



An Optimized Architecture for COVID-19 Prediction Using Chest X-Ray Images

Yasser Fouad¹, Ahmed M. Osman², Ibrahim E. Abdelmaged², Ahmed Mohamed Zaki³, Ahmed M. Elshewey*¹

¹ Department of Computer Science, Faculty of Computers and Information, Suez University, Suez 43533, Egypt

² Department of Information Systems, Faculty of Computers and Information, Suez University, Suez 43533, Egypt

³ Computer Science and Intelligent Systems Research Center, Blacksburg 24060, Virginia, USA
Emails: yasser.ramadan@suezuni.edu.eg; a.osman@suezuni.edu.eg; hemased111@gmail.com; azaki@jcsis.org; Ahmed.Elshewey@fci.suezuni.edu.eg

*Corresponding Author: Ahmed.Elshewey@fci.suezuni.edu.eg

Abstract

In modern times, a disease known as COVID-19 that is highly contagious is continuing to have a profoundly negative influence on the people of the entire world. The fundamental purpose of the model that has been proposed is to improve its predictive capabilities while also providing an effective model for predicting COVID-19 that has a robust diagnostic. Image scaling and noise reduction are two examples of the types of pre-processing techniques that are used at the very first step. The adoption of picture scaling and median filtering techniques, both of which work to enhance the quality of the input data in preparation for further processing steps, allows this goal to be accomplished. Several distinct data augmentation strategies, like flipping and rotation, are utilized to improve the model's performance on a limited dataset and assist it in better comprehending the differences present in the training data. In this article, we will provide a unique Optimized Architecture for COVID-19 Prediction (OACP) model to classify COVID-19 situations as either positive or negative effectively. Using CXR pictures, this novel method, based on a tunable deep learning technique called DenseNet, may predict the presence of COVID-19-positive patients. Based on the findings, it was determined that the proposed model utilized achieved better outcomes, with an accuracy of 98%.

Keywords: COVID-19; Pre-processing Optimized DenseNet, CNN; Data augmentation, Classification.

1. Introduction

In December 2019, a coronavirus was discovered in Wuhan, China, marking the beginning of a big outbreak of a hitherto unknown viral disease. The International Committee on Taxonomy of Viruses (ICTV), an organization that researches the classification of viruses, has given the coronavirus the name Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). The COVID-19 virus-caused disease is real, according to the World Health Organization [1]. COVID-19 belongs to a vast group of viruses that can result in human sickness, often of a severe and fatal nature. Among the available options, chest X-ray (CXR) stands out as the most readily obtainable and cost-effective choice. COVID-19 is classified as a prominent ribose nuclear acid (RNA) virus [2]. COVID-19 has a direct impact on the respiratory system, specifically the lungs, resulting in harm to the alveoli.

Furthermore, transmission of the virus occurs by interpersonal contact, with an incubation period ranging from 1 to 14 days [3]. The transmission of COVID-19 occurs by the inhalation of respiratory droplets and saliva in the air, as well as through direct or indirect contact with infected individuals [4]. Coronaviruses are to blame for both the Middle East Respiratory Syndrome (MERS) and the severe acute respiratory syndrome (SARS). There is an approximate 34% increase in the risk of death when these types are used. People have been infected with SARS-CoV-2, the seventh strain of the coronavirus. It comes after MERS-CoV, HCoV-NL63 (also known as Netherland 63), OC43 (Human Coronavirus OC43), and HCoV-229E (Human Coronavirus 229E). This strain has been shown to infect individuals subsequent to MERS-CoV [5]. The symptoms associated with COVID-19 include dizziness, dry cough, dyspnea, headache, diarrhea, exhaustion, and loss of taste and smell, as documented in many sources [6]. There is a variety of COVID-19 testing methods, with nasal aspirate and swab tests being the two most often employed methods. The nasal aspirate procedure involves the insertion of a saline solution into the nasal cavity, followed by the extraction of the sample through the application of gentle suction. A swab test is employed to obtain a specimen from the oropharynx or nasal cavity [7]. To diagnose COVID-19, you need to find positive results in blood samples using the reverse transcription (RT) polymerase chain reaction (PCR) or the nucleic acid amplification test on samples from the respiratory tract [8]. Medical imaging techniques such as computed tomography (CT) scans and chest x-rays (CXR) are commonly utilized for the purpose of detecting pneumonia in patients diagnosed with COVID-19 [9]. A chest X-ray (also known as a CXR) is a diagnostic imaging method that makes use of X-rays to provide a visual representation of the many organs and structures that are housed within the thoracic cavity. When it comes to evaluating how well the cardiovascular and respiratory systems are working, the image that was collected is of great assistance. There are a number of conditions that have the capability of having an effect on and modifying the anatomical composition of the lungs and the heart. CXR has the potential to visualize blood vessels, spinal bones, and cardiac structures, in addition to being able to produce images of the chest and lungs [10]. CXR is able to detect the existence of fluid accumulation in the pleural area that surrounds the lungs in a patient. Radiography of the chest from three different angles is a technique that is frequently used to evaluate individuals who have lung metastases [11]. The use of CXR imaging allowed for a speedy identification of the COVID-19 process [12], which had previously been elusive. The process of integrating a series of X-ray images taken of the human body from a variety of different angles is called a computed tomography (CT) scan. After these images have been saved on a computer, they are processed to create cross-sectional images that can be used to show objects inside the body, such as blood vessels passing through soft tissue inside the skeletal framework [13]. These images can be used to see things like this. The main idea behind a computed tomography (CT) scan is to figure out attenuation coefficients to get an idea of how much tissue an X-ray beam has passed through. It is possible for medical practitioners to detect and diagnose cases of internal bleeding and injury by making use of CT scans [14]. There are many different kinds of CT scans, some of which are focused on bones, such as bone CT scans, while others, including CT arthrography and CT angiography, examine other parts of the body. The sensitivity, comparability, and time efficiency of CT scans and CXRs are three of the most notable benefits of these diagnostic tools. The Computer-Aided Design (CAD) automated system is now being used with the aim of diagnosing COVID-19 through the examination of pictures received from CXR and CT scans. This is done by using the system to perform image analysis. In addition, the benefits include low cost as well as portability, increased speed, heightened sophistication, enhanced efficiency, and higher accuracy [15]. [16] The subfields of artificial intelligence (AI), known as machine learning (ML) and deep learning (DL), are two separate branches within the subject. ML is a topic of computational statistics that focuses on the utilization of computer systems to make decisions. It is strongly interwoven with other areas of science. The technology has widespread applications in many fields, including speech recognition, health, computer vision, and email filtering [17], to name just a few of those fields. Decision Trees, Logistic Regression, Support Vector Machines (SVM), Naive Bayes, Perceptron, and k-Nearest Neighbor algorithms are the types of machine learning classifiers that are used in the process of detecting COVID-19. The problems in data gathering, the potential for high error rates, and the complications in interpreting the results gained are some of the limits connected with machine learning [18]. Other limitations include time and resource constraints. In addition, the quality of the features that are extracted is the only aspect that plays a role in determining how accurate machine learning approaches can be when it comes to forecasting the outcomes of future occurrences. The subsequent selection of the qualities that are judged to be the most optimal and their incorporation into the process of machine learning both result in an increase in computational complexity. DL stands for deep learning and is a subsection of ML that focuses on the development of algorithms that contain multiple layers. The raw

