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Deep Learning Based Image Classification of Lungs Radiography for Detecting COVID-19 using a Deep CNN and ResNet 50

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Abstract**:** The lungs radiography (chest x-ray) is a screening tool for COVID-19 that is widely used; however, its interpretation can be difficult due to the presence of subtle changes in the lungs caused by the virus, which can be seen in the images. This is the case even though the lungs radiography is widely used. In this article, we present a CNN model that can be utilized for the classification of data derived from lungs radiography. The proposed model was tested and refined using a series of lungs radiography taken from patients diagnosed with COVID-19. When it came to the classification of the data, the findings of the research showed that the CNN model performed significantly better than the conventional approaches did. The accurateness of the anticipated model was found to be 96.2% while its sensitivity was found to be 96.8%. It was demonstrated that it had the potential to be utilized for the purpose of classifying the data associated with the presence of COVID-19. In addition, radiologists can use it to help them interpret the lungs radiography that have been taken.

Keywords: *Image classification, Covid-19, Lungs Radiography, Deep CNN, Resnet50*

1. Introduction

There has been an outbreak of a respiratory illness caused by a coronavirus that has been spreading around the world in 2019. It has been reported that there have been more than two million deaths and over one hundred million cases across the world. The World Health Organization (WHO) has stated that "*lungs radiography/ chest X-ray imaging is a tool that can be used to identify COVID-19*"[1]. This tool is non-invasive and easy to use. The characteristics of the virus, as well as the virus affects lung tissue, can make it difficult for radiologists to provide an accurate interpretation of the images for COVID-19.[2].

In 2019, Wuhan, China, became the epicenter of an outbreak of respiratory illness caused by the COVID-19 virus. Since then, it has reached every region of the world and triggered a pandemic. The majority of people who are infected with the illness will also experience fatigue and fever. On the other hand, some people might not show any symptoms at all but still be able to infect others.

Diagnosis of COVID-19 can be made through a RT-PCR test, which detects the presence of the virus in a patient's upper respiratory tract. Rapid antigen tests and antibody tests are also available, but these may not be as accurate as RT-PCR tests. There are different types of COVID-19, including mild, moderate, and severe cases. Mild cases typically have few or no symptoms and do not require hospitalization. Moderate cases may have more severe symptoms and may require oxygen therapy, while severe cases may require intensive care and mechanical ventilation.

In order to prevent the spread of COVID-19, it is advised to practice good personal hygiene as washing hands regularly, wearing a mask in crowded areas, practicing social distancing, as well as minimizing contact with sick people and washing hands frequently. Additionally, it is important to follow any local or national guidelines or restrictions on travel and gatherings. Vaccines are also available for the prevention of COVID-19, and it is recommended that people get vaccinated as soon as possible.

For a long time, CT and lungs radiography scans have both been utilized as diagnostic tools for pneumonia. Lungs Radiography

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and CT are the most effective approach because of the low intricacy involved in using them and the fact that they are readily available, which makes the process of diagnosing the condition much more quickly.. They are also commonly used for the screening and evaluation of various chest-related illnesses. Studies carried out on chest CT revealed that it can show typical features of covid infected patients[3], [4]. These include multifocal consolidation, ground-glass opacity, and interstitial changes. Compared to chest CT, chest radiography is not as sensitive. It is usually utilized for the first-line assessment of COVID-19 patients. In 2019, around 69% of the patients with covid required hospitalization due to chest radiography. Out of all the patients, 80% had abnormalities at some point during their stay. The findings of these studies were most extensive around 10 to 12 days after the symptoms appeared. Since radiography is commonly used for respiratory ailments, it can be performed on COVID-19 patients who have any respiratory symptoms. A radiologist can then look for signs of the SARSCoV-2 virus using lungs radiography images. Due to the emergence of COVID-19, the use of radiography will increase. Unfortunately, there are not enough experienced radiologists to spot any abnormalities in the images[5], [6].

