A Chest X-Ray Image Based Model for Classification and Detection of Diseases

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Abstract. Radiography holds significant importance in the medical field, allowing for efficient and widespread access, primarily due to the predominant utilization of thoracic imaging equipments within healthcare infrastructure. However, radiologist's ability to understand radiography images is constrained by their inability to recognize the fine visual details present in the images. There have been numerous studies published in the literature describe machine learning (ML) recent advance models that use support vector machines do differentiate between COVID-19 and non COVID-19 cases by means of open-access chest radiograph databases. The AI can be familiar with characteristics observed in chest X-rays tasks that are typically beyond the scope of a radiologist. They did, however, produce poor categorization performance. Deep - learning techniques in artificial intelligence (AI) are high-performance classifiers engage in recreation a most important significance in the identification of the disease through analysis of chest radiograph metaphors. The major goal of this learning is to examine the enhancement of pre-trained ConvNet (CNNs) as XCOVNet for COVID-19 classification by means of chest radiograph, considering the abundance of newly developed deep learning models specifically designed for this task with more accuracy of 99.51% than previous methods.

Keywords: Radiography · Deep-Learning · Convolutional Neural Networks (ConvNet or CNN) · Artificial Intelligence (AI) · Machine Learning (ML)

1 Introduction

Since the pandemic disease (COVID-19) originating in Wuhan, China in December 2019, it has impacted billions of people. The virus caused an outbreak that spread quickly. The virus that caused COVID-19 sickness was identified after extensive investigation, and it was shown to be a member of a large family of respiratory viruses that may also cause diseases such as severe acute respiratory syndrome (SARS-CoV) and Middle East

P. Pareek et al. (Eds.): IC4S 2023, LNICST 536, pp. 422–432, 2024.
https://doi.org/10.1007/978-3-031-48888-7_36

Respiratory Syndrome (MERS-CoV) are among the included. Viral pneumonitis can arise from the novel SARS-CoV-2 virus. In some states; there is very high mortality rate among the populace. The number of fatalities worldwide is rising daily. Therefore, it is essential to create a method that can accurately, quickly, and affordably diagnose viral pneumonia. This will be the first step in implementing other preventive measures, including as isolation, contact tracing, and treatment, to end the outbreak. Real-time polymerase chain reaction (RT-PCR) testing for the detection of viral nucleic acid is one well-liked technique for virus detection. This exam has a lot of restrictions and is quite sensitive. For instance, it cannot find corona vi-ruses that were already present when DNA sequence samples were taken [1].

However, only with the assistance of specialized knowledge is perfect and quick analysis of an X-Ray image possible. The typical diagnosis of pneumonia is based on the presence of fever, chills, and a dry cough; however, because many asymptomatic patients test positive, it is imperative to enhance the screening procedure by using X-ray metaphors and testing as many people as possible as quickly as feasible. The screening procedure becomes a challenging work as a result of an increase in cases and a decrease in the number of professionals available to make diagnoses. Therefore, for a quick and precise diagnosis, clinicians must rely on machine learning algorithms. The X-ray images have already been examined using a number of machine learning techniques [2]. Support vector methods (SVMs), a type of conventional approach, have a number of drawbacks. Their performance has declined over time and is no longer seen as meeting realistic criteria. Additionally, their development takes a long time. Deep learning techniques have produced significant improvements in the classification of medical images, and they are now a useful tool for clinicians to examine the photos and identify the issue. They can now do many of the activities currently associated with medical image analysis, including pathological abnormality recognition, staging, and explanation. CNN is a common method for image analysis that has achieved great success in the medical industry [3].

