# Detection of Covid-19 in chest X-ray images using a Resnet-50

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***Abstract*— Covid-19 is a serious illness that has affected millions of individuals worldwide, it has been declared as a pandemic by the World Health Organization (WHO) on 11th March 2020. One critical element in combating COVID-19 is the capacity to identify infected individuals early and place them under special care. Chest computed tomography (CT) and chest X-ray are two medical imaging methods widely used to identify lung infection. This study presents a deep convolutional neural network (DCNN) based on a pre-trained deep CNN model Residual Network (Resnet-50) that can distinguish COVID-19 from two other classes (normal and pneumonia) by using 4-fold cross validation. The dataset used consists of 317 frontal x-ray images of COVID-19, 5836 pneumonia, and 1203 normal chest x-ray images.**

**The experimental results demonstrate that the proposed model is effective at identifying COVID-19 from normal and pneumonia cases, with average accuracy, precision, and sensitivity cases of 97.3 %, 98.1 %, and 95.1%, respectively.**

**Keywords—COVID-19, Chest X-ray images, Classification, Deep-learning, Pre-trained deep CNN model**

## I. Introduction

Covid-19 is a severe disease where millions of people are infected by this dangerous virus around the world. The outbreak of COVID-19 started in Wuhan, China in December 2019, and it quickly spread throughout the world in a few months [1]. This virus causes significant symptoms in humans such as fever (98%), cough (76%), and myalgia or fatigue (44%) [2]. The coronavirus (CoV) belongs to a large family of viruses that cause diseases such as the Middle East Respiratory Syndrome (MERS-CoV) and the Severe Acute Respiratory Syndrome (SARS-CoV) [3]. On March 11,2020 ,when the number of COVID-19 cases in 114 countries exceeded 118,000 cases, with over 4,000 deaths, WHO declared a Coronavirus is a pandemic [4]. Chest radiography imaging (CXR and CT scan images) is very important and standard tools for the alternative means of COVID-19 testing [5]. CXR images are one of the popular and useful methods for detecting COVID-19 and monitoring disease progression [6] because it is widely available, faster and cheaper than CT images [7].

Deep learning has been one of the fastest developing fields in computer and data science in recent years. In the area of medical imaging, deep learning (DL) has many more successes in terms of analysis and interpretation. DL solves the problem of diagnostic COVID-19 where their accuracy in the prediction of the disease is the same and sometimes even greater than an average radiologist [8]. Deep Convolutional Neural Networks (DCNN) are among the deep learning approaches that have showed significant promise in medical image classification and have therefore been widely adopted by the research community [9].

In this paper, we present an approach for differentiating COVID-19 from two other classes normal and pneumonia chest X-ray images using a DCNN model based on the Residual Network architecture with 50 layers (ResNet-50) [10].Our method has been evaluated in multi-class (normal (healthy), COVID-19 and pneumonia) classifications. We then compared the results with other literature research. The model can enable doctors to diagnose a chest X-ray (CXR) infection with COVID-19.

To evaluate the framework in a robust and effective way, a number of evaluation metrics such as multiclass accuracy, F1-scores [11], sensitivity, specificity [12], precision, and confusion matrix has been used. The values of these metrics have been determined on different ratios of training and test samples considering a number of layers in deep model.

The rest of the paper is organized as follows: Section II presents related works. Section III reports the materials and methodology. Section VI provides the experimental results and discussion, performance evaluation, and the result comparison of our proposed approach with existing approaches, and finally, the conclusion of the paper residues in section V.