input data is processed through each of these layers, which gradually extract higher-level features. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), deep neural networks (DNNs), deep belief networks (DBNs), and deep reinforcement learning (DRL) are some of the fundamental components that make up the architecture of deep learning (DL). The analysis of medical images, the production of board game programs, machine translation, computer vision, bioinformatics, the manufacturing of medications, and the inspection of materials are only some of the applications that have made use of these structures. [19] The outcomes they produce are superior to those of human specialists with a similar level of training. In recent times, there has been a noticeable increase in the focus placed on the use of DL models in the classification of COVID-19 based on CXR images. This strategy is beneficial because deep learning models have the capacity to independently acquire relevant features. As a result, it reduces the challenges that are connected with resolving complex issues that are largely focused on image classification. The challenges presented by COVID-19 can be evaluated using DL models on many different levels, including epidemiological, molecular, and medical domains [20, 21]. In the context of COVID-19, deep learning models and large amounts of data are deployed for the objectives of contact tracking and case detection. DL models have been utilized in the past to diagnose a variety of lung conditions by employing semi-automated and automatic algorithms that search for irregularities within the body of a patient. Nevertheless, there is a possibility of inconsistencies occurring during the classification process due to the absence of procedures that are both dependable and precise. As a result, the application of an effective methodology is essential if one is to improve the classification accuracy of the COVID-19 prediction. This work attempts to improve upon the existing body of knowledge on automatic classification models by focusing on the process of two-class categorization between images that are either COVID-19 positive or negative. In doing so, we want to add to the existing body of knowledge on automatic classification models. The proposed methodology employs an adaptable deep learning-based prediction classifier (DenseNet) in the final step to classify both the CXR dataset and the CT dataset. The urgency to optimize patient care for COVID-19 has escalated significantly. In order to address this highly lethal illness, it is imperative to promptly and cost-effectively assess individuals who have been impacted. Radiological examination is often regarded as the most practical approach for achieving this goal.

The primary contribution of the suggested method is outlined below in the following manner:

- This study aims to provide a novel COVID-19 prediction model that enhances diagnostic accuracy, utilizing the OACP model as its foundation.
- The pre-trained architecture DenseNet-201 by OACP Optimized has been improved using a new optimization method that cuts down on the number of layers. This makes the prediction performance better.
- The imbalance present in the public dataset has led to the implementation of data augmentation as a strategy to address the issues it poses.

The subsequent section of the document outlines the remaining framework of the paper. Section 2 provides an overview of the relevant literature, encompassing various studies conducted in the field. The proposed methodology is briefly addressed in Section 3. The simulations conducted in Section 4 aim to evaluate the performance of the suggested technique. Lastly, the conclusion and potential avenues for future research are presented in Section 5.

2. Related Work

Bhattacharyya et al. [22] presented a method for detecting COVID-19 that makes use of DL techniques in conjunction with CXR images. Even CXR pictures displaying normal conditions or pneumonia can be used to locate COVID-19 thanks to the combination of classification and segmentation in DL architecture, which produces an extremely effective method for doing so. The CXR images were used to train a conditional generative adversarial network (GAN), which was then used to use the pix-to-pix method to separate the lung images. The Conditional Generative Adversarial Network, often known as the C-GAN, is made up of several different parts, one of which is the classification network