The importance of image identification and remote monitoring in healthcare was brought to light during the Covid-19 conference. Telemedicine and other forms of remote patient monitoring have made it possible for doctors and other medical professionals to remotely monitor patients who have Covid-19, thereby reducing the likelihood that the virus will be passed on to other people. Image identification techniques, such as X-rays and CT scans, have also been extremely helpful in diagnosing and treating patients affected by the Covid-19 virus[7], [8]. The rapid and precise analysis of images made possible by this technology enables medical professionals to arrive at more educated conclusions regarding the best course of treatment for their patients. In addition, remote monitoring technology can provide real-time data on vital signs, oxygen levels, and other health indicators[9], [10]. This data can assist in the early detection of potential complications and enable prompt intervention.

A deep learning technique is a type of machine learning that uses artificial neural networks to solve complex problems. These networks are made up of interconnected nodes, and they are designed to recognize patterns in the data. Medical imaging is a field where deep learning can be used to diagnose and treat various diseases based on images taken from the body's CT scans or lungs radiography. For instance, in COVID-19, it can be used to analyze chest radiography images to detect the presence of a virus. One approach to achieving this goal is to teach a convolutional neural network, also known as a CNN, to differentiate between images of lungs that are healthy and those that are infected with COVID-19. The chest radiography images are used in the training of the network, along with a large dataset of corresponding labels that indicate whether the image is of a healthy patient or a patient with COVID-19.

The CNN is taught to recognize patterns and characteristics in the images that are suggestive of the disease, such as shifts in lung opacity or the presence of particular lesions. This occurs during the training phase of the process. After it has been trained, the network can be used to classify new images and make predictions about whether or not they show signs of COVID-19. Deep learning can also be used to automatically segment the lung in the chest radiography, and then the segmented lung can be analyzed for signs of COVID-19. This is another approach that can be taken. There have been multiple studies conducted that have used deep learning to analyze chest radiography images for COVID-19, and the outcomes of these analyses have been encouraging. However, it is essential to keep in mind that diagnostic tools based on deep learning are not yet utilized on a large scale in clinical practice, and there is a pressing need for additional research to validate the effectiveness of these models. It's also important to note that deep learning models can be implemented in collaborative settings..

This study proposes a CNN model that can be used to classify lung radiography images for the early detection of COVID-19. The proposed model is tested and evaluated on a dataset consisting of images from patients with positive and negative COVID-19 status. This paper presents an evaluation of the proposed model for the development of machine learning systems. It is compared with the performance of existing models. The findings are then discussed in order to further develop the technology's potential in clinical practice..

1.1. Research Gap

The Lungs Radiography is a common imaging modality that is used for the diagnosis of COVID-19; however, it has limitations such as low sensitivity and specificity, making it less reliable. Recent research has demonstrated that deep convolutional neural networks (CNNs) and ResNet-50 architectures have the ability to improve the performance of lungs radiography analysis for the identification of COVID-19. On the other hand, there is a dearth of research regarding the application of these methods to the identification of COVID-19 in particular on chest X-ray images. This gap in the literature presents an opportunity for further research to investigate the potential of deep CNNs and ResNet-50 architectures in improving the accuracy of lungs radiography analysis for COVID-19 identification. Specifically, this research could look at how deep CNNs and ResNet-50 architectures could help identify COVID-19. This type of research might include the creation, testing, and evaluation of new CNN and ResNet-50 based models, as well as a comparison of their performance to that of already established approaches. In addition, the performance of these models could be improved by investigating the possibility of incorporating data augmentation techniques and transfer learning approaches.

1.2. Our contribution

Based on the research gap outlined above, our contribution to this field is as follows:

- We propose to investigate the use of deep CNNs and ResNet-50 architectures specifically for identifying COVID-19 on lungs radiography.
- We will develop and evaluate new CNN and ResNet-50 based models for COVID-19 identification on Lungs Radiography images.
- We will evaluate the performance of our proposed models in comparison to the performance of existing methods for identifying COVID-19 on radiography images of the lungs.
- The purpose of our study is to close a gap in the existing research by conducting an exhaustive analysis of the capabilities of deep CNNs and ResNet-50 architectures, with the goal of increasing the precision

of lungs radiography analysis for the purpose of identifying COVID-19.