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## II. RELATED WORKS

Deep learning (DL) techniques on chest X-ray for COVID-19 classification have been actively used by researchers from all over the world, with over 40,000 studies published [13], including the work presented in [14], in which the authors proposed the DarkNet model for classifying X-ray images into two classes (COVID vs. No-Findings) and three classes (COVID vs. No-Findings vs. Pneumonia). The model obtained 98.08 % and 87.02 % accuracy in binary and multi-class classification, respectively. Horry et al. [15] evaluated the effectiveness of five (5) pre-trained CNNs in identifying COVID-19 from X-ray images: VGG16/VGG19 Resnet50, Inception V3, and Xception. Wang and Wong [13] created COVID-Net, an algorithm that detects COVID-19 from two other classes, normal and pneumonia (bacterial and viral), with an accuracy of 83.5%.In the work [16], a deep learning network of 101 layers (ResNet-101) was used, and it obtained an accuracy of 77.3 %. The Optimized Convolutional Neural Network (OptCoNet) proposed in [17] is divided into two components: optimized feature extraction and classification. Using a publicly accessible dataset of COVID-19, normal, and pneumonia images, the model was evaluated and compared with different classification approaches. OptCoNet achieved an accuracy of 97.78 %.

Furthermore, the authors of [18] proposed a novel approach called Decompose, Transfer, and Compose (DeTraC) address to classify COVID-19 from chest X-ray images, with an accuracy of 95.12 %. To identify COVID-19-infected patients based on X-ray images the authors of proposed a model in [19] that combined a pre-trained CNN model with a support vector machine (SVM). The proposed approach in [20] consists of three pre-trained CNN models: DenseNet201, Resnet50V2, and Inceptionv3. The model was used to classify Covid-19 patients based on CXR images; it achieved an accuracy of 95.7 %. Khan et al. [21] developed a Deep Convolutional Neural Network model (CoroNet) based on exception architecture that has been pre-trained to identify COVID-19 infection from chest X-ray images, with an overall accuracy of 89.6% . In [22], the performance of four pre-trained convolutional models (ResNet18, ResNet50, SqueezeNet, and DenseNet121) for detecting COVID-19 from Chest X-ray images was evaluated using a dataset including 224 COVID-19, 700 pneumonia, and 504 normal X-ray images. The majority of these networks achieved a sensitivity of 98 %.

The researchers in [23] developed a novel algorithm called Domain Extension Transfer Learning (DETL), which used a pre-trained deep convolutional neural network to classify datasets into four categories (normal, pneumonia, other diseases, and Covid – 19). Their model achieved an accuracy of 90.13 %. Narin et al. [24] evaluated the performance of five convolutional neural network-based models (ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2) to predict COVID-19 patients automatically using chest X-ray images .The dataset used including four categories : normal, COVID-19, bacterial, and viral pneumonia patients. They obtained a performance accuracy of 99.7 % with model ResNet50.

Moreover, the performance of -stats of-the-art convolutional neural network architectures was evaluated in [25]. The authors determined that vgg19 is the best classification model, with an accuracy of 98.75 % in 2-class classifications and 93.48 % in 3-class classifications respectively. Punn and Agarwal [26] tested the performance of six pre-trained convolutional (baseline ResNet, Inception-v3, Inception ResNet-v2, DenseNet169, and NASNetLarge) on binary classification (as normal and COVID-19 cases) and multiclass classification (as COVID-19, pneumonia, and normal cases) from CXR images.

Following the results, the authors conclude that NASNetLarge performed better, especially in the binary classification of COVID-19 samples. The authors of [27] evaluated the performance of pre-trained convolutional neural networks for identifying COVID-19 infection from chest X-ray images. The experimental results show that VGG16 and VGG19 obtained a better accuracy of 95 %.

## III. MATERIALS AND METHODOLOGY

The dataset used in this study will be introduced in this part, followed by the approved preprocessing and data augmentation methods. Finally, the architecture of the deep convolutional neural network (DCNN) suggested in this research will be described.

### *A. Chest x-ray dataset*

In our study, we collected datasets from two different sources. The first dataset is normal and pneumonia x-ray images obtained from the source Kaggle repository “Chest X-Ray Images (Pneumonia)” [28], and it contains 1583 normal, 2780 bacterial pneumonia, and 1493 viral pneumonia cases with a total of 4273 images. The second dataset from the open-source GitHub repository shared by Dr. Joseph Cohen et al. [29], which was largely assembled from websites such as (Radiological Society of North America (RSNA), Radiopaedia, the Italian Society of Medical, and others). It includes 317 frontal x-ray images of COVID-19 positive patients.

