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# Deep Convolutional Neural Network Architecture to Detect COVID-19 from Chest X-Ray Images

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**Abstract**

Today, the world is living in a time of epidemic diseases that spread unnaturally and infect and kill millions of people worldwide. The COVID-19 virus, which is one of the most well-known epidemic diseases currently spreading, has killed more than six million people as of May 2022. The World Health Organization (WHO) declared the 2019 coronavirus disease (COVID-19) after an outbreak of SARS-CoV-2 infection. COVID-19 is a severe and potentially fatal respiratory disease caused by the SARS-CoV-2 virus, which was first noticed at the end of 2019 in Wuhan city. Artificial intelligence plays a meaningful role in analyzing medical images and giving accurate results that serve healthcare workers, especially X-ray images, which are complex images in their interpretation. In this article, two deep convolutional neural network (DCNN) classifiers, such as Inception-v2 and VGG-16, are utilized to detect COVID-19 from a set of chest X-ray images. The dataset for this article was collected from the Kaggle platform (COVID-19 Radiography Database) and consists of images of positive and healthy people. This article concludes that the most suitable performance is the Inception-v2 classifier, which has achieved an accuracy of 97% in comparison to the VGG-16 classifier, which has achieved an accuracy of 93%.

**Keywords:** COVID-19, Deep Learning, Deep Convolutional Neural Network, X-ray Images, SARS-CoV-2.

# بنية الشبكة العصبية التلافيفية العميقة لاكتشاف كوفيد–١٩ من صور الأشعة السينية للصدر

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**الخلاصة**

اليوم، يعيش العالم في زمن الأمراض الوبائية التي تنتشر بشكل غير طبيعي وتصيب وتقتل ملايين الأشخاص في جميع أنحاء العالم. تسبب فيروس كوفيد–١٩ ، وهو أحد أكثر الأمراض الوبائية المعروفة التي تنتشر حاليًا ، في وفاة أكثر من ستة ملايين شخص حتى مايو ٢٠٢٢. وقد كان تفشي عدوى سارس كوف–2 الذي تسبب في تفشي مرض فيروس كورونا ٢٠١٩ المسمى (كوفيد–١٩) من قبل منظمة الصحة العالمية . كوفيد–١٩ هو مرض تنفسي خطير ومميت يسببه فيروس سارس كوف –2 ، والذي لوحظ لأول مرة في نهاية عام ٢٠١٩ في مدينة ووهان. يلعب الذكاء الاصطناعي دورًا مهمًا في تحليل الصور الطبية وإعطاء نتائج دقيقة تخدم العاملين في مجال الرعاية الصحية ، وخاصة صور الأشعة السينية ، وهي صور معقدة في

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تفسيرها. في هذه المقالة ، يتم استعمال مصنفي الشبكة العصبية التلافيفية العميقة (DCNN) مثل Inception-v2 و VGG-16 للكشف عن كوفيد-١٩ من مجموعة من صور الأشعة السينية للصدر. يتم جمع مجموعة بيانات هذه المقالة من منصة كاغل (قاعدة بيانات التصوير الشعاعي لكوفيد-١٩) وتتكون من صور لأشخاص إيجابيين وأصحاء. تخلص هذه المقالة إلى أن الأداء الأنسب هو المصنف inception-v2 ، والذي حقق دقة تصل إلى ٩٧ ٪، مقارنةً بمصنف VGG-16 الذي حقق دقة تصل إلى ٩٣٪.

## 1. Introduction

Nowadays, the computer science society is growing progressively, especially the science of artificial intelligence [1], which has become the most influential science and is being continuously developed by a large number of programmers and researchers in order to have the ability to compete with the human mind. This science can be described as the general name for systems that seek to simulate a specific part of human intelligence and imitate human senses. Thanks to this science, many complex transactions are solved, and obstacles are annihilated quickly, no matter how much data increases [2]. With the rapid development of computer science, recent studies conducted on making computers capable of thinking and accomplishing tasks like humans revealed that the most straightforward example is machine learning and its applications [3]. Unlike other artificial intelligence applications, machine learning has a set of techniques for analyzing big data. However, these techniques do not need specific rules for interpretation but rather work according to the data entered into the system [4, 5]. The growth of machine learning, especially deep learning, which is a part of it, plays a vital role in diagnosing many diseases and helping professionals discover a suitable treatment or vaccine for these diseases [6]. In healthcare, machine learning and deep learning have a tremendous ability to detect diseases while analyzing data entered by healthcare workers [7]. With the growth of medical data in recent years, there have been increased opportunities to discover the behavior of diseases, their spread, classification, and division [8]. With the spread of the COVID-19 pandemic, artificial intelligence technologies have a vital and influential role in diagnosing, detecting, and determining the extent of human infection with a virus [9]. COVID-19 is one of the dangerous and deadly coronaviruses that have killed millions of people worldwide [10, 11]. The number of deaths had reached more than 6 million people, with more than 516 million confirmed cases worldwide until May 2022. It was first noticed in China in Wuhan in December 2019 and spread quickly. This disease has been able to control everything in the universe [12]. This pandemic has developed alarmingly since 2020 and has created major and severe problems in the health system in many nations. It is a zoonotic, as it is transmitted from bats to a group of animals that are slaughtered incorrectly and sold in Chinese markets, as shown in Figure 1 [13].

