented proportions in recent human history. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a highly transmissible and pathogenic coronavirus that emerged in late 2019 and has caused a pandemic of acute respiratory disease [1], named 'coronavirus disease 2019' (COVID-19), which threatens human health and public safety. COVID-19 is a zoonotic disease. SARS-CoV-2 transmission occurs with high efficacy and infectivity mainly through the respiratory route, where droplet transmission is the main recognized route. As of June 12, 2022, the number of confirmed cases of COVID-19 worldwide was around 535.1 million. As can be seen from this statistic, all regions of the world have already been affected by SARS-Cov-2, responsible for the disease also known as Wuhan pneumonia. Among them, Europe stands out with about 218.7 million infected. In fact, the number of confirmed cases exceeds by more than 80 million the figure recorded in Asia, the continent where the outbreak originated [2].

In this context, it is vital to quickly identify the patient's involvement in order to act efficiently in the shortest possible time. For this, PCR (Polymerase Chain Reaction) has been used in the examination of the patient, which is characterized by having the best quality for detecting COVID-19. However, the time it takes to give the results of this examination is very long in relation to the speed of the spread of the virus. Therefore, examinations with medical imaging such as X-ray and computed tomography have taken an important role for the detection of COVID-19. Chest computed tomography (CT) imaging may likewise aid in the diagnosis of COVID-19; however, current guidelines do not suggest utilizing CT imaging for routine screening [3].

The use of X-rays for the detection of the condition has several advantages, for example, their high availability in medical centers around the world. Their ease of access and the few resources needed to make them highly recommended by radiologists for this type of study. In addition, the effectiveness of the diagnosis and the speed of the results obtained are great assets. However, specialized radiologists can distinguish COVID-19 from images with high specificity but with moderate sensitivity [4].

As the transmission spreads through the community, it is necessary to find an optimal equilibrium between the precision of the diagnosis of COVID-19 and the time required for testing. To address this challenge, it is necessary to have an X-ray chest radiology system to perform a rapid and effective diagnosis. According to Khan et al., a chest radiology-based system can be an effective tool in detecting, quantifying, and following COVID-19 cases [5]. Subsequently, many researchers and data scientists have been working on the development of a highly accurate and reliable deep-learning technique to detect COVID-19 from X-Ray chest images. Through the years, deep learning has had a significant impact on various visual tasks which involve medical images as well [6]. This achievement is because deep learning only needs a set of data with minor processing in order to reproduce features automatically itself [7]. Therefore, this allows nonexperts in engineering to use machine learning effectively and apply it to future applications in medical imaging. Convolutional Neural Network (CNN) is an artificial neural network used in image recognition and processing. CNN is a deep learning algorithm involved in many medical imaging applications [3][8].

Convolutional networks are capable of handling matrices through neural structures where pixel correlation is maintained and used externally. Mathematically, the following formula is generally used:

$$x^1 \to w^1 \to x^2 \to \cdots \to x^{L-1} \to w^{L-1} \to x^L \to w^L \to z \quad (1)$$

The equation (1) illustrates how a CNN runs layer by layer in a forward pass. $x^1$is usually the input image, which will go through a layered processing, involving parameters such as a tensor w1. The output of the first layer is x^2, which is the new input for the next processing of the second layer. The processing is constant until all layers of the CNN are finished, which outputs x^L. One additional layer, however, is added for backward error propagation, a method that learns good parameter values in the CNN[9][10].

Jayanth Koushik [11] represents the convolutional network in the following way:

$$x_j = \rho W_j x_{j-1} \quad (2)$$

Here, Wj is a linear operator, and ρ is a non-linearity. Typically, in a CNN, Wj is a convolution, and ρ is a rectifier max(x, 0) or sigmoid 1/1+exp(−x). It is easier to think of the operator Wj as a stack of convolutional filters. So the layers are filter maps and each layer can be written as a sum of convolutions of the previous layer.

