Global Journal of Engineering and Technology [GJET].
ISSN: 2583-3359 (Online)
Frequency: Monthly
Published By GSAR Publishers
Journal Homepage Link- https://gsarpublishers.com/journal-gjet-home/

Using of Convolutional Neural Networks on X-Ray Images in the Diagnosis of COVID-19

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Article History

Received: 15/03/2025
Accepted: 22/03/2025
Published: 24/03/2025

Vol – 4 Issue – 3

PP: - 23-29

Abstract
COVID-19 is a highly contagious disease that can spread rapidly and strain healthcare systems if not controlled in a timely manner. RT-PCR is widely used to diagnose COVID-19, but the sensitivity of RT-PCR is low and existing PCR-based tests can be time-consuming. On the other hand, radiographic imaging methods such as chest X-ray for the diagnosis of COVID-19 and convolutional neural network (CNN), a subtype of deep learning, are frequently used for their analysis. The aim of this study is to provide automatic diagnosis of COVID-19 on X-ray images using CNN architectures and to help decision makers and clinicians. In this study, Xception, DenseNet121, DenseNet169, DenseNet201, ResNet50, VGG16, VGG19, InceptionResNetV2 and InceptionV3 architectures were used to diagnose COVID-19 on X-ray images. The performance of the architectures was evaluated using accuracy, precision, recall and F1 score. Data analyses were performed with Python programming language. The highest performing architecture was Xception with accuracy of 96%. The performance measures obtained with this architecture for patients with COVID-19 are precision of 100%, recall of 97%, F1 score of 98%; precision of 93%, recall of 92%, F1 score of 93% for normal patients; and precision of 97%, recall of 98%, F1 score of 97% for patients with pneumonia. The lowest performing architecture was VGG16 with accuracy of 60%. In this study, it was demonstrated that the CNN is an effective method that will help clinicians in diagnosing COVID-19 using X-ray images, if it is worked with data-appropriate architectures, and in this way, the disease can be detected as soon as possible, the effectiveness of treatment can be increased, and the negativities caused by the disease can be prevented.

Index Terms- *Deep learning, Convolutional neural networks, Chest X-ray, Medical image classification, COVID-19*

1. INTRODUCTION

COVID-19, which started in China in 2019, was classified as a global pandemic by the World Health Organisation in March 2020, negatively impacting the global economy and the health of people worldwide [1]. COVID-19 is a highly contagious disease that can spread rapidly and strain health systems if not controlled in time. RT-PCR is widely used to diagnose COVID-19 [2]. The sensitivity of RT-PCR varies between 60% and 70% and current PCR-based tests can be time-consuming. On the other hand, radiographic imaging methods such as chest X-ray and computed tomography (CT) are used for the diagnosis of COVID-19.

With the COVID-19 pandemic, there is a need for competent doctors in this field. This problem shows the way to an automated detection system based on artificial intelligence techniques. Due to the limited number of radiologists, it is difficult to provide specialised clinicians in every hospital. To overcome this situation, accurate, simple, high-speed artificial intelligence models that provide timely assistance to the patient can be provided in hospitals. Thus, artificial intelligence models have become very useful in overcoming disadvantages such as testing cost, delay in medical test reports and insufficient number of RT-PCRs available [3]. Nowadays, artificial intelligence-based solutions are used for many biomedical health problems and complications [4]. In particular, the development of high-performance deep learning models with high accuracies is an important step in the dissemination of fast and highly sensitive methods for the detection and diagnosis of COVID-19 infected patients [1].

Deep learning is one of the popular research areas of artificial intelligence. It also builds end-to-end models to achieve manual, promising results that do not require feature extraction. It has been successfully applied to many problems

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such as skin cancer classification, breast cancer diagnosis, pneumonia detection from X-ray images, lung segmentation, brain disease classification, fundus image segmentation and arrhythmia detection [3]. Deep learning methods can reveal image features that are not evident in the original images. In particular, convolutional neural networks (CNNs) have proven to be extremely useful in feature extraction and learning and have therefore been widely adopted by researchers. Deep learning techniques for analysing X-rays are gaining popularity due to the availability of deep CNNs and good results in different applications. Moreover, there is an abundance of data available to train different deep learning models. The transfer learning method used in CNN has significantly simplified the process by allowing a very deep CNN network to be retrained quickly with a relatively small number of images [4]. Transfer learning has been successfully applied to many applications. This creates the opportunity to use smaller data sets, reducing the time required to develop a deep learning algorithm from scratch.