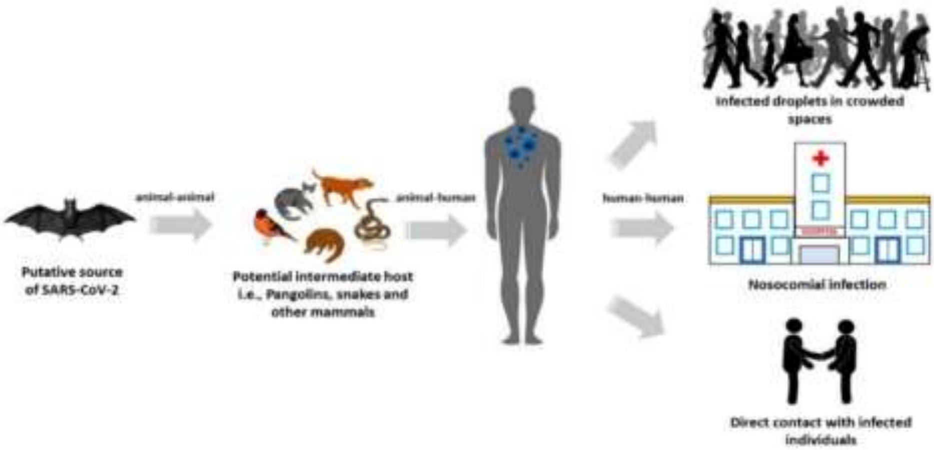



**Figure 1:** COVID-19 transmission modes [13]

In Iraq, the percentage of infected people and deaths increased until it was considered one of the most dangerous Arab nations in terms of the rate of infected people. According to Google statistics, the total number of cases was 2,325,522, the number of people who died was 25,213, and the number of people who were fully vaccinated was 7,403,714 [14].In the last period of 2022, the performance level of the pandemic decreased, especially in Iraq, where infections became infrequent and the number of deaths decreased. Figure 2 illustrates that the number of confirmed cases on May 8, 2022, amounted to 55 people, while the number of fatalities was zero [15].