that has been trained. This method is utilized for the purpose of classifying images that have already been processed. After that, the images of the lungs were processed using a network-based method for the extraction of features. There were a few different DNNs that were built, including SCNN, DenseNet 160, VGG19, DenseNet 200, and VGG 16. Keypoint detection is done in a few different ways. Two of these are BRISK (for Binary Robust Invariant Scalable Keypoints) and SIFT (for Substitution of Hospital and Other Institutional Focus Technology). The data set that was utilized in this proposition was known as SCR data, which stands for silicon-controlled rectifier data. In order to identify photographs as belonging to various classes, the collected characteristics are enumerated through the use of several machine learning algorithms. These approaches include XG Boost (extreme gradient boosting), RF (radio frequency), SVM (support vector machine), and softmax. When the last layer of RF was applied alongside the BRISK key point extraction approach, the accuracy reached a maximum of 96.6% in almost all cases. The fact that a larger dataset was required in order to carry out an accurate performance evaluation was one of the drawbacks of the study. Shastri and colleagues [23] presented a COVID-19 classification approach that makes use of a deep convolution neural network and bases its findings on the examination of CXR pictures. The computer method that was utilized to locate COVID-19 by looking at digital photos of CXR used a three-class grouping binary approach, which means that the computer did all of the work on its own and no one had to interact with it. The ability of the systems to successfully process ever-growing datasets demonstrated their level of intelligence. The importance of COVID-19 in this field is highlighted by the fact that digital X-ray photos have been subjected to a variety of machine learning and DL approaches in order to detect the virus. The CXR image net model was utilized as part of the performance measurement for the Deep Convolutional Neural Network. In order to make a correct diagnosis of COVID-19, imaging modalities such as CXR and CT are utilized. The proficiency of the radiologist, which is said to be 90%, is directly proportional to the accuracy of various diagnostic tests, which range from 80% to 95%. The relatively low accuracy of the RT-PCR test was one limitation that was identified throughout the diagnostic process that was carried out by professionals in the medical field. Khan et al. [24] developed a classification algorithm for CXR pictures that makes use of DL techniques in order to identify instances of COVID-19. The application of cutting-edge technologies in deep learning approaches is becoming increasingly widespread across a variety of fields that are part of typical day-to-day living. COVID-19 has been identified as a disease that has a high risk of spreading to others, whereas CXR has been determined to be safe to use in most situations. In order to complete the enumeration of COVID-19, we utilized MobileNetV2, EfficientNetB1, and NasNet Mobile, each of which is a distinct methodology. The augmented dataset was used for training deep learning methods, while two other training sets were used for classification purposes. The deep learning model was fine-tuned for this proposal, and in addition, the hyper-parameters were also fine-tuned. This resulted in an improvement in the performance of the deep learning model that had been fine-tuned. This method distinguishes between lung capacity that has been impaired by COVID-19 and pneumonia that has been caused by viral infections, with a classification accuracy of 96.13%. One restriction observed in the study was that when larger datasets were employed, the classification task required more than four classifications. Alshazly et al. [25] proposed the use of DL methods with the aim of diagnosing COVID-19 via CT images. DL algorithms were utilized in the analysis of CT scans of the chest in order to facilitate the rapid and automated detection of patients who were infected with COVID-19. In the testing, a complete collection of two CT image datasets, specifically a SARS-CoV-2 scan and a COVID-19 CT, was utilized. The findings point to a greater degree of performance when the present model is contrasted with the one that came before it. On the COVID-19 CT dataset, the modified model attained mean values of specificity, sensitivity, accuracy, and precision that were 92.2%, 93.7%, 92.9%, and 91.3%, respectively. It also earned an F1-score of 92.5%. On the dataset containing SARS-CoV-2, the equivalent values were 99.6%, 99.8%, 99.4%, 99.6%, and 99.4%, respectively. The collected characteristics effectively exhibit the visualization of distinct clusters, indicating the differentiation between CT images representing COVID-19 and non-COVID-19 cases. This is accomplished by demonstrating the differentiation between COVID-19 and non-COVID-19 occurrences. The difficulty of correctly recognizing and localizing aberrant regions within CT scans was one of the obstacles that this idea ran into. This was one of the constraints that was encountered. Using X-ray and CT scans as training data. Maghdid HS et al. [26] developed a deep learning system for the purpose of identifying COVID-19. Through the examination of CT scans and CXRs, the CNN model has shown that it is effective in diagnosing the disease known as COVID-19. This was accomplished in conjunction with testing that was conducted before the model was trained. In spite of the great levels of specificity, sensitivity, and accuracy that were achieved in the process of detecting COVID-19, the data scientist made the decision to use a straightforward CNN model for the goal of

early diagnosis of the disease. For the purpose of prospective assessment of radiography images, the CNN model has shown that it is effective while also being user-friendly, and it requires a small amount of processing resources. In addition to this, the fact that it is compatible with smart phones makes it more easily accessible and usable. The development of more advanced ways for recognizing COVID-19 disease through the utilization of CT or CXR imaging techniques has been made possible thanks to the building of a small-scale intervention, which has resulted in important life-saving outcomes for a number of different individuals. A level of accuracy of 94.1% was reached using the CNN model. The necessity for additional space that the performance model had was one of its many drawbacks. Ismael and colleagues [27] presented the diagnosis of COVID-19 by DL with CXR as the diagnostic tool. It is well established that COVID-19 can cause respiratory problems as well as pulmonary infections. For the purpose of classifying normal CXR and those showing indicators of COVID-19, the deep learning method known as pre-trained fine-tuning of CNN has been utilized in this proposal. This is done with the intention of achieving the aforementioned purpose. The goal of this strategy is to achieve accurate classification, and it accomplishes this by involving the collection of deep features as well as the training of a CNN model. CNN models that have been subjected to deep pre-training, such as ResNet50, VGG19, ResNet101, ResNet18, and VGG16, were used in the process of extracting deep features. The process of classifying deep features using SVM classifiers required the application of a variety of kernel functions, including Gaussian, linear, cubic, and quadratic, respectively. The archive has 360 images in total, including 200 pictures of people in perfect health and 180 pictures of people who have been identified as having COVID-19. The majority of the time, CXR images were applied to research endeavors. In contrast, the training end-to-end CNN model only achieved a performance of 91.6%, while the ResNet50 model, after undergoing fine-tuning, was able to achieve a performance of 92.6%. The acquired CXR photos for COVID-19 were not as thorough as the CNN models that were assessed for the goal of recognizing COVID-19, which is one of the drawbacks of the study. Deep learning classification strategies were applied to X-ray images by Chen Ji et al. [28] in order to develop a method for detecting COVID-19. This method was published. The CNN method displays increased accuracy in the detection process while still preserving efficiency and speed. The objective of this approach is to recognize and classify instances of COVID-19 within the framework of medical picture applications within the domain of deep learning. When it came to reliably identifying COVID-19 instances in the context of large rural communities, the CNN algorithm proved to be extremely useful. This was done with the intention of preventing the spread of the virus. This approach has a high level of success in reducing the likelihood that COVID-19 will harm people. In order to distinguish between the various illnesses that lung infections might cause, the study also integrated the use of cross-validation tenfold and confusion metrics. Therefore, a dataset consisting of X-ray pictures was used in order to test and train the CNN approach. The level of accuracy that was reached was 85%. The exploitation of datasets gathered from a variety of sources, which makes the construction of robust models possible, is one of the limitations encountered when implementing this idea. Hussain et al. [29] presented a classification strategy in DL with the intention of identifying COVID-19 by utilizing CXR pictures as the data source. The extremely contagious disease known as COVID-19 has had a significant influence on society, contributing to the emergence of pneumonia and having an effect on a variety of organ systems. In most cases, the disease is passed on from person to person through interactions with other people in close quarters, such as in public areas, places of employment, and educational institutions. In a great number of developing countries, there has been a growing need for COVID-19 testing kits. Recent investigations in radiology imaging, such as CT scans and X-rays, have revealed considerable new insights into the spread of the COVID-19 virus. Radiologists were the ones who carried out these studies. The use of CNN, in conjunction with CT and X-ray images of the lungs, was implemented in order to accelerate the diagnosis of diseases and improve the accuracy of testing kits. The highest percentage of accuracy that could be attained was 94.2 percent. This idea had a number of flaws, one of which was the demand for a significant quantity of testing kits. Benmalek et al. [30] carried out an investigation of the effectiveness of several CNN models in diagnosing COVID-19 infection through the use of chest imaging procedures. In the context of CXR and CT images, a comparison analysis was carried out as part of this proposal to evaluate how well the performance of many distinct CNN models, including MobileNetV2, InceptionV3, and ResNet-18, compared. When the diagnostic performance of CT scans and CXR photos was compared using identical CNN architectures, it was revealed that CT scans were better at discovering COVID-19-positive cases. CXR pictures, on the other hand, were not as effective. In comparison to CXR, computed tomography (CT) provides better contrast and generates high-resolution pictures, which makes it easier to extract important information from medical images. In spite of the fact that the findings of the study are optimistic in terms of chest imaging detection for COVID-19, it is essential