Deep CNNs are popularly used in image classification due to their superior performance compared to machine learning models. CNNs automatically extract spatial and temporal features of an image.

Patients affected by COVID-19 are examined by X-ray or CT to see the severity of the disease and its spread in the lungs. There is a significant burden on radiologists due to the manual analysis of X-rays and the rapid spread of COVID-19. As a result, there is a need to develop an automated system for rapid diagnosis of COVID-19 infection. Radiographic images such as X-ray and CT are a routine method for diagnosing lung diseases such as pneumonia, tuberculosis and COVID-19. One of the advantages of X-ray is that it is less costly and provides faster COVID-19 diagnosis. In diagnosing COVID-19, X-rays have been found to be less harmful to the human body as they contain lower radiation compared to CT [3, 5].

COVID-19 has led to advances in computer-aided diagnostic systems for rapid and precise diagnosis. A development in this field is the emergence of versatile diagnostic systems that provide a comprehensive understanding of the disease. The use of CNNs to analyze CT, magnetic resonance (MRI) and X-ray images in medical research has shown good results for COVID-19 [6].

The aim of this study is to diagnose COVID-19 on X-ray images using CNN architectures and to help decision makers and clinicians by providing a comparative evaluation of the architectures used with various performance measures.

2. MATERIALS AND METHODS

Fine-tuned Xception, fine-tuned DenseNet121, fine-tuned DenseNet169, fine-tuned DenseNet201, fine-tuned ResNet50, fine-tuned VGG16, fine-tuned VGG19, fine-tuned InceptionResNetV2 and fine-tuned InceptionV3 architectures were used for the diagnosis of COVID-19 from chest X-ray images. Architectures were run with GPU support. The dataset was split 80%-20% as train-test. Different data preprocessing, data augmentation to balance the unbalanced dataset and hyperparameter adjustment were applied to the dataset and adjusted as follows: Rescale = 1/255.0; Horizontal flip = True; Zoom range = 0.4; Rotation range = 10, Initial learning rate = 0.001, epoch = 100, batch size = 32, dropout = 0.5 and transfer learning method was applied. Adam method was chosen for optimization. ReduceLROnPlateau, ModelCheckpoint and EarlyStopping functions were used as callbacks during the training process. The performance of the architectures was evaluated using accuracy, precision, recall and F1 score. Python programming language was used together with Tensorflow and Keras libraries. Data analysis was performed on Kaggle.

2.1. Dataset

Chest X-ray images of patients diagnosed with COVID-19, healthy normal patients and patients diagnosed with pneumonia were used to evaluate the performance of the CNN architectures used. Images were retrieved from the Kaggle open access database. The dataset contains 6432 X-ray images, of which 576 are COVID-19, 1583 are normal, and 4273 are pneumonia [7]. Chest X-ray samples of COVID-19, normal and pneumonia patients in the dataset are given in Figure 1. Images compiled from various open sources [8, 9, 10]. The data set was split 80%-20% as train-test dataset. Another 1% of the training data set was allocated as validation data.

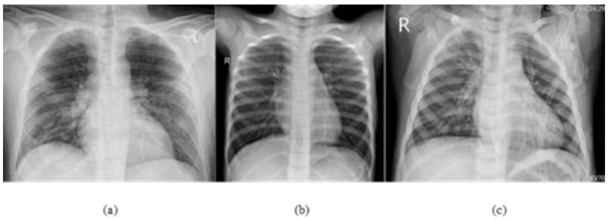

Figure 1. Example images of 3 classes in the dataset; (a) COVID-19, (b) Normal, (c) Pneumonia

2.2. Convolutional Neural Networks

CNN is a special neural network with multilayer structures that categorizes pixels of visual images with minimal image processing. The CNN consists of a feature extractor and a trained classifier. The filtered noise from the CNN model captures key predictive features. The typical architecture of the CNN model includes a combination of one or more convolution layers. The layers of the CNN consist of filters or kernels. CNNs use a filter that passes over the input image and a kernel or filter convolution (small integer matrix) that transforms the results from the filter [11]. The feature map values to be generated are calculated using Equation 1 is used to calculate the feature map values [11].