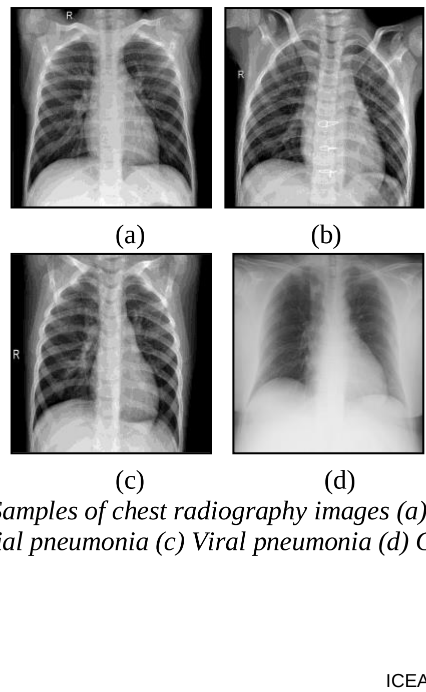


*Fig .1. Samples of chest radiography images (a) Normal (b) Bacterial pneumonia (c) Viral pneumonia (d) COVID-19.*

### A. *Preprocessing*

In this work, a preprocessing step was employed, which comprised several techniques for enhancing the quality of the original images and eliminating undesirable characteristics in order to increase the efficacy of training the classifier. In the first stage, all x-ray images were converted to grayscale and scaled to 224×224×3 pixels. The datasets used in this experiment were acquired from several hospitals. Most images in these datasets have poor quality and low contrast; thus, in the final step, we used an enhancement technique that includes a method called Contrast Limited Adaptive Histogram Equalization (CLAHE) and a wavelet image de-noising algorithm for increasing contrast and changing the brightness level of an image to make it look better.

*Adaptive histogram equalization (CLAHE):* Contrast limited adaptive histogram equalization (CLAHE) is an effective contrast enhancement approach because it improves textural characteristics and resolvable details based on the contrast or intensity of the pixels [30]. The CLAHE procedure is divided into two phases. To begin, the input images are divided into a number of sub-images (tiles) of about similar size [31]. This division results in three distinct sets of regions: corner region (CR), border region (BR), and inner region (IR) . Second, the histogram of each group is generated [32]. The difficulty of enhancing contrast in CLAHE may be solved by providing the boundary value on the histogram , is determined using Equation (1).

$$\beta = \frac{M}{N}\left(1 + \frac{1}{\alpha}(S_{max} - 1)\right) \quad (1)$$

Where

- $\beta$ is the clip limit
- M and N are the number of pixels and gray-levels in each region, respectively.
- The parameter $\alpha$ is a clip factor (0-100) [33].

*1) Denoising algorithm :* The de-noising approach works by first decomposing the image into wavelets using the Daubechies (db3) transform, and then determining soft threshold values, is provided in Equation (2).

$$Soft(w,T) = \begin{cases} sgn(w)(|w| - T)_+ & : |w| \geq 0 \\ 0 & : |w| < 0 \end{cases} \quad (2)$$

The thresholding results discriminate between undesired coefficients and those containing important image components, and it is over smoothing in the reconstructed image.

The Bayes technique was then used to apply wavelet shrinkage based on the idea of thresholding the wavelet coefficient. The Bayes threshold, $t_B$, is shown in Equation (3).

$$t_B = \frac{\sigma^2}{\sigma_s} \quad (3)$$

Where $\sigma^2$ represents the noise variance and $\sigma_s$ represents the signal variance without noise.

The variance of the signal $\sigma_s$ is computed in Equation (4).

$$\sigma_s = \sqrt{max(\sigma_w^2 - \sigma^2, 0)} \quad (4)$$

However, the noise and the signal are independent of one another; they may be approximated as follows:

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \quad (5)$$

The additive noise variance can be calculated as illustrated in Equation (6).

$$\sigma_w^2 = \frac{1}{n^2}\sum_{x,y=1}^{n}(w^2(x,y)) \quad (6)$$

- *n* represents the number of sub-band
- $w_{X,Y}$ means wavelet coefficients

Finally, using the Inverse transform, the image was de-noised (wavelet reconstruction).