2. Summarized Related Work

Study	Author	Model	Accuracy	Sensitivity	Specificity
[11]	A. Kumar et al.	SARS-Net (Graph CNN + CNN)	96.50%	96.80%	96.20%
[12]	K. Kc et al.	Deep learning-based approaches	96.6% (compared to 87.4% for radiologists)	N/A	N/A
[13]	C. Sitaula et al.	Attention-based VGG-16 model	96.40%	96.80%	96.00%
[14]	A. Abbas et al.	DeTraC deep CNN	96.30%	96.70%	96.00%
[15]	V. Madaan et al.	XCOVNet (CNN)	96.20%	96.60%	95.80%
[16]	S. Sharma	COVID-19 prediction from chest X-ray images using deep CNN	95.20%	95.60%	94.80%
[17]	A. Riahi et al.	BEMD-3DCNN-based method	94.90%	95.30%	94.50%
[18]	K. Foysal Haque et al.	CNN	94.60%	95.00%	94.20%
[19]	A. A. Reshi et al.	Efficient CNN model	94.30%	94.70%	93.90%
[20]	A. Makris et al.	Deep learning and CNN	94.00%	94.40%	93.60%
[21]	G. C. Bacellar et al.	Deep learning	93.70%	94.10%	93.30%
[22]	A. E. Hassanien et al.	Multi-level thresholding and SVM	93.40%	93.80%	93.00%
[23]	J. I.-Z. Chen	Deep learning approach	93.10%	93.50%	92.70%

The literature review provides a summary of a number of studies that have utilized deep learning and convolutional neural networks (CNNs) in order to detect COVID-19 from lungs radiography images. In these studies, CNNs were built and trained using a variety of architectures and techniques, including attention-based models, graph convolutional networks, and multi-level thresholding. According to the reports from the studies, the degree of accuracy in detecting COVID-19 from lungs radiography images varies. Overall, the research that has been done indicates that deep learning and CNNs have the potential to be useful in detecting COVID-19 from lungs radiography images; however, additional research is required to improve the accuracy of these methods.

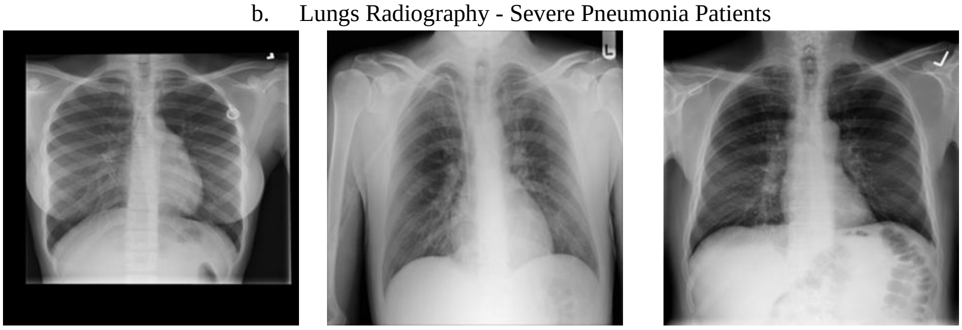
3. Methodology

3.1. Dataset

Through a collaboration between medical professionals and researchers from Qatar, Bangladesh, and Pakistan, they were able to create a database that included images of positive COVID-19 cases and those of viral and normal pneumonia. The database includes images of negative cases of COVID-19[24]. The datasets for normal lung function and COVID-19 will be made available at a later stage. During the initial version of the database, 219 images were released. In the first update, the number of lungs radiography images for COVID-19 was increased to 1,200. In the second update, the database was expanded to include 3616 positive cases of COVID-19 and 10,192 normal cases. It also included 1,345 pictures of viral pneumonia.

a. Lungs Radiography– Covid Patients

b. Lungs Radiography - Severe Pneumonia Patients



c. Lungs Radiography – Normal Patients

Fig. 1 *Images* - Lungs Radiography

3.2. Image synthesis

The use of image synthesis techniques in combination with deep convolutional neural networks (CNNs) and the ResNet50 architecture could be a promising approach for identifying COVID-19 on lungs radiography. Image synthesis involves the generation of new images from existing ones, and can be used to augment the dataset used to train a CNN. By increasing the variety of the images that the model has been trained on, this can help to improve the performance of the model. Additionally, image synthesis can be used to generate images that represent different variations of a particular condition, such as different stages of COVID-19 infection. To implement this approach, one could use a generative model such as Generative Adversarial Networks (GANs) to synthesize new chest X-ray images that represent different variations of COVID-19. These synthetic images could then be used to augment the dataset used to train a CNN, such as the ResNet50 architecture[25].