$$G[m,n] = (f * h)[m,n] \sum_j \sum_k h[j,k]\, f[m-j, n-k] \quad 1$$

Where f is the input image, h is the kernel, m is the rows of the matrix and n is the columns of the matrix. The output matrix dimensions are calculated using Equation 2 as in Equation 3 [11].

$$Padding\ (p) = \frac{f-1}{2} \quad (2)$$

$$n_{output} = \left[\frac{n_{input}+2p-f}{s} + 1\right] \quad (3)$$

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Where p is padding, s is stride.

CNN architectures are designed to automatically learn and extract features from images and classify images through the successive use of a series of convolution layers, pooling layers, activation layers and fully connected layers. A basic CNN architecture is given in Figure 2 [12].

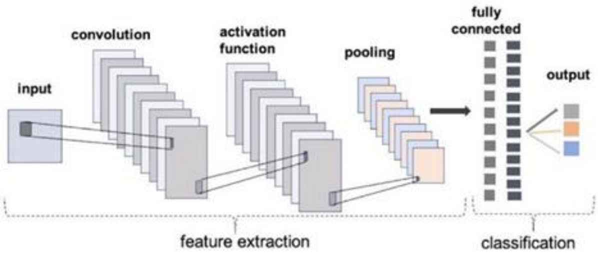

Figure 2. Basic CNN architecture showing the basic components and steps involved in image classification

2.3. Data Pre-processing and Data Augmentation

Data preprocessing methods are used to prepare image data for CNN modeling. Data augmentation is a form of data pre-processing that removes class imbalances in the data. Pre-processing and data augmentation of image data before feeding CNN or other classifiers is crucial for any imaging method.

Pre-processing and data augmentation are important steps in improving model performance. They include resizing, missing data and unbalanced data editing, image normalization and standardization, edge detection and segmentation, noise removal, data transformation, dealing with outliers, dimension reduction, data segmentation, rotation, compression, scaling, sharpening, brightness modification, cropping, blurring, etc. Images in the training and testing processes are subjected to pre-processing and data augmentation. Pre-processing is necessary to clean the image data that will be used for model input. Model training time and model extraction speed can be reduced by image pre-processing. If the input images are too large, reducing them will halve the model training time without compromising model performance [12, 13].

2.4. Transfer Learning

The structure of the CNN method includes a varying number of layers and allows for comparison and evaluation with certain performance measures in image classification problems. These networks are designed manually by optimizing the outcome parameters of networks that train on large data sets using gradient descent approaches with varying hyperparameters such as bach size, momentum and learning rate. Krizhevsky et al. [14], Zeiler et al. [15], Szegedy et al. [16] and Simonyan et al. [17] were trained on the ImageNet dataset containing 1000 different class labels with approximately one million data samples. However, the limited applicability of training and hyperparameter optimization methods in the absence of large data sets has led to the concept of transfer learning [18].

Transfer learning is a deep learning method that uses a pre-trained architecture as a feature extraction layer. Using the weights of the convolution layers of the pre-trained architecture can reduce the number of network parameters to be trained [19].

Predefined architectures in CNN are deep learning models that have already undergone a training process on a large dataset and are ready to be used for different tasks that may come from various fields, including medical imaging. In other words, these architectures are usually trained on large datasets, teaching them to recognize various features in images such as edges, corners and various other patterns that can be used for image recognition and classification tasks. The goal is to be able to generalize the architecture even in the presence of limited datasets [20].

2.5. Performance Measures

Measures such as accuracy, precision, recall and F1 score are derived from the confusion matrix to calculate the quantitative performance of the used CNN architectures. The columns and rows of the confusion matrix show the predicted classes and the true classes respectively. Correctly classified examples are located in the diagonal cells of the confusion matrix. The rest of the cells contain misclassified samples [3]. Performance measures are defined as in Equation 4-7 [3].