A. Architecture description

Late research on deep convolutional neural networks (CNNs) focuses on increasing the accuracy of computer vision dataset standard convolutional neural networks [12]. Multiple CNNs architectures reach accurate values due to the conventional approach of extracting features with specified algorithms through the novel feature extraction approach using deep learning techniques [13]. The Standard convolutional neural networks assume that a grid-structured input is available and exploit discrete convolutions as their fundamental building blocks [14]. A standard network usually consists of an input layer, convolution layer, max pooling, and the fully connected layer, which gives the output.

Visual Geometry Group-16 (VGG-16) is widely recognized as a CNN with good regenerative capacity. It uses the stack of small convolutional kernels instead of large ones to reduce the number of parameters [15]. VGG-16 uses size 3 × 3 as its kernel size. And the last three layers are fully connected. Finally, Neural Architecture Search Net (NAS-Net) searches for the best convolutional layer using recurrent neural networks on the provided dataset [16]. Then the selected layers are transferred to the ImageNet dataset. Finally, the selected convolutional layers are stacked together to produce the final architecture.

This study presents a deep learning-based system to detect COVID-19 from chest X-Ray images, that pretend to adapt to the unique characteristics of medical images [17]. We propose a convolutional neural network (CNN) to classify patients who present COVID-19, and healthy patients. Also, 3 architectures are presented to compare the result with the literature. Those proposed architectures are CNN Standard, VGG-16, and NASNet. These architectures will be compared to know which of them is the best model and with higher accuracy to help to detect COVID-19. . Generally, to check the performance of the method proposed, it is used parameters such as sensitivity, specificity and accuracy [18]. This research is important to help doctors identify earlier if the patient has present or no COVID-19 virus through deep-learning-based systems.

The following TABLE I is a collection of information on related articles where different convolutional neural network architectures have been investigated and tested, including those discussed in the current project.

TABLE I. Related papers about Convolutional Neural Network

Article	Arch.	Accu. (%)	Sens. (%)	Spec. (%)	Ref.
SARS-Net: COVID-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network	SARS-Net	97.60	92.90	-	[19]
Performance Evaluation of the NASNet Convolutional Network in the Automatic Identification of COVID-19	NASNet	97.00	97.00	-	[20]
OptCoNet: an optimized convolutional neural network for an automatic diagnosis of COVID-19	OptCoNet	97.78	97.75	96.25	[21]

COVID-19 Pulmonary Lesion Classification Using CNN Software in Chest X-ray with Quadrant Scoring Severity Parameters	U-Net	92.86	-	-	[22]
COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images	COVID-Net	93.30	95.00	-	[23]
CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images	CoroNet	89.60	96.40	-	[24]
Improving the performance of CNN to predict the likelihood of COVID-19 using chest X-ray images with preprocessing algorithms.	VGG16	94.50	98.40	98.00	[25]
A machine learning-based framework for the diagnosis of COVID-19 from chest X-ray images	VGG16	100.00	98.85	-	[26]
COVID faster R–CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-Ray images	R–CNN + VGG16	97.36	97.65	-	[27]
A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images	CNN-LSTM	99.20	99.30	99.20	[28]

* Arch: Architecture, Accu: Accuracy, Sens: Sensitivity, Spec: Specificity, Ref: Reference.

II. Methodology

A. Dataset

The dataset was collected from different repositories such as GitHub, Radiopaedia, the Italian Society of Radiology (SIRM), and others. Then, a total of 10000 X-ray images were collected. From this group, 5000 images were from healthy patients, and 5000 images were from patients diagnosed with COVID19. The database used for network training was made up of 8000 images which included 4000 images from healthy patients and 4000 images from COVID-19 patients. In the same way, 2000 images were used for the network validation, divided into healthy and sick patients.

B. Image processing

The images within the dataset were collected from different repositories, so they present color and format variations. Some of the images were in PNG and JPEG, and we converted all of them to JPG so they could be used to train the neural network. As many of the images were in color, they needed to be converted to greyscale; for this, the rgb2gray function of MATLAB was used to convert RGB images to grayscale by removing hue and saturation information and preserving brightness at the same time.