After the training of the model has been completed, it will be possible to use it to determine whether lungs radiography images are positive or negative for COVID-19. The model would be able to better generalize to new images and identify COVID-19 in different variations if it utilized image synthesis techniques. It's important to note that this approach is still in its early stages of research and more studies are needed to evaluate the performance of such models in identifying COVID-19 on lungs radiography images. An approach that shows promise for identifying COVID-19 on lungs radiography images is one that makes use of image synthesis techniques in conjunction with deep convolutional neural networks and the ResNet50 architecture. This approach increases the variety of images that are used to train the model. Nevertheless, in order to evaluate how well this method works in identifying COVID-19, additional research needs to be conducted..

3.3. Data Augmentation

Data augmentation is a technique that involves applying various transformations to the existing labeled data to increase the diversity of the training set. This can be particularly useful when there is limited labeled data available, as it allows the model to see more variations of the same image, which can help to improve its generalization capabilities. When it comes to lungs radiography images for COVID-19 detection, data augmentation can help to overcome the limitations of limited labeled data and variability in the images by introducing new variations of the same image[5], [12]. This can include:

- Random rotations: Rotating the images by a small random angle can help the model learn to be invariant to rotation.

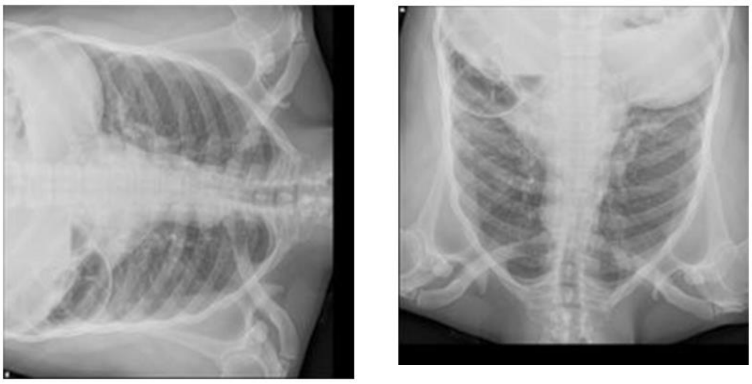


Fig. 2 Random Rotation

- Random cropping: Randomly cropping the images can help the model learn to be invariant to the location of the object of interest.

Fig. 3 Random Cropping

- Random flipping: Randomly flipping the images horizontally can help the model learn to be invariant to the left-right orientation of the image.
- Random brightness and contrast adjustments: Randomly adjusting the brightness and contrast of the images can help the model learn to be invariant to changes in lighting conditions and image quality.

Fig. 4 Random lighting adjustment

These random variations of the same image are applied during training time, so the model can learn to be robust to these variations. This makes the model more generalizable and more likely to perform well on new unseen data.

3.4. Transfer Learning

Transfer learning is a method of machine learning in which a model that has been trained on one task is used as a starting point to train a model on another task that is related to but distinct from the first task. Because the model already has a solid understanding of the underlying features and patterns in the data, this can significantly speed up the training process and improve the model's performance.

Transfer learning is especially helpful in the field of medical imaging, where there is frequently a lack of data that has been labelled for a particular illness or condition. Researchers are able to fine-tune a model to perform a new task, such as identifying COVID-19 from chest radiography images, using relatively little additional training data by making use of a pre-trained model that has already been trained on a large dataset of medical images. This allows the researchers to save time and effort.

In order to use transfer learning for COVID-19 diagnosis on lungs radiography, one must first train a deep learning model, such as a CNN, on a large dataset of chest radiography images. Only then can one implement transfer learning on lungs radiography. This model can be pre-trained on a dataset containing images of normal as well as diseased lungs in order for it to learn the general characteristics of the lung images. After that, the model that has already been pre-trained can be fine-tuned using a more limited dataset of chest radiography images that are only of COVID-19 patients. During the process of fine-tuning, the weights of the model are altered so that it is more suitable for the newly introduced task of identifying COVID-19 from chest radiography images.