to be aware of the challenges that arise from the combination of diverse datasets as well as the ways in which insufficient picture quality may influence how successfully the classification is carried out.

3. Materials and Methods

More recent studies have shown that adding shorter connections between layers in convolutional networks, especially those close to the input and output, can make the networks much deeper, more accurate, and easier to train. This paper acknowledges the aforementioned fact and presents the Dense Convolutional Network (DenseNet) as a solution. The DenseNet model, comprising 15 layers, is introduced in this paper. Each layer in the model is connected to every other layer in a feed-forward manner. The proposed model architecture consists of a single input layer, followed by four convolutional layers, three pooling layers, four dropout layers, one flattening layer, and two DenseNet layers, as stated in Figure [1]. The development of the enhanced model involves a series of eight steps. These steps include:

- (1) Collecting the dataset
- (2) Data Augmentation
- (3) performing data preprocessing
- (4) Determining training and testing sets
- (5) using an optimized model and
- (6) evaluating the performance.

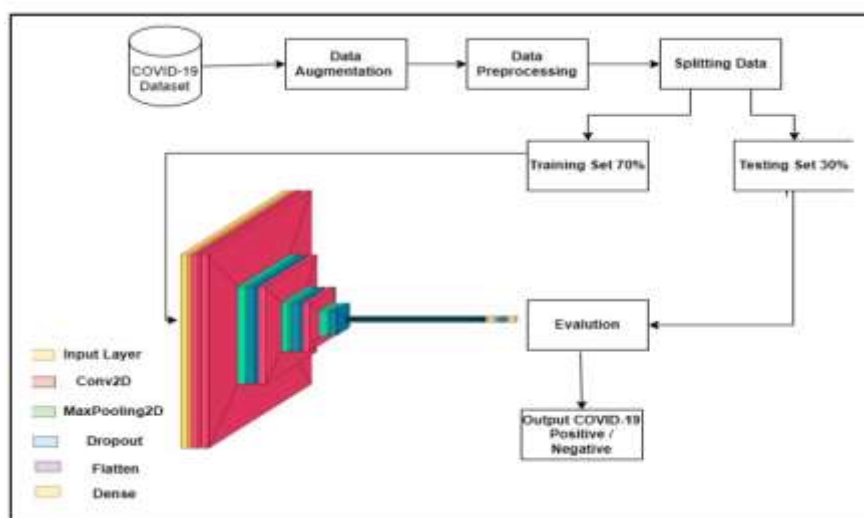


Figure 1: optimized COVID-19 prediction model (OACP)

3.1 Dataset Collection and Description

A cohort including 930 posteroanterior CXR images was utilized from a publicly available COVID-19 image data repository, specifically focusing on images of patients who tested positive for the virus. All individuals included in the study were confirmed to have tested positive for COVID-19 and were sourced from multiple hospitals worldwide between December 2019 and March 2020. In this paper, a cohort of 3340 posteroanterior CXR images was utilized from a publicly available dataset on Kaggle, specifically the "CXR Images (Pneumonia)" dataset. The cohort consisted of individuals categorized as normal or negative patients. However, it is worth noting that a total of 930 photos were captured specifically in relation to the COVID-19 pandemic available at [31, 32].

3.2 Data augmentation

It is common practice to apply a method known as data augmentation in order to expand both the variety and the quantity of labeled datasets used in the training process. The application of input transformations that preserve the corresponding output labels is what makes this possible. Data augmentation is a method often used in machine learning (ML) to fix issues like class imbalance, over-fitting, and convergence issues in deep learning [33]. This strategy seeks to improve the overall

performance of ML models as well as the results they produce by supplementing the data that is already available. In the context of deep learning, several different photo enhancement techniques, such as flipping, cropping, noise injection, rotation, random erasing, color change, and geometrical transformation, are utilized in order to improve the images. In order to successfully collect and learn the various changes that occur throughout the training phase of the OACP classifier, the suggested method utilizes a number of data augmentation techniques. These techniques include flipping and rotation.