In order to evaluate chest images, identify prevalent thoracic disorders, and distinguish between viral and non-viral pneumonia, Deep Convolutional Networks (DCNNs) are being developed [4, 5]. Though many common viruses, including influenza A/B, only viruses that cause viral pneumonia significantly alter X-Ray images. This implies that each incidence of viral pneumonia will have a unique visual presentation. Another issue is locating a dataset with positive sample sizes. It is imperative to create a representation that can circumvent these pathological anomalies and accurately identify the virus. Since 2012, these techniques have been applied in the medical field and have demonstrated noticeably superior performance to earlier techniques. CNN with 121 layers that was skilled using a dataset comprising 112,120 frontal-view chest X-ray images from the ChestX-ray 14 dataset outperformed four radiologists on average [6]. CNN differs from traditional machine learning techniques since it can learn automatically from domain-specific images. Healthcare systems around the world are being overloaded by the COVID-19 patient population's exponential growth. Every patient with a respiratory ailment cannot be checked using traditional methods (RT-PCR) due to a lack of testing kits. High risk patients may benefit from being quarantined while test results are awaiting if suspected COVID-19 infections are found on chest X-rays. In this work, a methodology has been developed using chest X-rays to priorities the patient selection for additional RT-PCR testing. In a hospital context where the current systems are having trouble making decisions, this could be helpful.

2 Literature Review

The research on utilizing machine learning algorithms for disease diagnosis and classification using chest X-ray metaphors have been dominated from last decade. Numerous authors have utilized and developed various algorithms for training and testing, and the reported performance metrics. In today the radiologist's data increased drastically by thin-slice chest scans, which have become necessary in thoracic radiology. Because of this it is important to automate the processing of such data; as a result it has led to a fast escalating study field in medical imaging. Various pulmonary structures can be segmented, chest images can be registered, and applications for the detection, classification, and quantification of chest anomalies addressed in [7].

Recent research indicates that several physiologic mechanisms used by pulmonary vascular disorders can specially affect arteries or veins. Physicians by hand examine the patients' chest computed tomography (CT) images in search of anomalies to recognize changes in the two vascular trees. The classification of veins and arteries from chest computed tomography (CT) images has been proposed in [8]. The authors of [9] described a methodology that identifies disease classification issue for the chest X-ray (CXR). In databases of medical, general illnesses are regularly overrepresented while unusual medical conditions are underrepresented. As a result of privacy issues it is difficult to unite massive datasets across health care facilities. To deal with these issues, the authors of [10] recommended synthesizing pathology in medical imagery.

Based on a modestly large labeled dataset, a deep convolutional generative adversarial network (DCGAN) has been proposed to generate synthetic chest X-rays. This improved performance is partly due to the dataset's balance using DCGAN synthesized images, which preferentially enhance classes that lack example photos. To provide more useful picture representations, the authors of [11] have considered the modeling of relations of image-level. Therefore, it was suggested in [12] that a distance map have to be estimate. And use it to compel a more comprehensive and classification-appropriate semantic segmentation prediction. The recent pandemic COVID 19 affected many of the humans, from which many of them get examined by the different methods like CT and CXR. These methods created the datasets for the researchers to get the abundant data in the format of images for their evaluation of the biomedical features. Due to privacy issues, small collection of data is available for the researchers.

A comprehensive collection of COVID-19 CXR and CT metaphors take out from publications in the Pub Med Central Open Access (PMC-OA) Subset, relevant to COVID-19; can be accessed through [13]. The authors of [14, 15] proposed a neural network in order to improve pneumothorax detection by incorporating both frontal and lateral X-ray data. This network has two inputs and three outputs. Accurate and automated interpretation of medical images, including tasks like segmentation, detection, and classification, is crucial for current illness analysis and prediction. Computer-aided diagnosis (CAD) systems play a significant role in providing fast and reliable diagnoses for a wide range of medical conditions. Over the past decade, deep learning (DL)-based CAD systems have shown remarkable performance in various healthcare applications.

To address this gap, the authors in [16] have introduced the Hercules model, an innovative a specialized uncertainty-aware hierarchical considerate multilevel feature fusion model tailored for medical image categorization. In [17] the authors present pre-processing techniques proposed by various researchers to address the issue of artifacts in metaphors attained from automated diagnostic equipments. Systems so far we discussed show the value of further research in this field for enhancing medical diagnosis and patient outcomes by demonstrating the potential of DL and ensemble representations for the categorization and detection of diseases using chest X-ray images [18–24].