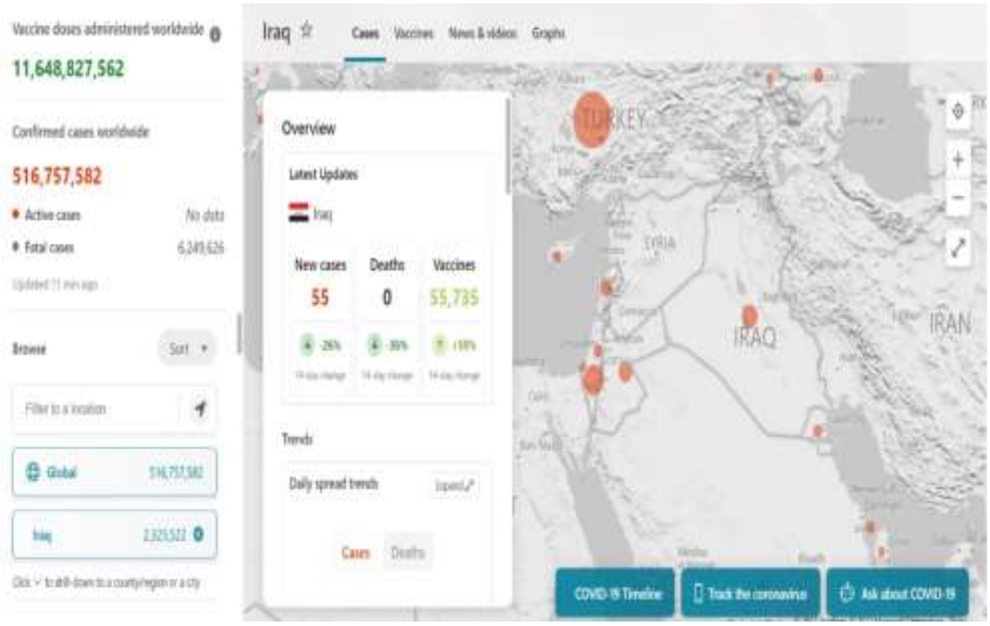



**Figure 2:** Covid-19 statistics in Iraq as of May 8, 2022.

This pandemic can be described as a fatal viral respiratory disease characterized by high temperatures and shortness of breath [16]. It is known that droplets and contact transmit the disease. This virus causes SARS-CoV-2 [17], and its symptoms include fever, cough, shortness of breath, and difficulty breathing. Infections can cause pneumonia, acute respiratory failure, kidney failure, and even death in more severe cases. Figure 3 illustrates the stages of entry of the COVID-19 virus into the human lung and the stage of its development. In particular, this disease is considered more dangerous for those with weak resistance or immune systems, chronic diseases, and the elderly, in contrast to the Spanish flu that infected more than 500 million people in two years and focused on the young and healthy [18]. COVID-19 is usually transmitted by droplets emitted from coughs and sneezes from someone infected with the virus and by contact with the mouth, eyes, and nasal mucosa of the hands after touching surfaces with which patients' respiratory secretions come into contact [19, 20]. Reverse transcription-polymerase chain reaction (RT-PCR) is the most widely used procedure for detecting COVID-19 [21]. However, the duration of this test is extended. Radiographic techniques such as X-rays and computerized tomography (CT) are selected for early-stage COVID-19 diagnosis [22-24]. One challenging practice during a pandemic is to manually review each report for each patient, which requires multiple radiologists with sufficient experience reviewing the information [25]. The rapid spread of COVID-19 has increased death rates in many countries. For these reasons, it is vital to control the spread of this virus, including by developing an effective treatment method, diagnosis, quarantine, early treatment, and full vaccination [26]. In addition, the existing vaccines have proven their effectiveness in developing the body's immunity against this virus [27, 28]. Also, this virus impacts the health system due to the large number of people who need intensive care units and ventilators for a long time. Thus, early diagnosis is critical for suitable treatment and to reduce stress on the healthcare system.

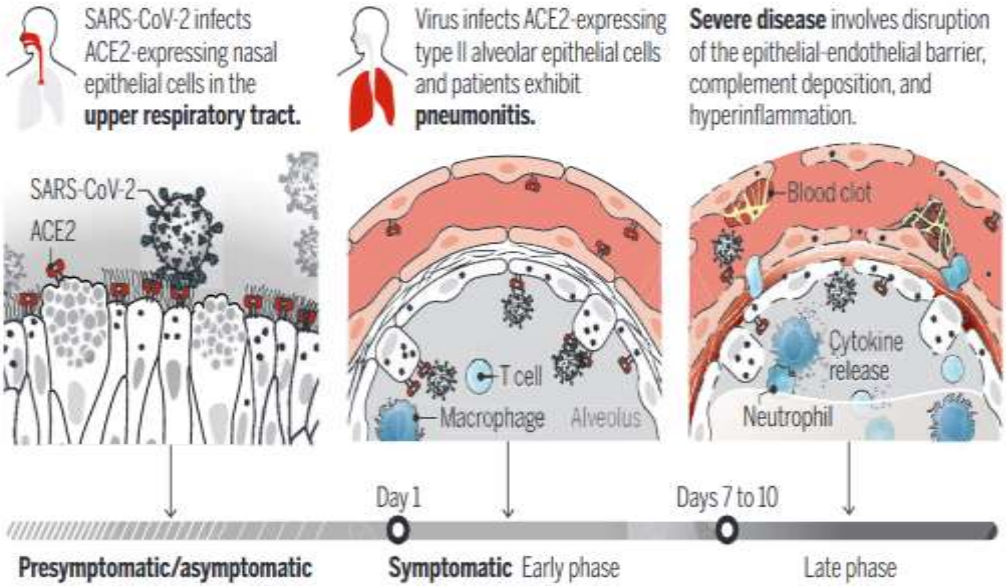



**Figure 3:** The stages of admission of the COVID-19 into the human lung [17].

The foremost contribution of this article is to classify a set of chest x-rays, which are divided into two categories: images of people with COVID-19 (positive situations) and other images of people who are not infected (negative situations), by distributing them into a set of layers in two DCNN classifiers. After that, the performance of each classifier is measured, and their level of implementation is determined in order to select the most suitable by measuring the effect of each classifier through a set of arithmetic procedures in classifying these images.