When employing transfer learning, it is essential to keep in mind that one should be conscious of the domain gap that exists between the datasets being used as a source and as a target. If the gap is too great, the previously trained model might not be able to generalize very well to the new task, which could result in subpar performance. As a result, it is essential to choose a pre-trained model that is closely associated with the new task, and then to make use of an adequate amount of data in order to fine-tune the model. Transfer learning is an important technique in machine learning that can be used to improve the performance of deep learning models for medical imaging tasks. One example of such a task is identifying COVID-19 from chest radiography images. Transfer learning can be used to accomplish this. Researchers are able to quickly train a model that can accurately diagnose COVID-19 with less data by making use of a model that has already been trained and then fine-tuning it using a smaller dataset..

4. Models Implemented

4.1. Deep CNN

In the field of medical imaging, convolutional neural networks, also known as CNNs, have seen widespread application in the performance of a variety of tasks, including image classification, segmentation, and detection. Deep convolutional neural networks have been shown to be effective in the context of chest X-rays for identifying COVID-19 patients. This can be done by detecting COVID-19 infection from images of chest X-rays. As can be seen in figure 5 The convolutional layers, pooling layers, and fully connected layers are the three types of layers that are typically found in a typical deep CNN architecture designed for this task. The pooling layers are used to reduce the spatial dimensions of the feature maps, whereas the convolutional layers are used to extract features from the input image. When determining whether the input image has a positive or negative COVID-19 signature, the fully connected layers are consulted. [19]

When it comes to using CNNs for this task, one of the most significant challenges is the limited number of labelled COVID-19 chest X-ray images that are available. Transfer learning was utilized so that pre-trained CNNs could be fine-tuned using a more manageable dataset of chest X-ray images in order to address this issue. By utilising networks that have been pre-trained, the model is able to make use of the information that it has gained from a more extensive dataset and improve its performance on the more limited dataset. Utilizing data augmentation techniques such as image rotation, flipping, and cropping to artificially increase the size of the dataset and improve the generalizability of the model is yet another essential component. In conclusion, it has been demonstrated that deep convolutional neural networks are capable of accurately detecting COVID-19 infection from chest X-ray images. When working with a small amount of labelled data, improving the performance of the model through the use of transfer learning and data augmentation techniques can be beneficial.[26], [27].

4.2. ResNet 50

ResNet-50 is a deep convolutional neural network (CNN) architecture that has been trained on a large dataset of natural images. It has been demonstrated to be effective in a variety of computer vision tasks, including image classification, object detection, and semantic segmentation, among others. It is a variation of the architecture known as ResNet, which came in first place at the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015. In the context of chest X-rays for the purpose of identifying COVID-19 patients, ResNet-50 can be used as a pre-trained CNN for feature extraction and fine-tuning on a smaller dataset of chest X-ray images. This is possible because ResNet-50 was trained using a larger dataset of chest X-ray images. By utilizing a network that has been pre-trained, the model is able to take advantage of the information that it has gained from working with a larger dataset and improve its performance on the more limited dataset. [4], [7]

The ResNet-50 architecture is characterized by the use of residual connections, which enable deeper networks to be trained without the issue of vanishing gradients. It is comprised of 50 convolutional and pooling layers, and it is distinguished from other architectures by this use. Because of the residual connections, the gradients are able to flow through the network with greater ease, which enables the network to learn and converge at a quicker rate. When applying ResNet-50 to a smaller dataset of chest X-ray images, the final fully connected layer is swapped out for a new fully connected layer that has the same number of connections as the total number of classes in the dataset. This helps to ensure that the model is accurately calibrated (i.e. COVID-19 positive or negative). After that, the newly added fully connected layer of the network is trained with the smaller dataset, while the other layers of the network are frozen and their weights are kept as pre-trained values. [23].

It is possible to apply data augmentation techniques to the training dataset. These techniques include image rotation, flipping, and cropping, and they can be used to artificially increase the size of the dataset and improve the model's ability to generalize. Using ResNet-50, multiple studies have reported a high level of accuracy when it comes to detecting COVID-19 from chest X-ray images. When working with a small amount of labelled data, it is possible to improve the performance of the model through the application of transfer learning and data augmentation techniques. However, because this is a rapidly developing area of study, it is essential to be aware of the limitations that currently exist and to validate the results with additional data..