Table 1. Performance comparison of literature

Ref. No	Method	Accuracy	Gap
[8]	3-D Convolutional neural network (CNN)	94%	Need to increase Accuracy
[9]	ConsultNet	82.2%	Disease recognition problem in case of saliency detection
[25]	Deep learning method	99%	Restricted only to analyze diseases by doctors who are deals outpatients
[26]	Ensemble Bootstrap aggregating training and Multiple NN methods	93%	Need to increase Accuracy
[27]	Capsule Networks	95.7%	New versions of covid not detected

In [25] authors proposed classification of chest X-ray view, in this method they achieved accuracy of 97%. Authors applied Deep learning to the classification of COVID-19 disease using X-ray images and got accuracy of 93% in [26]. Authors' proposed in [27] capsule networks for corona disease separation and got accuracy of 95.7%. The following Table 1 depicts the Performance comparison of some of the literature. Therefore, it can be concluded that additional feature extraction operations are not necessary for multiple classifications. The training complexity hinders the analysis of image properties, leading to poor performance metrics such as low accuracy [28–32].

3 Methodology

The proposed system suggested the solution which uses chest X-ray metaphors to classify and identify diseases using a deep learning-based model. The system classifies the input photos into several disease categories and given to CNN architecture by extracting features from input [15]. The method begins by gathering chest X-ray dataset metaphors, which contains metaphors of various illnesses like pneumonia, COVID-19, and tuberculosis. The dataset is then preprocessed to accommodate missing data and normalize the image intensities. The preprocessed dataset is then separated into three sets: training, validation and testing. The validation set is utilized to adjustment of hyper parameter and selection of model, while the CNN model trained by training set. The testing set is used to assess the trained model performance.

3.1 Block Diagram

For the categorization and detection of diseases from chest X-ray a block schematic has been developed and is depicted in Fig. 1. The system's brain is a deep learning model, which examines chest X-ray metaphors to find patterns that can be used to identify thoracic disorders like pneumonia, TB, and COVID-19. CNN used to train the model using a sizable dataset of chest X-ray metaphors labeled with various dis-eases. Before the chest X-ray metaphors are put into the DL model, the pre-processing part of the system is in charge of cleaning, normalizing, and improving them. The data management component of the system is responsible for storing, retrieving, and managing the large dataset of chest X-ray images with disease labels. Therefore, the proposed block diagram significance for integrating different components to create a robust and precise system for the classification and detection of thoracic diseases from chest X-ray images.

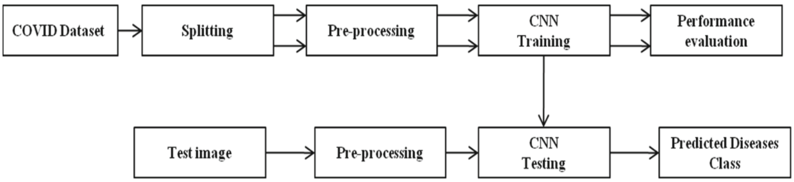

Fig. 1. Proposed Block Diagram

3.2 Deep COVID NET CNN Architecture

The below Fig. 2 shows the Deep COVID NET CNN Architecture which describes four Convolutional layers sequential model architecture for classify X-ray images. The first layer consists of 32 filters, second layer consists of 64 filters, third layer consists of 64 filters and the final layer consists of 128 filters.

4 Simulation Results

In below Fig. 3 detected 820 dataset processed images. The next step is to generate CNN model for given images and get the following window.

In below Fig. 4 represents newly developed deep learning models specifically designed with more accuracy of 99.51% than previous methods.

The Fig. 5 shows no of images have different sizes are suppressed at different layers.