The article is structured as follows: In Section 2, pieces of literature are presented that have contributed to the classification of chest X-rays of people with COVID-19 using deep learning techniques. Section 3 discusses the data obtained in detail and gives a simplified explanation of the applied classifiers, while Section 4 presents in detail the effects obtained. Eventually, the major conclusion of this work and the lines identified for future work close the article in Section 5.

## 2. Literature Review

Recently, deep learning techniques have been utilized to analyze chest X-ray images, especially during the COVID-19 pandemic. This section reviews a set of literature in which deep learning techniques have been utilized to analyze these images. In a study executed by Chowdhury et al. [29], they suggest implementing the Parallel-Dilated COVIDNet (PDCOVIDNet) method to classify, improve, and extract radiological features from more than 2,900 chest X-ray images. This analysis has concluded that the accuracy of the proposed method is greater than 96%. Also, the precision, recall, and F1 scores achieve more than 96%, respectively.

Ztürk et al. [30] used the DarkNet model to develop a new method for binary classification (COVID vs. No-Findings) and multi-class classification (COVID vs. No-

Findings vs. Pneumonia) of chest X-ray images. In addition, they utilized seventeen convolutional layers, with each layer executing a different filter. This work has found that the accuracy of the suggested model in binary classification is 98.08%, while in multi-class classification, it earned more than 87%.

Another analysis by Hassantabar et al. [31] has suggested two approaches for diagnosing images of COVID-19 patients: deep neural networks (DNN) and convolutional neural networks (CNN). Experiments show that the CNN architecture's execution is more useful than the DNN architecture, with an accuracy of more than 93% and a sensitivity of more than 96%.Furthermore, the CNN architecture construct is utilized to find affected tissues in lung images.

In [32], it aims to develop a CNN technique for classifying COVID-19 from chest x-rays. The development is based on 368 images of people infected with COVID-19 and 850 images of people with other pneumonia cases. The architectures (DenseNet-201, ResNet-18, and SqueezeNet) for training and testing data are analyzed. The data in this study consisted of 90% training data, 10% testing data, and 20% of the training data employed as a validation set to prevent overfitting situations. Besides, a comparison is made between the classifiers, and it is found that the best performance was for the DenseNet-201 architecture, which achieved an accuracy of more than 94%.

A study conducted by Mousavi et al. [33] has suggested applying the Convolutional Neural Network-Long Short Time Memory model to refine a set of X-ray images (Bacterial, Viral, Healthy, and COVID-19 classes), where the proposed work achieved an accuracy of more than 90%. In contrast, Shastri et al. [34] suggest involving the CheXImageNet mode to refine X-ray images (COVID-19, normal, and pneumonia disease) from the binary and multi-class data. For both types, this method achieved 100% accuracy.

## 3. Implementation Details

### 3.1 Dataset

In general, medical images help adults and children diagnose their conditions and receive the necessary treatment. X-rays are described as a procedure carried out through the use of electromagnetic rays emitted by a radioactive device that penetrate the body's tissues to hit a plate placed behind the body, on which the image of the organs of the body penetrated by the rays is formed. This process is carried out by people who have sufficient experience in taking these images. Physicians and healthcare workers need computers to diagnose these images quickly and accurately. Here comes the role of artificial intelligence due to its high ability to analyze a large set of images and help physicians make the right decision. The dataset for this article was collected from the Kaggle platform [35]. This platform is an open-source and publicly available website. This file contained 3,616 positive images (people with COVID-19) and 10,192 negative images (people without COVID-19).