Image normalization: To normalize images, it was necessary to rescale the pixel's intensity values by using Imagenet. Also, we had to normalize the intensity of all images from [1, 255] to the standard normal distribution by min-max normalization to the intensity rage [0,1]. Normalization of images is necessary for balancing features, decreasing bias, speeding up training, increasing generalization, and assuring numerical stability. All of these advantages help to improve model performance and efficiency in computer vision and image processing applications.

C. Architectures

For the detection process, convolutional neural networks involve a process of data extraction, flattening and classification [29]. As shown in Fig. 1, the convolutional neural networks will have an input of data which in this case are X-ray images, to later move on to feature extraction, which will be aided by layers between convolution+ReLU and max pooling. In the classification zone, there will be fully connected layers that will vectorize the extracted information and subsequently classify and learn from it. Finally, under a sigmoid activation as mentioned earlier to obtain a binary response.

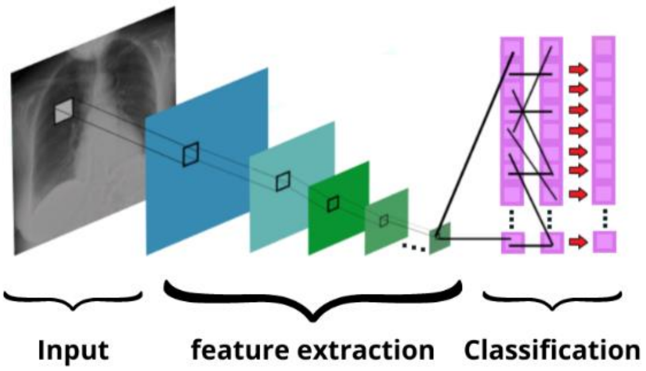

Fig. 1. The structure of CNN

1) Standard Convolutional Network: The standard convolutional network is used with low 3 RGB channels being an entry of 224x224 pixels; in addition to these three layers of convolution and 3 layers of max-pooling were used for processing during training, see Fig. 2 . It worked using 50 images in the batch size with standardization on the grayscale per image. Finally, a single prediction neuron was used under a sigmoid activation where the weight of the neuron represented whether the patient was healthy or presented COVID19.

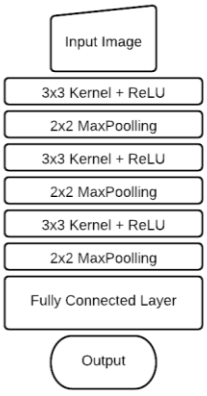

Fig. 2. Standard CNN Architecture

2) NASNet Convolutional Network: NasNet is a neural network architecture with an input size of 256x256 pixels. It comprises three RGB arrays, each consisting of 256x256 pixels. The architecture shares similarities with the conventional Convolutional Neural Network (CNN) Standard, but it deviates in a distinct manner: specifically, the prediction process involves the use of two neurons with softmax activation. Additionally, the patient's state is predicted through weight comparison as is shown in Fig. 3.

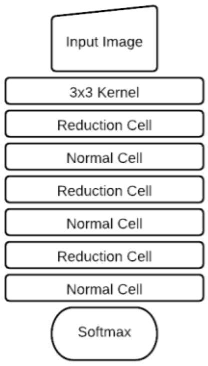

Fig. 3. NasNet Architecture

3) VGG-16 Architecture: The VGG-16 architecture is composed of 16 layers that have weights with 30 convolutions, 5 max pooling, and 3 Dense layers as is shown in Fig. 4. The input tensor size is 224 pixels to 224 pixels and 3 RGB channels. For the training, it used the same conditions as other CNN, and this is similar to CNN standard because it only used one neuron for the output. For this reason, we can use a sigmoid activation and a batch size of 64.

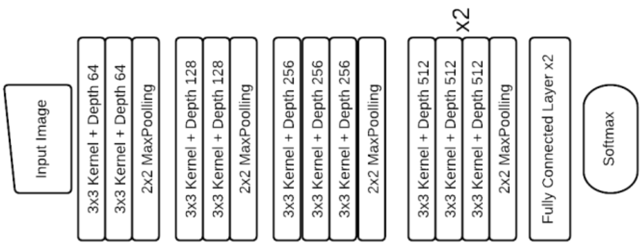

Fig. 4. VGG16 Architecture

D. Flowchart of the methods used to identy COVID-19 patients

The general process is illustrated in Fig. 5, which shows a flow chart to obtain the trained architectures. This is also a summary of the methodology, as it displays the division between the training and validation of the dataset composed of two types of patients: covid and normal. Next, we apply the preprocessing in Matlab to start training the convolutional neural networks. After training, we perform the comparison and identification of the results.