Fig. 2. Illustrates the results of each technique that was used in the preprocessing step.

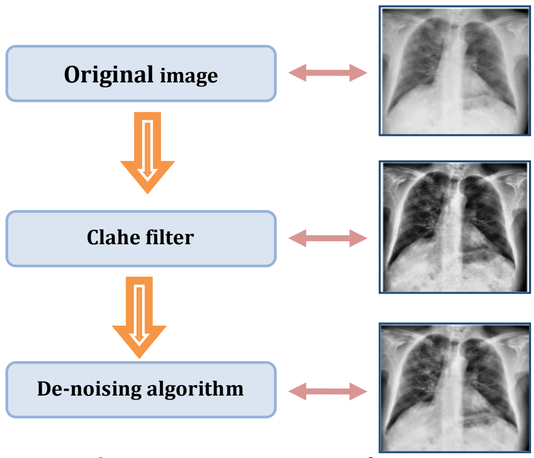


*Fig.2. Schematic representation of preprocessing steps to obtain the final images for the dataset.*

In this study, data augmentation techniques were used after the preprocessing stage to expand the number of samples in the constrained database by producing additional labeled images without changing the semantic meaning of the images. The transformations used in this research include horizontal flip, rotation (10%), and translation (10% in x and y dimensions).

### B. *Proposed deep convolutional neural network (DCNN)*

Transfer learning (TL) has been more popular in medical imaging applications in recent years since it is a good feature extractor. Among the many deep learning models, ResNet-50 based on a residual network created by He et al. [10] was used in the proposed deep convolutional neural network (DCNN).

DCNN is composed of a base network and a classification network. The base network is a deep transfer learning model (Resnet-50) that is used to generate feature values for each image. It consists of 16 residual bottleneck blocks, each of which is composed of a convolutional layer, batch normalization, and rectified linear regularization unit (ReLU). The convolution layer sizes in each block are 1x1, 3x3, and 1x1 with feature maps (64, 128, 256, 512, and 1024) while the classification network in DCNN replaces the fully connected layer of the ResNet-50 to classify COVID-19 chest x-ray images from two other categories (Normal and Pneumonia). This stage comprises three sets of fully connected layers and three sets of dropout layers. The sizes of the two initial sets of fully connected layers in this architecture were chosen to be 200 and 300, respectively, while the size of the last depends on the number of categories in the dataset.

Dropout ratios of 0.12, 0.2, and 0.15 have been chosen. The dropout layer in the design helps to alleviate the overfitting problem and enhance model performance. In addition, in the final layers of the proposed model, the Softmax activation function is used to classify the images into three classes. A deep convolutional neural network (DCNN) is shown schematically in Fig. 3.

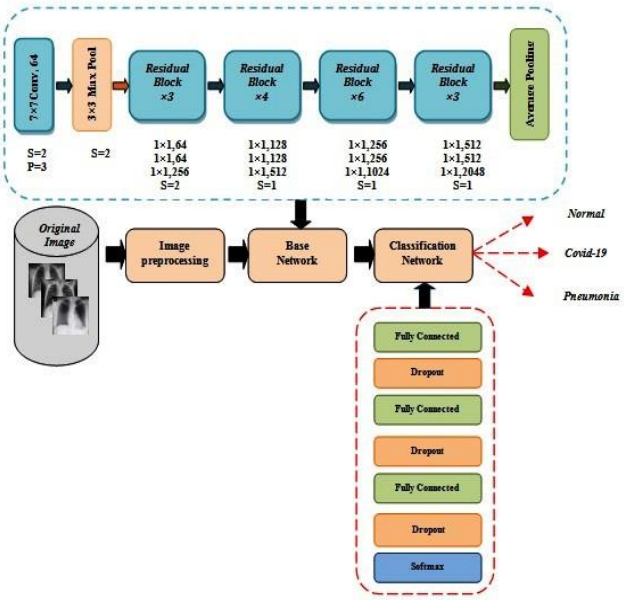


*Fig.3. A schematic of the DCNN model used to predict normal (healthy), COVID-19, and pneumonia patients.*