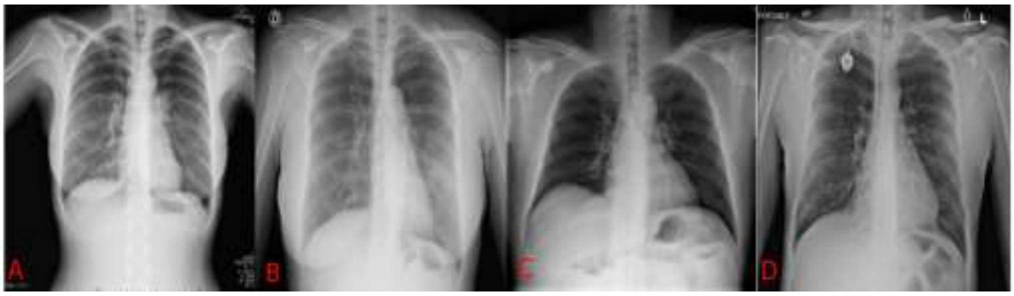



**Figure 4:** Four x- ray images applied in this work.

All images have been packaged in PNG file format for ease of handling, with a size of $299 \times 299$ pixels. Figure 4 shows four X-ray images of the images involved in this work, illustrating A and B people infected with COVID-19 (positive cases) and illustrating C and D healthy people (negative cases). 70% of the dataset is operated for the training stage and 30% for validation and testing purposes (see Figure 5).

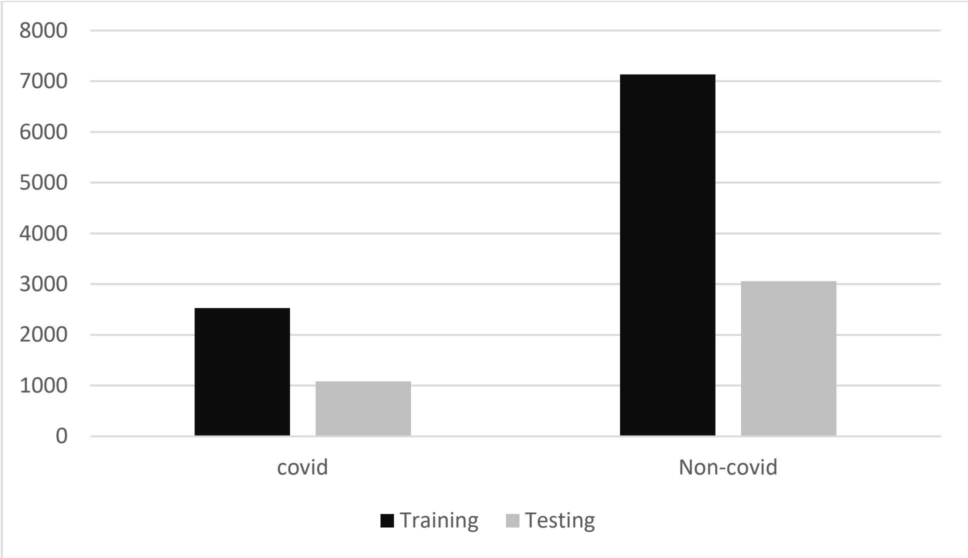



**Figure 5:** Training and testing dataset Distribution

### 3.2 The Classifiers

Machine learning is a set of techniques that are able to learn from the data they get [36, 37]. The primary goal of these techniques is to give people the ability to solve a complex job, perform an activity, and learn from their mistakes to gain more ability. The most popular machine learning technique is deep learning, a branch of machine learning that tries to be like the human brain in analyzing and explaining everything it notices [38, 39]. In addition, it is a set of mathematical approaches for analyzing images, the most famous of which is the deep convolutional neural network (DCNN) [40]. It is one of the deep learning algorithms [41]. We can understand these images and distinguish one from the other by analyzing a large group of images, defining the input images, and assigning learnable weights and biases to various aspects. Furthermore, it has the distinction of requiring much less pre-processing compared to other classification algorithms. Figure 6 shows the architecture of DCNN from the input step to the output step. Moreover, the DCNN consists of several classifiers, namely: LeNet-5, AlexNet, VGG-16, Inception, ResNet, ResNeXt, and DenseNet. Two of them were selected and employed in this work due to their high ability to process and classify medical images, as follows:

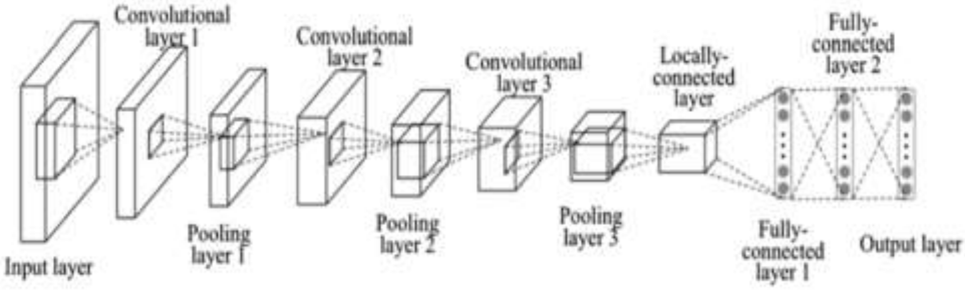



**Figure 6**: The architecture of DCNN [44]

**Inception-v2 classifier:** It is a convolutional neural network with a depth of 164 layers [42]. It is characterized by its ability to classify millions of images, as it can classify 1000 object categories in a very large set of images as it is trained on millions of images stored in a large dataset. The main task of this architecture is to decompose the sensations obtained by superimposing a large convolution ($3 \times 3$ $and$ $5 \times 5$). Moreover, this architecture employs three convolutional layers with a dimensionality reduction filter bank, five layers with a deeper filter bank, and the next two layers with a wider filter bank. In other words, this architecture is suitable for big data because it can process and analyze large amounts of data at a low cost despite having limited memory (computational capacity). In general, there is a big problem, which is that during the work, data may be lost due to the dimensions of the input frames (bottleneck). To solve this problem, this architecture is used to reduce the dimensions by embodying the smart factorization method.

**VGG-16 classifier:** It is a convolutional neural network consisting of 16 depth layers that have weights [43]. It is one of the perfect vision models to date. This architecture emphasizes convolution layers of ($3 \times 3$) filter with stride one, always using the same padding, and a MaxPool layer of ($2 \times 2$) filter with stride two. This architecture contains a large number of parameters that reach about 130. Overall, the visual geometry group (VGG) is a pack of versions from 11 to 19. Their primary purpose is to understand how the depth of the convolutional network influences the accuracy of large-scale image recognition and classification models. In addition, this architecture focuses on reducing the number of hyperparameters and provides an excellent deep network that is essentially able to strip pixels as layers pass. The first part contains two layers with 64 filters ($3 \times 3$), padding, ReLU activation, and batch normalization. The second part contains 128 filters. The third part includes 256 filters, while the fourth part has 512 filters. The fifth part is the same as the fourth part in terms of the number of filters.

## 4. Results and Discussion

In this section, the performance of the executed architectures is proved by comparing them according to their performance through accuracy, sensitivity, specificity, precision, and F1-score criteria. The confusion matrix form presented in Table 1 is employed to estimate the performance criteria for the prediction model. Classical mathematical equations are employed to find the effect criteria (see Equations 1–5). At the beginning of this work, two different deep convolutional neural networks are constructed on 3,616 positive images and 10,192 negative images. In these two classifiers, images are passed through a group of convolution layers instead of one convolution layer in each convolution block, as illustrated in Figure 7, which is the third of the three primary steps of this work.

**Table 1:** Confusion Matrix form

| | | **Predicated category** | |
|---|---|---|---|
| | | **Positive** | **Negative** |
| **Actual category** | **Positive** | True Positive ($TP$) | **False Negative ($FN$)** |
| | **Negative** | False Positive ($FP$) | **True Negative ($TN$)** |