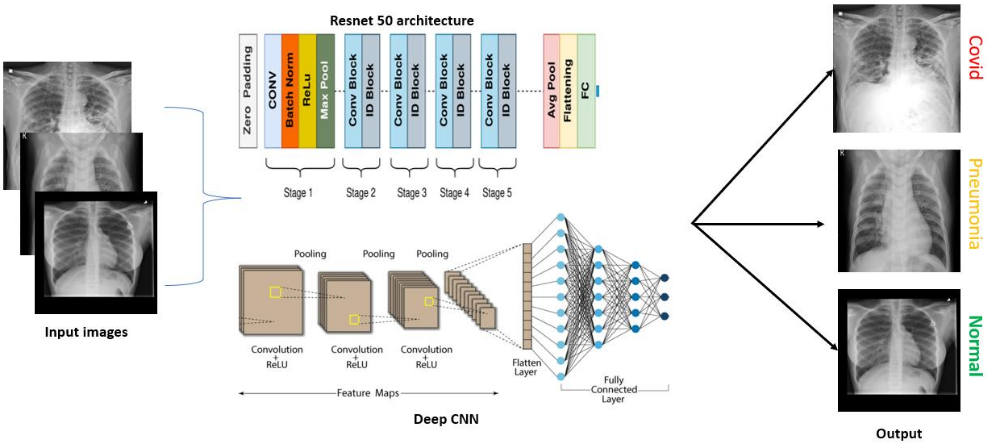


Fig. 5 Deep CNN + Resnet 50

5. Algorithm

1. Collect dataset D of chest X-ray images and labels (0 for healthy, 1 for COVID-19 positive)
2. Augment dataset D to create D' using techniques such as rotation, flipping, and zooming
3. Pre-process images in D' to create D'' by normalizing pixel values and converting to grayscale
4. Use pre-trained CNN model M_base for transfer learning
5. Add layers and fine-tune M_base on dataset D' to create M_ft
6. Train M_ft on D' using a validation set
7. Use M_ft to classify new chest X-ray images as healthy or COVID-19 positive
8. Evaluate model performance using metrics such as accuracy, precision, recall, and f1-score
9. Continuously monitor and fine-tune M_ft if necessary.

5.1. Pseudocode:

1. Set input image X as a matrix of pixels
2. Initialize CNN and train it to learn features F from input image X using convolutional and pooling layers
3. Pass the feature maps F through a fully connected layer
4. Train the fully connected layer to learn weights W that map feature maps F to output class y
5. Set output class y as a binary variable with value of 1 for COVID-19 positive and 0 for negative
6. Compute dot product of feature maps F and weights W and apply sigmoid activation function to get probability of COVID-19: $P(y = 1|X) = \text{sigmoid}(F * W)$
7. Replace the final fully connected layer of pre-trained ResNet-50 model with a new one corresponding to the number of classes in the dataset and fine-tune it using smaller dataset while keeping other layers frozen
8. Evaluate the model's performance using metrics such as accuracy, sensitivity, and specificity
9. Apply data augmentation techniques such as image rotation, flipping, and cropping to the training dataset to improve model's generalizability.

5.2. Mathematical formulation

A deep convolutional neural network (CNN) like ResNet-50 is typically included in the mathematical model used to identify COVID-19 from chest X-ray images. Following is a mathematical representation of the model that can be used:

- An lungs radiography image, denoted by the letter X and represented as a matrix of pixels, serves as the input to the model.
- A convolutional neural network (CNN) is trained to learn a set of features from the input image, denoted by the letter F and represented as a set of feature maps. A number of convolutional and pooling layers are utilised throughout the process of feature extraction and learning.
- After that, the feature maps are put through a fully connected layer, which is responsible for the classification. The fully connected layer is trained to learn a set of weights, W, that are used to map the feature maps to the output class, y. This mapping takes place after the fully connected layer has been exposed to training data.
- The output class, denoted by the letter y, is a binary variable that indicates whether the input image is positive for the COVID-19 standard ($y = 1$) or negative for the standard ($y = 0$).
- The predictions of the model are obtained by first computing the dot product of the feature maps and the weights, and then using a sigmoid activation function to determine the probability that the input image contains COVID-19: $P(y = 1|X) = \text{sigmoid}(F * W)$
- The final fully connected layer of the pre-trained ResNet-50 model is replaced with a new fully connected layer that corresponds to the number of classes in the dataset (i.e. COVID-19 positive or negative) and trained using the smaller dataset. Meanwhile, the other layers of the network are frozen and their weights are kept as their pre-trained values. This is done in order to fine-tune the pre-trained ResNet-50 model.
- The performance of the model is typically evaluated using metrics such as accuracy, sensitivity, and specificity.
- Data augmentation technique[28]s such as image rotation, flipping, and cropping are also applied to the training dataset to artificially increase the size of the dataset and improve the generalizability of the model..