3.3 Performing Data Preprocessing

The COVID-19 detection model that is being considered includes a pre-processing stage that has as its primary objective the enhancement of the image that is being used as input. The pre-processing stage is implemented so that undesirable distortions can be reduced and certain visual features can be enhanced. This was done in order to achieve the aforementioned goals. Image enhancement is a procedure that involves decreasing the impact of blurriness or noise that is present in the image that is being processed. The picture scaling method and the median filtering method are both included in the pre-processing stage's toolbox of techniques.

Image Scaling: The process of picture scaling is most useful in the resizing of input CXR images because of its ability to magnify or reduce the size of an image. Scaling is a process that comprises two distinct categories, which are called scaling up and scaling down, respectively. In these categories, you can change the size of the input photographs by either increasing or decreasing their dimensions. This can be done either way. It is absolutely necessary for the success of this technique that the quality of the image that is being input does not suffer in any way.

Median Filtering: This technique is used to generate an image that is free of noise through the application of median filtering. This technique makes use of a non-linear filter, and the median value is what's applied to it so that the image's sharpness is maintained where it matters most: at the image's edges. Gray level ranking, rather than the noise value, was utilized in order to accomplish the goal of restoring the median value, and this was successfully accomplished.

3.4 Determining Training and Testing Sets

The photos were divided into two portions, namely Train and Test, after being randomly rearranged. The Train section consists of 700 images categorized into two labels, positive and negative COVID-19, and is used for training the model. The test section, on the other hand, comprises 230 images also categorized into positive and negative COVID-19 labels and is utilized for evaluating the model.

3.5 Using an Optimized Model

The proposed architecture consists of a single input layer, followed by four Convolutional layers, three Pooling levels, four Dropout layers, one flatten layer, and finally two DenseNet layers. The input layer is responsible for obtaining processed photos that have been resized to a new dimension of (224, 224, 3). The Conv2D layer is designed with 32 filters, each having a kernel size of 3x3. These filters are utilized to extract tiny features, which are then multiplied by the Input layer. It is important to acknowledge that the subsequent levels will undergo multiplication by the variable X, which serves as a repository for the entire architecture. The Conv2D layer is configured with 64 filters, each having a kernel size of 3x3. This configuration allows for the extraction of features that are larger in size compared to the prior layer. The utilization of MaxPooling2D and Dropout techniques in neural networks serves the purpose of diminishing the quantity of neurons, extracting significant characteristics, and mitigating the risk of overfitting. The Conv2D layer is configured with 64 filters and a kernel size of 3x3, which enables the extraction of larger features. The utilization of MaxPooling2D and Dropout techniques in neural networks serves the purpose of diminishing the quantity of neurons, extracting significant characteristics, and mitigating the risk of overfitting. The Conv2D layer is configured with 128 filters and a kernel size of 3x3, which enables it to extract features that are larger in size compared to the preceding layer. The use of MaxPooling2D and Dropout techniques in neural networks serves to decrease the quantity of neurons, extract significant characteristics, and mitigate the risk of overfitting. To flatten a matrix is to convert it from a two-dimensional structure to a one-dimensional column. The dense layer is composed of 64 neurons. The dropout rate, in this case, deviates from the norm with a distinct value of 0.5. The utilization of the sigmoid function as an activation function is commonly employed in binary classification tasks.

3.6 Evaluations

The evaluation of the predictive capacities and performance of the offered prediction models involves the utilization of five metrics. The performance of each model is assessed by the utilization of many metrics, including accuracy, F1-score, recall, precision [34]. The calculation of accuracy is determined by utilizing Equation (1)

$$Accuracy = \frac{TPos + TNeg}{TPos + FPos + FNeg + TNeg} \quad (1)$$

where TPos is true positive, TNeg is true negative, FPos is false positive, and FNeg is false negative. Precision is calculated using Equation (2):

$$Precision = \frac{TPos}{TPos + FPos} \quad (2)$$

Recall is computed using Equation (3):

$$Recall = \frac{TPos}{TPos + FNeg} \quad (3)$$

F-measure is calculated using Equation (4):

$$F1 - score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (4)$$

4. Results and discussion

In this section, the results of running simulations based on the suggested ideal model for COVID-19 prediction are displayed. The Jupyter Notebook version (6.4.6) was utilized in the process of putting the machine learning models into action. Jupyter Notebook simplifies the process of writing and running code written in Python. Making a comparison between the outcomes from the proposed model and those from current deep learning algorithms in use allows for the determination of the prediction's accuracy. In addition, in order to evaluate the efficacy of the suggested method, accuracy, F1-score, recall, and precision are typically utilized metrics. These are the same metrics that are used to evaluate the efficacy of machine learning models. These metrics offer quantifiable measurements of how well a model performs in terms of correctly classifying instances, identifying true positives and true negatives, as well as false positives and false negatives, in addition to overall model performance. The experimental findings regarding accuracy are detailed in Table 1, which may be found here.

Table 1: Simulation outcomes of proposed OACP model and existing techniques using CXR dataset.

Models	accuracy	F1-score	Recall	Precision
VGG 19	85	88	81	85
Google Net	88	90	82	87
ResNet50	85	87	80	84.3
DenseNet201	90.5	88	83	89.6
Shuffle Net	91	89	82	90.1
Squeeze Net	92	84	86	91.6
OACP	98	98.6	90	97.6

The OACP model is the most accurate of all the experimental models that are included in Table 1. Its accuracy is significantly higher than that of the other models. To be more specific, its accuracy, F1-Score, recall, and precision are respectively 98%, 98.6%, 90%, and 97.6%. Additionally, the Squeezenet performs quite well, with an accuracy of 92%, an F1-Score of 84%, a recall of 86%, and a precision of 91.6%, respectively. In contrast, the VGG-19 exhibits the least amount of accuracy when compared to the other two models. Its accuracy, F1-Score, recall, and precision are all at 85%, while its accuracy is 88% and its precision is 81%. The accuracy of the OACP model in predicting COVID-19 is contrasted visually in Figure 2, which shows how it stacks up against other models.