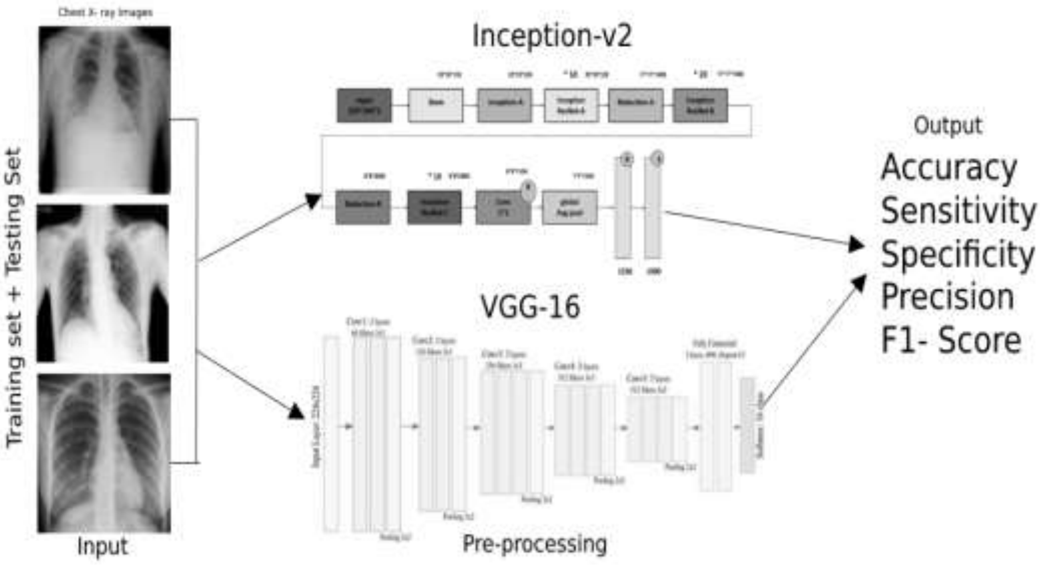



**Figure 7:** Work steps in the analysis of chest X-ray images.

The first step represents the input data, which is the images, and then passes these images to one of the architectures and inserts them in the pre-processing step, and then gets the effects of each architecture. Moreover, the activation function (ReLU) is employed in the convolutional layers, which can be formally expressed as $f(x) = \max(0; x)$, and for the output layer, the activation function (SoftMax) is employed. On the other hand, the Adam optimization method is applied to improve the performance of each network with a learning rate of 0.0001. A dropout layer is added to discourage overfitting. In addition, the early stopping method is employed to minimize the loss and prevent increased implementation time.

$$Accuracy\ (success\ rate) = \frac{TP+TN}{TN+TP+FN+FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TN+TP} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

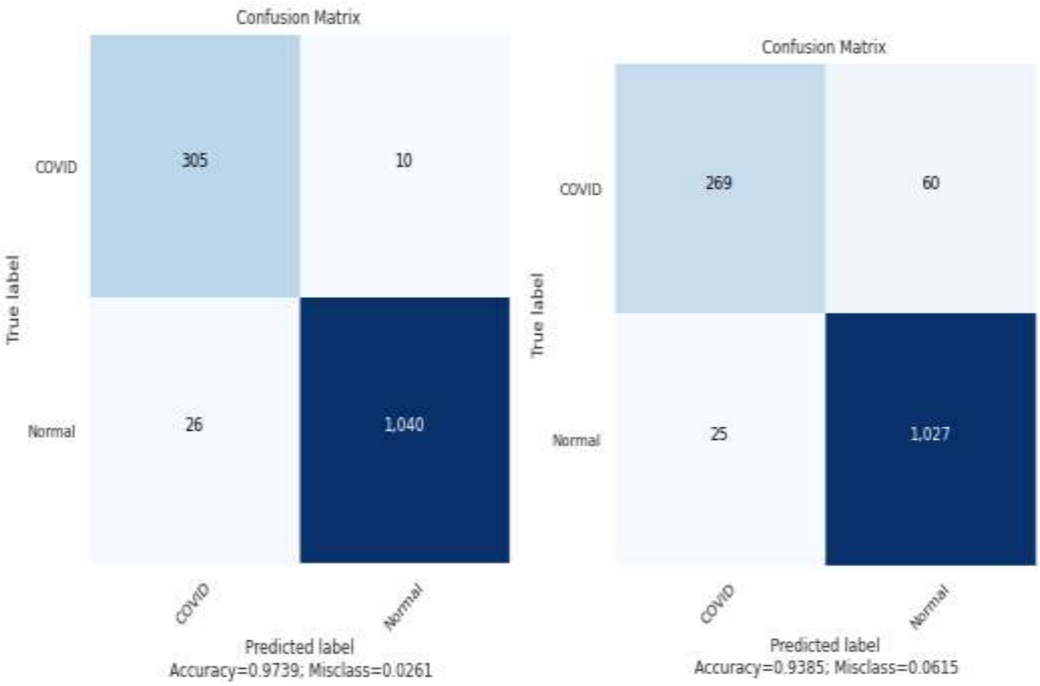
$$F1 - Score = \frac{2\times TP}{YN+FP*2+TP} \quad (5)$$

Where:
True Positive ($TP$): the classification measure accurately denotes the positive category.
True Negative ($TN$): the classification measure accurately denotes the negative category.
False Positive ($FP$): Refers to the classifier misclassifying the negative category as positive.
False Negative ($FN$): Refers to the classifier misclassifying the positive category as negative.
Some images have noise from the pre-processing step. The 2D Gaussian filter ($G$) is applied to get rid of them using the following mathematical equation:

$$G(x,y) = \frac{1}{\sqrt{2\pi\delta}}\exp(-\frac{x^2+y^2}{2\delta^2}) \quad (6)$$