In first layer 62×62 image size was used and in second layer 62×62 and goes on. Then XCOVNet model is willing to ready to accept test images and will predict disease in that image. The graph in Fig. 6 shows the relationship between epoch/iteration accuracy

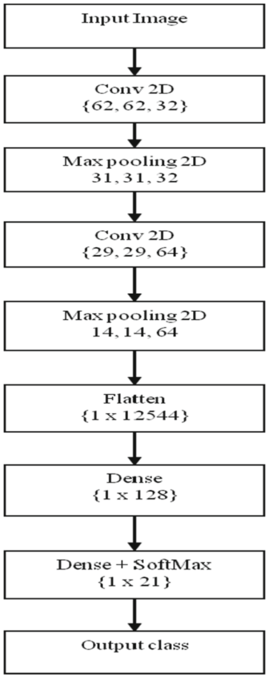

Fig. 2. Deep COVID NET CNN Architecture

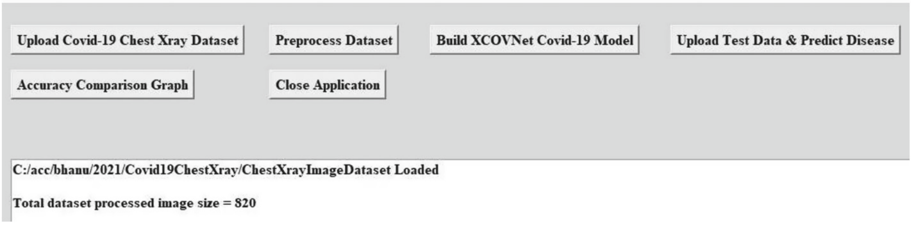

Fig. 3. XCOVNet Covid-19 Building Model

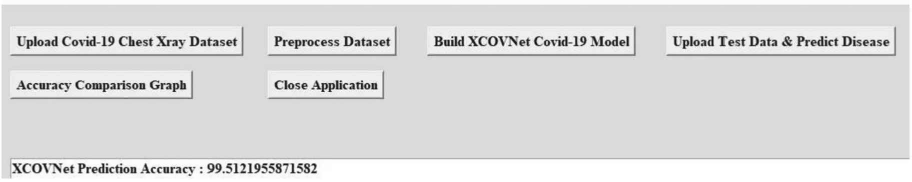

Fig. 4. XCOVNet Prediction accuracy of CNN Model

and loss values. Here consider 20 iterations to build XCOVNet. As number of iterations increase Accuracy will increase whereas Loss will decrease.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 29, 29, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 12544)             0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               1605760
_________________________________________________________________
dense_2 (Dense)              (None, 21)                2709
=================================================================
Total params: 1,627,861
Trainable params: 1,627,861
Non-trainable params: 0
_________________________________________________________________
None
```

Fig. 5. Details of proposed CNN Layers

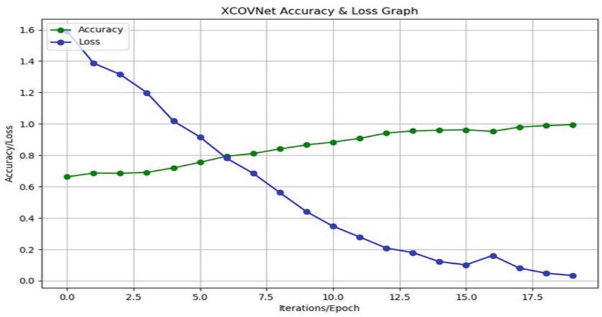

Fig. 6. Loss and Accuracy graph

In above graph we can see accuracy starts from 0.65 and reached to 1.0% accuracy and loss reached to 0%.Chest X-ray image classification and virus detection using CNNs broadly explored and proven to be valuable in medical image analysis. In this scenario, a CNN can be trained for classification of chest X-ray metaphors into different disease categories or detect the presence of specific diseases. Figure 7.a shows the pneumonia decease detection.

After processed the test image (operations like trained, validated, and tested), predicted the images and labeled as like this, this is the Pneumonia disease predicted image (see Fig. 7.b). After processing the test image through the trained, validated, and tested phases, the system predicted the label for the image. In this case, the image was classified as a Pneumonia disease image; indicating varying intensities of the disease (see Fig. 7.c). After undergoing the