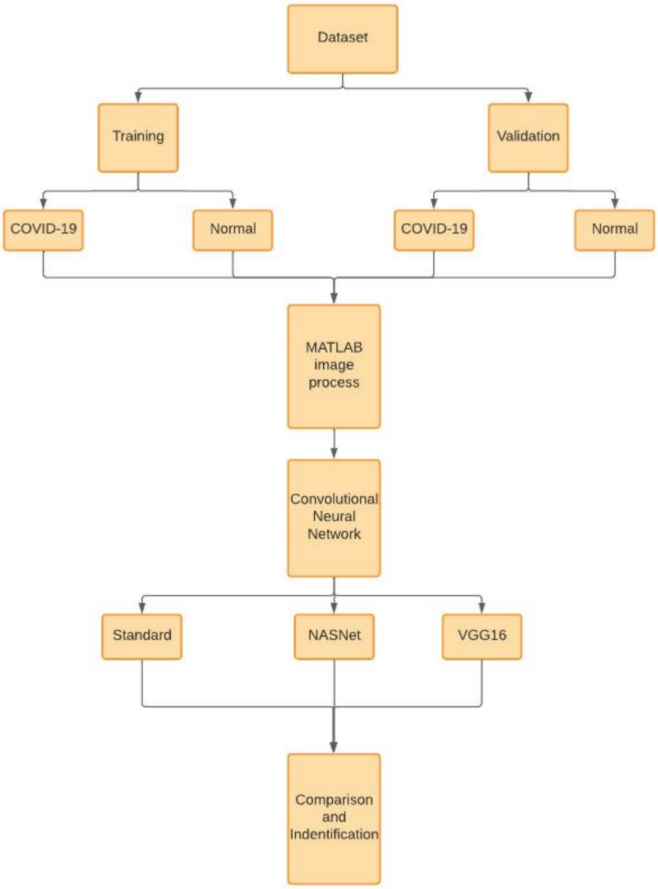

Fig. 5. Methods used for the identification of Covid-19 and healthy patients by Convolutional Neural Networks

E. Identification Patterns

According to the journal Radiology, the most frequent radiological findings in patients with COVID-19 are airspace opacities in the form of consolidations and ground-glass opacities, with typically bilateral, peripheral distribution and predominantly in the lower fields [30]. As seen in Fig 1, the upper side (A) shows a X-Ray test where healthy and well-inflated lungs can be appreciated. However, in the lower side (B) of the person with COVID-19 shows opacities in the patient's chest. These opacities are areas in the image that appear whiter than the rest of the lung tissue and may indicate the presence of fluid or inflammation.

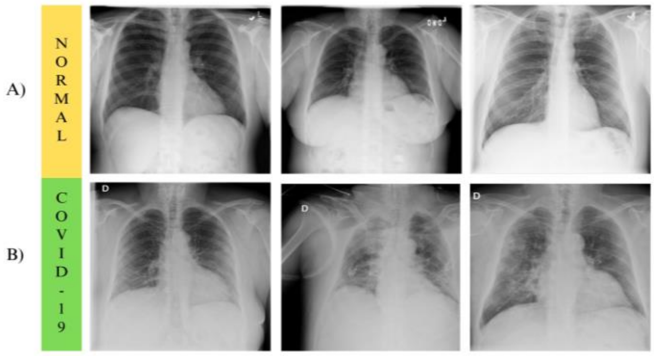

Fig. 6. A) X-ray chest study applied to a healthy patient and B) X-ray chest study applied to COVID-19 patient.