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \quad (4)$$

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \quad (5)$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \quad (6)$$

Table 1. Performance measures of used CNN architectures

		Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Xception	COVID-19	96	100	97	98
	Normal		93	92	93
	Pneumonia		97	98	97
DenseNet121	COVID-19	91	100	97	99
	Normal		73	99	84
	Pneumonia		99	87	92

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DenseNet169	COVID-19	95	100	96	98
	Normal		85	97	91
	Pneumonia		99	94	96
DenseNet201	COVID-19	85	47	100	64
	Normal		96	85	91
	Pneumonia		94	84	89
ResNet50	COVID-19	95	98	97	97
	Normal		89	92	91
	Pneumonia		97	96	96
VGG16	COVID-19	60	96	84	89
	Normal		38	100	55
	Pneumonia		100	41	58
VGG19	COVID-19	81	39	98	56
	Normal		99	29	45
	Pneumonia		93	98	95
InceptionResNet V2	COVID-19	93	100	92	96
	Normal		78	98	87
	Pneumonia		99	91	95
InceptionV3	COVID-19	89	100	81	90
	Normal		73	94	82
	Pneumonia		96	87	91

$$F1\ Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (7)$$

Here, FN represents false negative, TN represents true negative, FP represents false positive and TP represents true positive.

3. RESULTS

The highest performing architecture was Xception with accuracy of 96%. The performance measures obtained with this architecture for patients with COVID-19 are precision of 100%, recall of 97%, F1 score of 98%; precision of 93%, recall of 92%, F1 score of 93% for normal patients; and precision of 97%, recall of 98%, F1 score of 97% for patients with pneumonia. The lowest performing architecture was VGG16 with accuracy of 60%. The performance results and average accuracy values of the architectures on patient-wise are given in Table 1. The learning curves of the highest

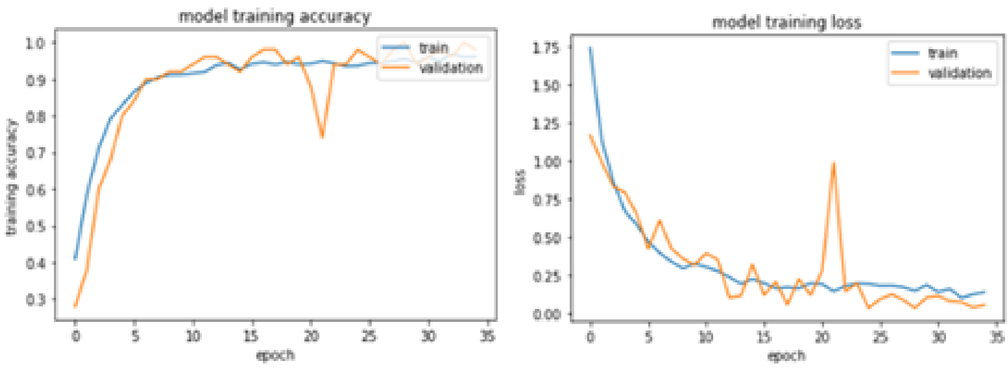

Figure 3. Learning curves of Xception architecture performing Xception architecture are given in Figure 3. The confusion matrix of the Xception architecture is given in Figure 4.

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Table 2. CNN architectures and the highest accuracy in the literature