Where:
$\delta^2$ is the variance and size of the filter kernel. By involving this filter, the signal-to-noise ratio (SNR) of the images has been improved.
The VGG-16 classifier achieved more than 93% accuracy by conducting experiments on the training data, while the loss is approximately 21%. At the same time, the inception-v2 classifier achieved an accuracy of more than 97% with a loss of more than 8%. Moreover, by

applying the VGG-16 classifier to the testing data, it achieved an accuracy of more than 93% with a loss of approximately 18%. In comparison, Inception-v2 achieved a correct result of approximately 97% and a loss of 10%. Figure 8 illustrates the confusion matrix for both architectures, where (a) describes the VGG-16 classifier and (b) describes the nception-v2 classifier. Table 2 illustrates the effects of both architectures, measures the performance level, and determines the most suitable and inadequate performances. Table 3 compares the performance of this article with other articles that have utilized DCNN architectures.




(a) (b)

**Figure 8**: Confusion matrix for both architectures, (a) VGG-16 classifier performance and (b) Inception-v2 classifier performance

**Table 2:** The effects of both classifiers

| Classifiers | Accuracy | Specificity | Sensitivity | Precision | F1-score |
|---|---|---|---|---|---|
| **VGG-16** | 93% | 97% | 81% | 91% | 86% |
| **Inception-v2** | 97% | 97% | 96% | 92% | 94% |
| **The total training times of Inception-v2, VGG-16 are 16028 s, 14639 s, respectively.** | | | | | |

**Table 3:** Comparison of this work with other existing deep learning methods

| State-of-the-art | Chest X-ray | Computational approaches | Classifiers | Best performance | Accuracy |
|---|---|---|---|---|---|
| **Narin et al. [45]** | Normal: 2800 COVID: 2772 | Healthy, Pneumonia, and COVID-19 | InceptionV3, ResNet50, ResNet101, and ResNet152 | ResNet50 | 99% |
| **Qi et al. [46]** | Normal: 8851 COVID: 3323 | Healthy, Pneumonia, and COVID-19 | AlexNet, ResNet50, and SonoNet64 | ResNet50 | 95% |
| **Apostolopoulos and Mpesiana [47]** | Normal: 244 COVID: 504 | Healthy, Pneumonia, and COVID-19 | VGG19, MobileNet v2, Inception, Xception, and Inception ResNet v2 | VGG-19 | 98% |
| **Sahinbas and Catak [48]** | Normal: 50 COVID: 50 | Non-COVID-19 and COVID-19 | VGG16, VGG19, ResNet, DenseNet, and InceptionV3 | VGG-16 | 80% |
| **Chowdhury et al. [49]** | Normal: 1579 COVID: 423 | Healthy, Pneumonia, and COVID-19 | MobileNetv2, SqueezeNet, ResNet-18, ResNet-101, DenseNet-201, CheXNet, Inception-v3 and VGG-19 | DenseNet-201 | 97% |
| **Das et al. [44]** | Normal: Negative COVID: Positive | Pneumonia, COVID-19, and Other | Xception | Xception | 97% |
| **Moura et al. [50]** | Normal: 1583 COVID: 4273 | Healthy, Pneumonia, and COVID-19 | DenseNet-121, DenseNet-161, ResNet-34, VGG-16 and VGG-19, and ResNet-18 | ResNet-18 | 97% |
| **This article** | Normal: 10192 COVID: 3616 | Non-COVID-19 and COVID-19 | VGG-16 & Inception-v2 | Inception-v2 | 97% |

## 5. Conclusions and future direction

In this article, two deep convolutional neural network (DCNN) classifiers are utilized to classify chest X-ray images to identify images of people infected with COVID-19. In this work, the performance of both architectures is determined, and which is the best and fastest in training, testing, and verification is also identified. In other words, this work is to measure the performance of both applied classifiers and determine their ability to analyze the most significant number of chest X-ray images for COVID-19 patients. It is found that the most suitable performance is for the inception-v2 classifier, where it has gained an accuracy of more than 97%, which is a perfect effect. As for VGG-16, its performance is also excellent, as it has achieved an accuracy of more than 93%. The inception-v2 architecture is the soundest in the performance and analysis of X-ray images. However, it takes a longer period of time in the training stage, and its sensitivity level is greater than the sensitivity level of VGG-16. In the data training stage, VGG-16 takes less time than Inception-v2. In the future, other architectures will be used in order to study their performance and know the effects of classifying X-ray images of the chest of people infected with COVID-19.

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