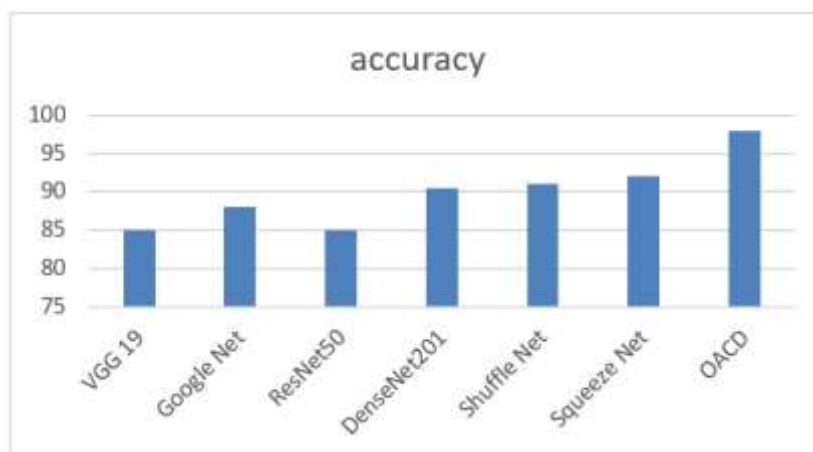


Figure 2: Comparison between models in terms of accuracy.

In the context of COVID-19 prediction, the evaluation of accuracy and loss serves as a mechanism to evaluate the effectiveness of OACP. This evaluation may be found in the context of the COVID-19 prediction. In addition to this, it assists medical practitioners in correctly recognizing COVID-19 patients in a timely manner. During the training and testing of the dataset, there was a considerable improvement in both the accuracy and loss of OACP. The OACP model's accuracy is superior to that of other methods, including VGG 19, GoogleNet, ResNet50, DenseNet201, ShuffleNet, and SqueezeNet. The results of OACP's performance in terms of both its training and testing accuracy are depicted in Figure 3. The data obtained from the training samples as well as the testing samples are used in an in-depth analysis to determine how accurately the OACP method performs.

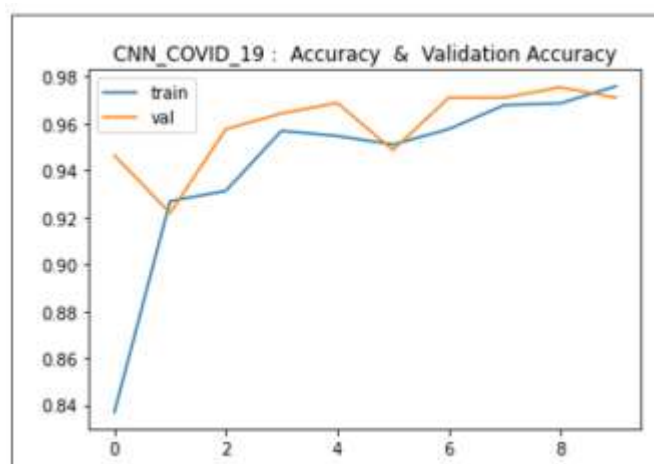


Figure 3: Training and testing accuracy for proposed OACP.

The training and testing losses of OACP can be seen across a number of epochs, as shown in Figure 4. In order to conduct an analysis of the loss value, the results of the training and testing samples taken from the dataset are considered. The figure that has been provided shows that both the training loss and the testing loss of the suggested method show a trend toward reducing with time. However, the figure also shows that the test loss is consistently somewhat larger than the training loss. The OACP that has been proposed has shown that it is significantly better in terms of performance, with an overall loss of 0.8. This value is far lower than that which can be reached using the approaches that are currently being used for the prediction of suitable classes. In addition, it has been demonstrated that the curve does not display any indications of overfitting. By utilizing the maximum number of epochs possible, the OACP was able to bring the issues of over-fitting and under-fitting that were present in the COVID-19 prediction to a condition of equilibrium. In addition to this, it can be seen from the graph that there is a considerable drop in the value of the loss that occurs after 10 epochs have passed.

After some time had passed, the training and testing curves eventually met in the middle to produce an accurate forecast of COVID-19 classifications.

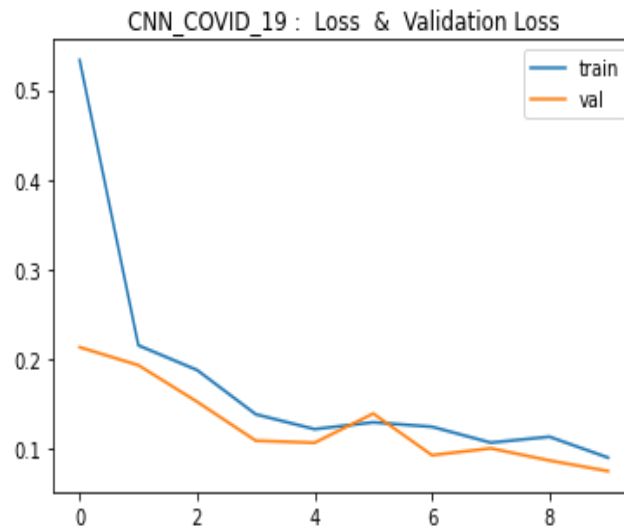


Figure 4: Training and testing loss for proposed OACP.