III. Results

In the following chart (TABLE II), it is presented the accuracy percentage of the three architectures proposed and those found in articles. According to the literature, the best architectures are NASNet and SarsNet for their high levels of accuracy. But being the NASNet, VG1-66, and the Standard are the most used networks, we will compare its action with the values obtained in the literature. Taking into consideration that the training conditions were the same for all the neural networks studied.

TABLE II. Chart of the accuracy of the architectures.

	Architecture	Accuracy
Proposed	CNN standard	93.3%
	VGG-16	94.5 %
	NASNet	97.0%
Literature	U-Net	92.86%
	CoroNet	89.6%
	SARS-Net	97.60%

In Fig. 7, it can be seen the values obtained after training and validation of neural networks. Also, it can be noted that the standard neuronal network and the VGG-16 achieved acceptable values because their curves do not present very out of the central curve. The Standard and VGG16 architectures are considered as an adequate model for the problem and the data studied, relating that the data is prepared for these networks to analyze the expected information. In addition, both training and validation values tend to look very similar. On the other hand, the NASNet architecture accuracy results were not as expected. It can be seen that the central training curve is away from the validation curve. The inadequate hyperparameters is the main reason for having obtained these results, such as the learning rate with the batch size, this because the mismanagement of hyperparameters causes the curve to converge to an optimal solution too quickly.

Finally, we can see the curves obtained for loss values during entertainment and validation in the Fig. 8. It is important to mention that these values decrease during their training. Standard and VGG-16 architectures show that the results have a relationship, even normalization of the data in the VGG-16 is noticed since it presents regularization avoiding overfitting and improving the model's capacity and being related to having a good learning rate., but this does not happen with NASNet architecture because these observed peaks are presented again in precision graphics. These peaks are interpreted as an overfitting of the parameters causing the training data to not generalize well, as well as it can be considered that it does not present an adequate learning rate since it is observed how it jumps the global minimum and never converges.

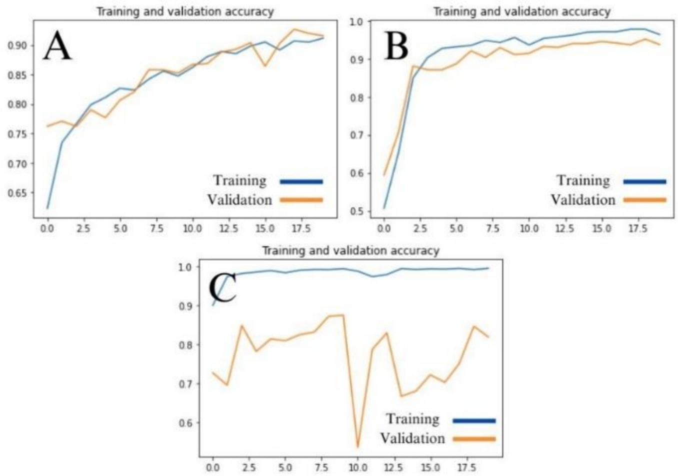

Fig. 7. Accuracy value of the architectures. A) Standard, B) VGG16 and C) NasNet.

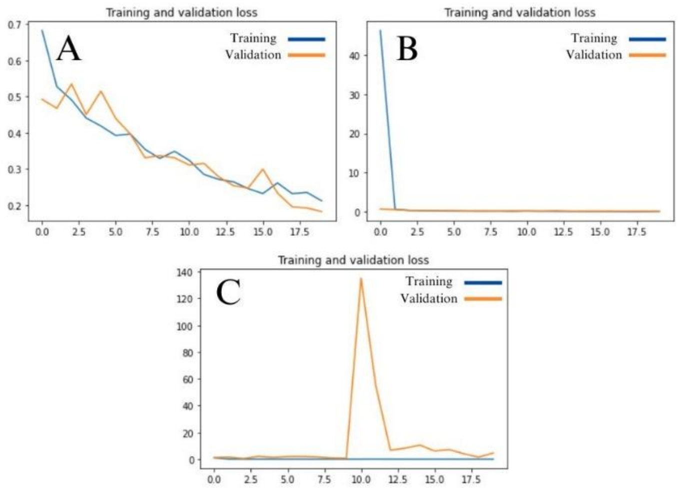

Fig. 8. Loss of the architectures A) Standard, B) VGG16 and C) NasNet.