## IV. RESULTS AND DISCUSSION

### A. Training

The effectiveness of our algorithm was tested by using X-ray images to detect and classify COVID-19 confirmed patients into two categories: normal and pneumonia. 317 COVID-19 images, 1583 normal images, and 4273 pneumonia cases were used to train the model. The system was trained using a different set of images from the dataset using K-fold cross-validation (K=4), which could give us a better assessment of our performance.

This type of validation involves dividing the data set into four equal-sized pieces, using one part as the test set and the remainder as the training set each time. The suggested model was run on a computer with 8 GB RAM and an Intel (R) Core (TM) i5-4460 CPU running on Windows 10 using MATLAB 2020a (64 bit). CXR images were used to evaluate the suggested model for multi-class classification (Normal, Covid-19, and pneumonia). For 35 epochs, we fine-tuned our model. The loss function is optimized using the ADAM optimizer with a learning rate of 0.0001 and a batch size of 25.

### B. Evaluation Metrics

The metrics of measurement $Acc_m$, $Sens_m$, $Spec_m$, $Prec_m$, and F1-score$_m$ are used to assess the success of multi-class classification, as illustrated in Equation (7) to Equation (11). Represents the multiclass accuracy, sensitivity, specificity, precision, and F1-scores measure.

$$Acc_m = \frac{TPn + TPc + TPp}{\text{total samples}} \times 100 \tag{7}$$

$$Sens_m = \frac{TPc + TPp}{TPc + TPp + FNc + FNp} \times 100 \tag{8}$$

$$Spec_m = \frac{TPn}{FPc + TPn + FPp} \times 100 \tag{9}$$

$$Prec_m = \frac{TPc + TPp}{TPc + FPc + TPp + FPp} \tag{10}$$

$$F_{1\text{-}Score m} = 2 \times \frac{Prec_m \times Recall_m}{Prec_m + Recall_m} \tag{11}$$

Where:

- TPc signifies correctly classified COVID-19 cases.
- TPp means correctly classified pneumonia cases.
- TPn defines correctly classified normal cases.
- FPc indicates healthy cases classified as COVID-19.
- FPp indicates healthy cases classified as pneumonia.
- FNc and FNp mean COVID-19 and pneumonia cases classified as normal cases.

### C. Results

The performance of our proposed model for identifying outputs in three-class classification (COVID-19 vs. Normal vs. Pneumonia) has been tested for each fold and is shown in Fig.4 as a separate Confusion matrix (CM). Table. I summarizes the findings of the performance measures sensitivity, specificity, precision, F1score, and accuracy, as well as their averages. The average values for sensitivity, specificity, precision, F1-score, and accuracy are 95.1%, 98.1%, 95%, 94.9%, and 97.3%, respectively.

TABLE I. PERFORMANCE RESULTS OF PROPOSED MODEL IN 3-CLASS CLASSIFICATION TASK.

| **Folds** | **Performance Metrics (%)** | | | | |
|---|---|---|---|---|---|
| | ***Sensitivity*** | ***Specificity*** | ***Precision*** | ***F1 score*** | ***Accuracy*** |
| Fold 1 | 95.5 | 98.4 | 95.7 | 95.5 | 97.7 |
| Fold 2 | 93.9 | 97.8 | 94.2 | 94.1 | 96.8 |
| Fold 3 | 95.2 | 98.6 | 97.2 | 96.0 | 97.7 |
| Fold 4 | 95.7 | 97.4 | 92.9 | 94.0 | 97.0 |
| **Average** | **95.1** | **98.1** | **95.0** | **94.9** | **97.3** |