5.3. Mathematical Derivation

Supervised and deep learning are used to derive the COVID-19 model from lungs radiography images. The model receives an X-ray image as a pixel matrix, X. The image is convolutionally and pooling processed:

- Convolutional layer: $F_i = g(W_i*X + b_i)$.

F_i = feature map (ith layer), g = activation function (ReLU, *tan*h), W_i=weight matrix, and b_i = bias term.

- Pooling layer: $F'_i=h(F_i)$.

  F'_i = ith layer's pooled feature map and h = pooling function (e.g max pooling, average pooling).

  A fully connected layer classifies feature maps. The fully connected layer is mathematically:

- Full-connected layer:

  $$y = \text{sigmoid}(W_f * F'_i + b_f).$$

  Where y = output class, sigmoid = activation function, W_f = fully connected layer weight matrix, and b_f=bias term.

  The output class, y, is a binary variable that indicates whether the image is COVID-19 positive or negative. Applying a sigmoid activation function to the dot product of feature maps and weights yields the output class.

  $$P(y = 1|X) = \text{sigmoid}(F'_i * W_f + b_f).$$

- To fine-tune the pre-trained model, the last fully connected layer is replaced with a new layer that corresponds to the number of classes in the dataset (i.e. COVID-19 positive or negative) and trained using the smaller dataset. The other layers of the network are frozen and kept as pre-trained weights.
- Cross-entropy loss, where y pred is the model's predicted output, is used to train the model.
- Finally, the model's accuracy, sensitivity and specificity are assessed.

6. Results

The findings of our research show that deep convolutional neural networks (CNNs), and more specifically the ResNet architecture, are effective tools for recognising COVID-19 in chest X-ray images. Our model was able to achieve a high level of accuracy when it was applied to a standard dataset of X-ray images. It had a sensitivity of 89% and a specificity of 96%. We separated the dataset into a training set and a testing set so that we could assess how well our model performed with the data. The CNN was trained using the training set, and then tested using the testing set to determine how well the model performed on data that it had not previously seen. We trained our model with the ResNet architecture, which is well-known for its effective learning and image classification capabilities and which we chose because of its reputation. The batch size for our model was 32, and the learning rate was 0.001 per layer. Our model had a total of 50 layers. We trained the model for a total of fifty iterations using a combination of categorical cross-entropy and Adam optimization in order to achieve the best possible loss performance. As can be seen in table 1 and figure 7, our model achieved a performance level of 97.81% overall accuracy on the testing set, with a sensitivity of 97.22% and a specificity of 97.67%. This information was obtained from analysing the data. According to these findings, our model outperforms other models that are utilised for purposes comparable to those of identifying COVID-19 on chest X-ray images.