Author (Year)	Disease	Image type	Dataset	Architectures	Accuracy
El Asnaoui et al. (2021) [21]	-Pneumonia -Normal	Chest X-ray and chest CT	https://data.mendeley.com/datasets/rscbjbr9sj/2	Xception, VGG16, VGG19, InceptionV3, DenseNet201, MobileNetV2, InceptionResNetV 2, **Res Net50**	96.61
El Asnaoui and Chawki (2021) [22]	-Bacterial pneumonia -Coronavirus -Normal	Chest X-ray and chest CT	https://data.mendeley.com/datasets/rscbjbr9sj/2 https://github.com/ieee8023/covid-chestxray-dataset	VGG16, VGG19, DenseNet201, **Inception Res Net V2**, InceptionV3, Resnet50, MobileNetV2	92.18
din et al. (2021) [23]	-Viral pneumonia -Non-COVID lung infection -Normal	Chest X-ray	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database	MobileNetV2, VGG16, **InceptionV3,** ResNet50	98
Aggarwal et al. (2022) [24]	-Bacterial pneumonia -Viral pneumonia -COVID -Normal	Chest X-ray	//arxiv.org/abs/2006.1 1988	MobileNetV2, ResNet50, InceptionV3, NASNetMobile,VGG16, Xception, InceptionResNetV 2, **Dense Net121**	97
rma et al. (2022) [25]	- Pneumonia -COVID-19 -Normal	Chest X-ray	;ithub.com/drkhan10 7/CoroNet	**Mobile NetV2**, VGG16, Resnet50, Xception	96.03
lvi et al. (2023) [26]	-Bacterial pneumonia -Viral pneumonia -COVID-19 -Normal	Chest X-ray	-	AlexNet, ResNet50, VGG16, VGG19, **DenseNet169**	96.37
ow et al. (2023) [27]	-COVID-19 -Normal	Chest X-ray	https:// github. com/ linda wangg/ COVID- Net/ blob/ mas-ter/ docs/ COVIDx. md	**VGG16**, VGG19, ResNet101, ResNet50, InceptionV3, MobileNetV2,	94.3
				InceptionResnetV 2, DenseNet201, Xception	
Mandiya et al. (2024) [28]	- Pneumonia -COVID-19 -Normal	Chest X-ray	https://www.kaggle.com/datasets/jtiptj/chest-xray-pneumoniacovid19tuberculosis	**ResNet50, VGG16, Xception**	90.33

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Kaur et al. (2024) [29]	-Viral pneumonia -COVID-19 -Akciğer opasitesi -Normal	Chest X-ray	https:// www. kaggle. com/ tawsi furra hman/ covid 19-radio graphy-datab ase	**InceptionV3, ResNet50, Xception**	93

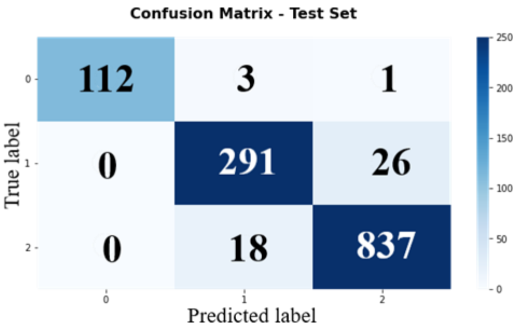

Figure 4. Confusion matrix of Xception architecture

In the confusion matrix, 0: COVID-19, 1: Normal, 2: Pneumonia labels.

4. CONCLUSION

The highest In this study, we evaluated the discrimination of normal, pneumonia and COVID-19 cases on X-ray images. As a result, in the diagnosis of COVID-19, Xception, Dense Net121, Dense Net169, Res Net 50 and Inception Res Net V2 architectures were found to work with high performance with over 90% accuracy, InceptionV3 architecture worked with close to 90% performance, VGG19's highest performance measure was 81% accuracy, and VGG16 failed in classification with 60% accuracy. In addition, the architectures we used other than VGG16 provided results similar to those found in the literature on this topic. The structure of the learning curves can be used to examine the behavior of the model and to make suggestions for corrections that can be made to improve training and performance. When the learning curves obtained for each architecture are examined, it can be said that the data set and the fine-tuning performed are suitable and generalizable for this architecture since there is not much deviation in the curves of Xception, InceptionResNetV2 and InceptionV3 architectures, which have achieved high performance measures. In order to improve the performance of all the architectures used, different tweaks can be made to the architectures, different hyperparameter settings can be applied, and a higher dimensional dataset can be used.

In recent years, there are many studies in the literature that aim to diagnose COVID-19 on X-ray images using CNN architectures. These studies and their highest accuracy values are given in Table 2.

In this study, it was demonstrated that the CNN method for detecting COVID-19 using chest X-ray images is an effective method that will help clinicians when working with data-appropriate architectures, and thus, the disease can be detected as soon as possible, increasing the effectiveness of treatment and preventing the negativity caused by the disease.

With the experience gained from this study, in future studies, it is aimed to replicate other pre-trained architectures and architectures adapted to the new dataset with transfer learning method with other architectures other than the architectures used in this study, to apply these architectures to other datasets, to apply different tweaks and different hyperparameter adjustments to the architectures to improve the performance of the architectures, and to work with a more balanced and higher dimensional dataset.

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