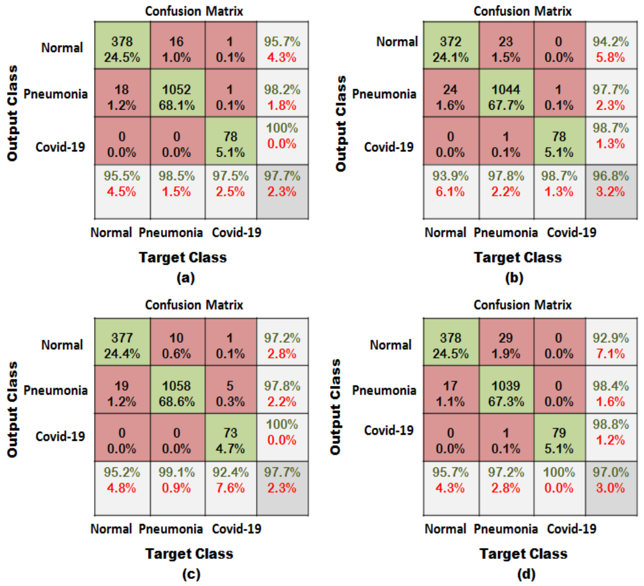


*Fig.4.Confusion Matrices of multi-class classification task (a) Fold 1 CM (b) Fold 2 CM (c) Fold 3 CM (d) Fold 4 CM.*

The suggested deep CNN outperforms other techniques according to the results in Table II. Basu et al. [23] established a new technique for the identification of Covid –19 of four grades (normal, pneumonia, other diseases and Covid–19) known as Domain Extension Transfer (DETL). They obtained 90% accuracy. The efficacy of different neural networks pretrained was examined by Punn and Agarwal [26]. They find that the NASNetLarge has fared better, with binary class accuracy of 98 % and multi class accuracy of 96 %.

TABLE II. COMPARISON OF THE PROPOSED APPROACH WITH PREVIOUS WORK

| *Authors* | *Architecture* | *Accuracy 2-class (%)* | *Accuracy 3-class (%)* |
|---|---|---|---|
| Khan et al. [21] | CoroNet | 99 | 89.6 |
| Ozturk et al. [14] | DarkNet | 87.02 | 98.08 |
| Wang and Wong.[13] | Covid-Net | 92.4 | NA |
| Goel et al. [17] | OptCoNet | NA | 97.78 |
| Sethy et al. [19] | ResNet50 + SVM | 95.38 | NA |
| Punn and Agarwal [26] | NASNetLarge | 98 | 96 |
| Apostolopoulos and Mpesiana [25] | VGG19 | 98.75 | 93.48 |
| **Our proposed model** | **DCNN** | **NA** | **97.3** |

Ozturk et al. [14] presented the DarkNet model, a Convolutional Neural Network (CNN), to detect X-ray images using two classification scenarios: binary (COVID vs. No-Findings) and multi-class (COVID vs. No-Findings vs. Pneumonia). They achieved an accuracy of 98.08 % in 2-class classification and 87.02 % in 3-class classification. Markis et al. [27] investigated the effectiveness of pre-trained convolutional neural networks in identifying the various classes (covid, pneumonia, normal). The classification performance showed that VGG16 and VGG19 offered the highest overall accuracy of 95%. Das et al. [20] developed a method for classifying Covid-19 patients from CXR images by combining three pre-trained CNN models, DenseNet201, Resnet50V2, and Inceptionv3, and obtained an accuracy of 95.7 %.

## V. CONCLUSION

In this work, we present a deep convolutional neural network (DCNN) model for automatically distinguishing COVID-19 from two other classes of chest X-ray images: normal and pneumonia. The proposed system is based on the Residual Network architecture (ResNet-50) with 50 layers. According to the experimental findings, our developed model obtained a maximum accuracy of 97.3 %. Preprocessing and data augmentation were employed to increase model performance. The model's performance was evaluated using the benchmark performance metrics of accuracy, F1 scores, precision, recall, and specificity. In addition to the literature research, it was observed that the proposed DCNN model outperforms the other models in the identification of COVID-19 from normal and pneumonia x-ray images. This system may assist medical doctors in making decisions about COVID-19 patients based on chest X-ray images.

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