The suggested OACP is subjected to an extensive amount of simulation, making use of the CXR datasets, so that the efficacy of COVID-19 prediction can be evaluated. Furthermore, in order to illustrate the efficacy of the prediction performance, OACP has been analyzed alongside other prediction approaches already in use. This was done in order to compare the two. The confusion matrix generated by OACP while using the CXR dataset is displayed in Figure 5. For the objective of identifying COVID-19 infection cases, the OACP has been utilizing patient data that has been retrieved from CXR databases. When compared to the input data, the confusion matrix revealed that OACP had increased accuracy when predicting class labels and a decreased rate of wrong predictions. Figure 5 of the confusion matrix also provides a visual representation of the total number of values in the samples that can be successfully predicted. On the other hand, the data that is still available has shown that a sizeable proportion of predictions were incorrect.

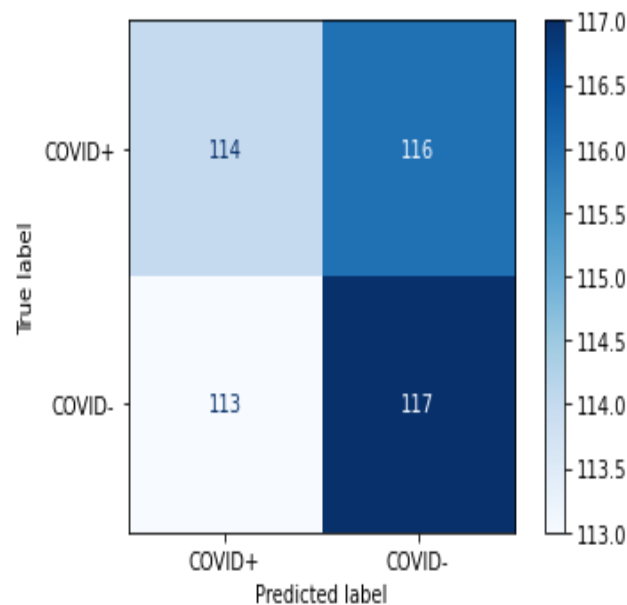


Figure 5: Confusion Matrix of proposed OACP for COVID-19 prediction.

Consequently, OACP model has undergone multiple training epochs to assess its predictive efficacy in relation to COVID-19. Moreover, if the number of epochs has been consistently maximized, OACP has exhibited superior training performance and achieved more favorable results.

6. Conclusions and Future Work

The proposed approach has employed publicly accessible CXR datasets to evaluate the effectiveness of the solution. Consequently, the simulated results demonstrated that OACP outperformed the currently employed techniques that achieved a remarkable performance with value of 97.8% for Accuracy and a computation time of 920 seconds when evaluated using the CXR dataset. OACP model optimized the pre-trained architecture, namely DenseNet-201, in order to accurately identify the class value. The implemented OACP is executed on the Python platform and assesses performance based on several metrics, such as accuracy, training score, testing score, F-measure, recall and precision. This paper presents a potentially effective method for identifying individuals with COVID-19 through the analysis of CXR images, employing a combination of deep learning techniques. OACP model utilizes picture scaling and median filtering as pre-processing techniques to enhance the quality of the image. OACP model exhibits superior accuracy compared to other models. Specifically, its accuracy, F1-Score, Recall, and precision are 98%, 98.6%, 90% and 97.6%, respectively. In contrast to the currently employed methodologies utilizing CXR datasets. Despite exhibiting enhanced performance, the proposed methodology continues to exhibit deficiencies in terms of real-time accuracy and efficiency enhancement. In the future, it is anticipated that OACP would undergo further refinement for the purpose of COVID-19 prediction. This will involve the utilization of additional meta-heuristic algorithms and the implementation of a hybrid model in order to boost the accuracy of the predictions.

Acknowledgment: Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2023R308), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Funding: Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2023R308), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Conflicts of Interest: “The authors declare no conflict of interest.”

References

- [1] Hua, J., Shaw, R.: Coronavirus (COVID-19) infodemic and emerging issues through a data lens: the case of China. *Int. J. Environ. Res. Public Health* 17(7), 2309 (2020).
- [2] Chhikara, B.S., Rathi, B., Singh, J., Poonam, F.N.U.: Coronavirus SARS-CoV-2 disease COVID-19: infection, prevention and clinical advances of the prospective chemical drug therapeutics. *Chem. Biol. Lett.* 7(1), 63–72 (2020)
- [3] Saif, L.J., Jung, K.: Comparative pathogenesis of bovine and porcine respiratory coronaviruses in the animal host species and SARS-CoV-2 in humans. *J. Clin. Microbiol.* 58(8), e01355-e1420 (2020)
- [4] Clementini, M., Raspini, M., Barbato, L., Bernardelli, F., Braga, G., Di Gioia, C., Cairo, F.: Aerosol transmission for SARSCoV-2 in the dental practice. A review by SidP COVID-19 taskforce. *Oral Dis.* 28, 852–857 (2020)
- [5] Guo, J.W., Radlof, C.L., Wawrzynski, S.E., Cloyes, K.G.: Mining twitter to explore the emergence of COVID-19 symptoms. *Public Health Nurs.* 37(6), 934–940 (2020)
- [6] Carter, L.J., Garner, L.V., Smoot, J.W., Li, Y., Zhou, Q., Saveson, C.J., Liu, C.: Assay techniques and test development for COVID-19 diagnosis. 6, 591–605 (2020)
- [7] Lu, Y., Li, L., Ren, S., Liu, X., Zhang, L., Li, W., Yu, H.: Comparison of the diagnostic efficacy between two PCR test kits for SARS-CoV-2 nucleic acid detection. *J. Clin. Lab. Anal.* 34(10), e23554 (2020)