IV. Discussions

Deep convolutional neural networks are one of the powerful deep learning architectures and have been widely applied in a broad range of machine learning tasks [31], [32]. The use of neural networks has increased in recent years due to their advantages in the detection and study of diseases being extremely important to ensure that no single COVID-19 patient goes undetected [33]–[35]. Specifically, in the present work, we focus on the detection of COVID-19 due to the great impact that its rapid detection generates, saving lives and reducing costs. For this study, the most used networks within the literature have been sought to demonstrate their importance in the effective diagnosis of COVID-19. Architecture chosen was the convolutional Standard network, the VGG-16, and the NASNet. In comparison to other architectures such as those shown in TABLE III. VGG-16 showed good accuracy in acquiring similar values to literature[36], [37], indicating that could be the best architecture for the diagnosis of the virus. Also, the NASNet convolution network presented very high values in comparison to the literature [38], low validation, and significant errors. All these results can be considered due to a possible excessive or over-shifting change when determining the parameters that the convolution network will take. As to current articles, our proposed models achieved the accuracy of more than 90% with the quantity of data we had [39]. According to the literature, this result suggests that overfitting is occurring and that the models are biasing towards negative predictions based on the imbalanced datasets at high number of epochs [40], [41]. Also, the development of these parameters can take time because everything is handled by proof and error. In that way, from compared to literature, the values did not change after many attempts[33] considered to require more study time in this network or may be due to the processing of the images. However, it cannot be considered that NASNet architecture does not work, but it is necessary to better understand its operation to determine the best possible parameters.

TABLE III. Comparison of previous with the proposed work

Paper	Model	Accuracy	Dataset
[29]	VGG16	77%	8461
	DenseNet121	83.7%	
	ResNet50	81%	
	ResNet152	80%	
[44]	VGG16	79.01%	16634
	DenseNet121	89.96%	
	Xception	88.03%	
	NASNet	85.03%	
[45]	VGG16	80%	140
	VGG19	60%	
	ResNeT	50%	
	DenseNet	60%	
	InceptionV3	60%	
Proposed Work	Standard	91.1%	1000
	VGG16	96.3%	
	NasNet	99.5%	

However, current neural networks are designed to identify and classify natural objects with different properties than those of medical images, making predictions based on them medically invalid[17], due to the difficulty and subjectivity of human interpretation[8]. To achieve a medical criterion, different validation parameters must be considered. Although the neural network has demonstrated acceptable efficacy and loss in training and validation, it does not mean that the network is ready to classify and diagnose the pathology under study. Among the most common validation methods, we have the confusion matrix, also known as the error matrix, which is the table used to visualize the performance of an algorithm and to calculate various evaluation metrics[42], such as true negatives and false positives. Among other metrics, we can find area under the curve (AUC), F-1 score, computational time and recovery[43]. All these validation metrics must be accurate, as an incorrect diagnosis can have serious consequences for the patient's health. Therefore, it is essential to use validation metrics to ensure that the neural network is making accurate and reliable predictions. That is, our study presents a novel method for diagnosing Covid 19, yet more study is needed with the different validation parameters mentioned above to obtain high reliability in the presented neural networks.

V. CONCLUSIONS

In conclusion, deep convolutional neural networks have been extensively utilized in a wide range of machine learning tasks, including the detection and study of diseases such as COVID-19. The use of neural networks has seen an increase in recent years due to their advantages in detecting diseases and ensuring that no COVID-19 patient goes undetected. This work focuses on the detection of COVID-19 using the most commonly used networks in the literature, including the Standard convolutional network, VGG-16, and NASNet. The VGG-16 architecture demonstrated good accuracy compared to other architectures, while the NASNet architecture presented high values but also significant errors. These results suggest that overfitting may be occurring and that further study is needed to better understand the operation of these networks and to determine the best possible parameters. To achieve a medical criterion, different validation parameters must be considered, including the confusion matrix, area under the curve (AUC), F-1 score, computational time, and recovery. All these validation metrics must be accurate to ensure that the neural network is making accurate and reliable predictions.

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