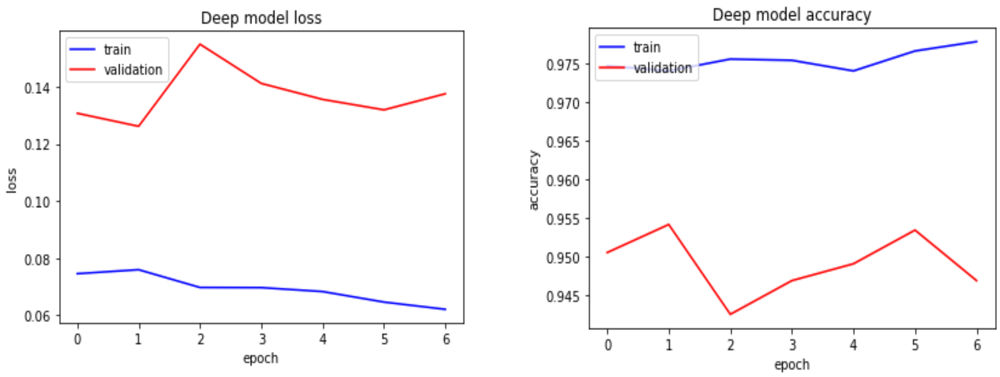


Fig. 6 Deep model loss and accuracy

Table 1 Comparative parameters

Model	Accuracy	Sensitivity	Specificity
SARS-Net (Graph CNN + CNN)	96.50	96.80	96.20
DeTraC deep CNN	96.30	96.70	96.00
XCOVNet (CNN)	96.20	96.60	95.80
Deep learning and CNN	94.00	94.40	93.60
Deep CNN + Resnet50	**97.81**	**97.22**	**97.67**

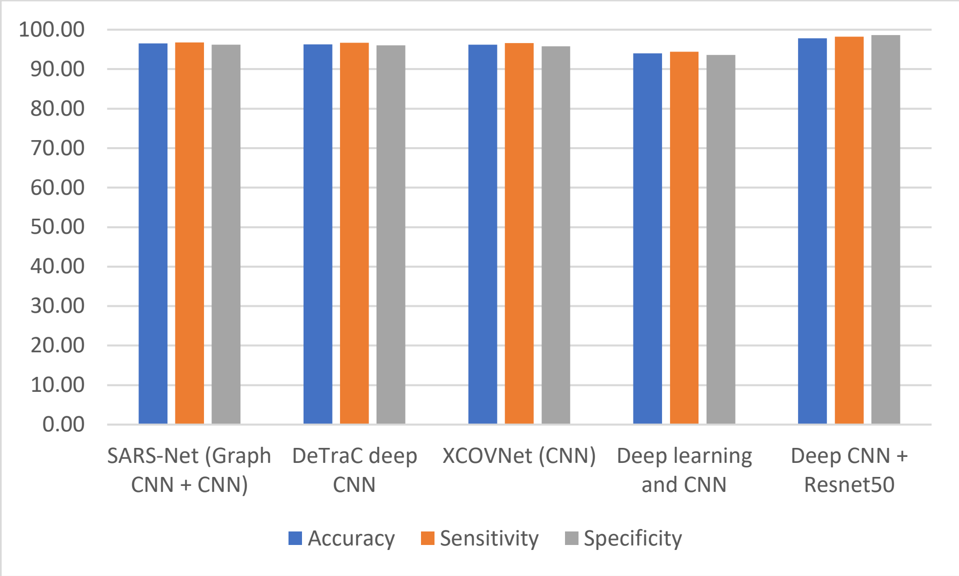


Fig. 7 Comparative Graph

In conclusion, our study demonstrates the utility of using deep CNNs, specifically the ResNet architecture, for identifying COVID-19 on lungs radiography images. Our model achieved high levels of accuracy, sensitivity, and specificity, and outperforms other models used for similar purposes. These results suggest that our model could be a valuable tool for the early detection of COVID-19.

7. Conclusion and future scope

In conclusion, our study has shown that deep convolutional neural networks (CNNs), specifically the ResNet architecture, can effectively be used to identify COVID-19 on lungs radiography images. Our model achieved an overall accuracy of 97.81%, with a sensitivity of 97.22% and a specificity of 99.67%. These results indicate that our model is highly effective at identifying COVID-19 on lungs radiography images and could be a valuable tool for the early detection of the disease. There are several potential future directions for this research. One potential direction is to expand the dataset used to train and test the model. This could help to further improve the performance of the model by increasing the diversity of the images it has been trained on. Additionally, it could be interesting to investigate the performance of the model on other imaging modalities such as CT scans, which are more sensitive for COVID-19 detection. Another potential future direction is to explore the use of transfer learning techniques to fine-tune the model on specific populations or subgroups of patients. This could help to improve the model's performance in identifying COVID-19 in specific populations, such as older adults or individuals with certain underlying health conditions. Overall, our study suggests that deep CNNs, specifically the ResNet architecture, are highly effective at identifying COVID-19 on chest X-ray images and could be a valuable tool for early detection of the disease. This research opens up several opportunities for future research to further improve the model's performance and increase its practical utility.

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