- [8] Bièche, I., Noguès, C., Paradis, V., Olivi, M., Bedossa, P., Lidereau, R., Vidaud, M.: Quantitation of hTERT gene expression in sporadic breast tumors with a real-time reverse transcription-polymerase chain reaction assay. *Clin. Cancer Res.* 6(2), 452–459 (2000).
- [9] Militante, S.V., Dionisio, N.V., Sibbaluca, B.G.: Pneumonia and COVID-19 detection using convolutional neural networks. In: 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE) IEEE, pp. 1–6. (2020)
- [10] Tang, Y.B., Tang, Y.X., Xiao, J., Summers, R.M.: Xlsor: A robust and accurate lung segmentor on chest x-rays using crisscross attention and customized radiorealistic abnormalities generation. In: International Conference on Medical Imaging with Deep Learning, pp. 457–467. PMLR. (2019)
- [11] Awadalla, B.A.E., Khalid, K.A.: The important positioning techniques for the investigation of chest diseases-practical approach. 1-62, (2000).
- [12] Tabik, S., Gómez-Ríos, A., Martín-Rodríguez, J.L., Sevillano García, I., Rey-Area, M., Charte, D., Herrera, F.: COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on chest X-ray images. *IEEE J. Biomed. Health Inform.* 24(12), 3595–3605 (2020)
- [13] Boussein, M.L., Boyd, S.K., Christiansen, B.A., Guldborg, R.E., Jepsen, K.J., Müller, R.: Guidelines for assessment of bone microstructure in rodents using micro-computed tomography. *J. Bone Miner. Res.* 25(7), 1468–1486 (2010)
- [14] Solovyev, R., Melekhov, I., Lesonen, T., Vaattovaara, E., Tervonen, O., Tiulpin, A. Bayesian feature pyramid networks for automatic multi-label segmentation of chest X-rays and assessment of cardio-thoracic ratio. In: International Conference on Advanced Concepts for Intelligent Vision Systems, pp. 117–130. (2020)
- [15] Cohen, J., Normile, D.: New SARS-like virus in China triggers alarm. *Science.* 367, 234–235 (2020)
- [16] Balyen, L., Peto, T.: Promising artificial intelligence-machine learning-deep learning algorithms in ophthalmology. *Asia Pac. J. Ophthalmol.* 8(3), 264–272 (2019)
- [17] Mair, C., Kadoda, G., Lefey, M., Phalp, K., Schofeld, C., Shepperd, M., Webster, S.: An investigation of machine learning based prediction systems. *J. Syst. Softw.* 53(1), 23–29 (2000)
- [18] Ibrahim, I., Abdulazeez, A.: The role of machine learning algorithms for diagnosing diseases. *J. Appl. Sci. Technol. Trends* 2(01), 10–19 (2021)
- [19] Fong, S., Deb, S., Yang, X.S.: How meta-heuristic algorithms contribute to deep learning in the hype of big data analytics. In: Progress in intelligent computing techniques: theory practice and applications, pp. 3–25. Springer, Singapore (2018)
- [20] Firouzi, F., Farahani, B., Daneshmand, M., Grise, K., Song, J., Saracco, R., Luo, A.: Harnessing the power of smart and connected health to tackle COVID-19: IoT, AI, robotics, and blockchain for a better world. *IEEE Internet Things J.* 8(16), 12826–12846 (2021)
- [21] Asada, K., Komatsu, M., Shimoyama, R., Takasawa, K., Shinkai, N., Sakai, A., Hamamoto, R.: Application of artificial intelligence in COVID-19 diagnosis and therapeutics. *J. Pers. Med.* 11(9), 886 (2021)
- [22] Bhattacharyya, A., Bhaik, D., Kumar, S., Thakur, P., Sharma, R., Pachori, R.B.: A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images. *Biomed. Signal Process. Control* 71, 103182 (2022)
- [23] Shastri, S., Kansal, I., Kumar, S., Singh, K., Popli, R., Mansotra, V.: CheXImageNet: a novel architecture for accurate classification of COVID-19 with chest x-ray digital images using deep convolutional neural networks. *Health Technol.* 12, 1–12 (2022)
- [24] Khan, E., Rehman, M.Z.U., Ahmed, F., Alfouzan, F.A., Alzahrani, N.M., Ahmad, J.: Chest X-ray classification for the detection of COVID-19 using deep learning techniques. *Sensors* 22(3), 1211 (2022)
- [25] Alshazly, H., Linse, C., Barth, E., Martinetz, T.: Explainable COVID-19 detection using chest CT scans and deep learning. *Sensors* 21(2), 455 (2021)
- [26] Maghdid, H.S., Asaad, A.T., Ghafoor, K.Z., Sadiq, A.S., Mirjalili, S., Khan, M.K.: Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms. In: Multimodal image exploitation and learning. *Int. Soc. Optics Photonics* 11734, 99–110 (2021)
- [27] Ismael, A.M., Şengür, A.: Deep learning approaches for COVID-19 detection based on chest X-ray images. *Expert Syst. Appl.* 164, 114054 (2021)

- [28] Chen, J.I.Z.: Design of accurate classification of COVID-19 disease in X-ray images using deep learning approach. *Journal of ISMAC* 3(2), 132–148 (2021)
- [29] Hussain, E., Hasan, M., Rahman, M.A., Lee, I., Tamanna, T., Parvez, M.Z.: CoroDet: a deep learning based classification for COVID-19 detection using chest X-ray images. *Chaos Solitons Fractals* 142, 110495 (2021)
- [30] Benmalek, E., Elmhamdi, J., Jilbab, A.: Comparing CT scan and chest X-ray imaging for COVID-19 diagnosis. *Biomed. Eng. Adv.* 1, 100003 (2021)
- [31] covid-chestxray-dataset <https://github.com/ieee8023/covid-chestxray-dataset>
- [32] chest-xray-pneumonia <https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>
- [33] Kermany, D., Zhang, K., Goldbaum, M.: Labeled optical coherence tomography (OCT) and chest X-ray images for classification. *Mendeley Data* V2 (2018).
- [34] Fouad, Y.; Osman, A.M.; Hassan, S.A.; El-Bakry, H.M.; Elshewey, A.M. Adaptive Visual Sentiment Prediction Model Based on Event Concepts and Object Detection Techniques in Social Media. *Int. J. Adv. Comput. Sci. Appl.* 14(7), 2023