necessary operations such as training, validation, and testing, the test image was processed, and the system successfully predicted its label. The image was classified as Pneumonia - Viral - COVID-19 disease, indicating the presence of COVID-19 with varying intensities of the disease (see Fig. 7.d).After going through the stages of training, validation, and testing, the test image was processed, and the system made a prediction and assigned a label.

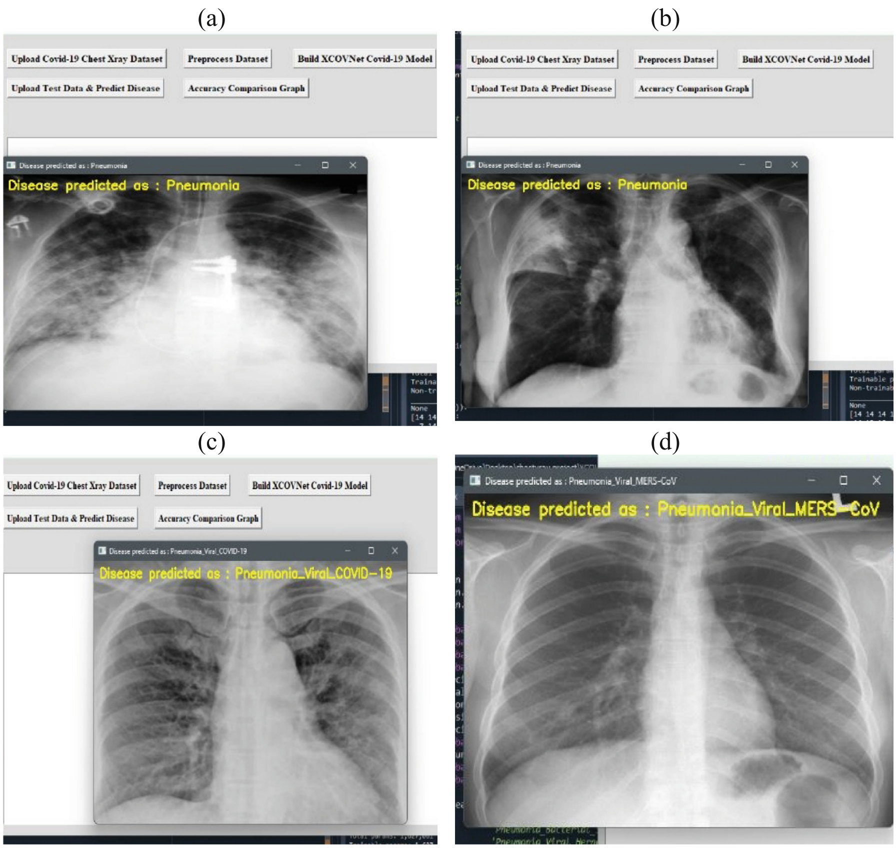

Fig. 7. Identification of various diseases: a) Low severity pneumonia disease, b)High severity pneumonia disease, c) Pneumonia-Viral-COVID-19 disease, d) Pneumonia-Viral-MERS-Cov disease

5 Conclusion

In this work, a model has been created to identify various diseases like COVID-19, pneumonia, Pneumonia-Viral-COVID-19, Pneumonia-Viral-MERS-Covinfection from chest X-ray metaphors. A dataset of 392 X-ray patient metaphors has been utilized with positive and negative COVID results. The proposed system utilizes a deep learning-based model and chest X-ray metaphors for classification and identification of diseases. The system employs CNN architecture to extract features from the input photos and categorize them into various disease categories. The process involves gathering chest X-ray images dataset, preprocessing it to handle missing data and normalize image intensities, and then dividing it into training, validation, and testing sets. The validation set is utilized to adjustment of hyper parameter and selection of model, while the CNN model is trained by training set. Finally, the performance of the trained model is evaluated using the testing set, providing a comprehensive assessment of the system's effectiveness in disease classification. The following Table 2 describes the performance of proposed method with existed methods. The proposed method gives the accuracy of 99.51% which is more than existed methods.

Table 2. Comparison of performance with existed methods.

Ref. No	Method	Accuracy	Research Gap/Future work
[8]	3-D CNN	94%	Need to increase Accuracy
[9]	ConsultNet	82.2%	Disease recognition problem in case of saliency detection
[25]	Deep learning method	99%	Restricted only to analyze diseases by doctors who are deals outpatients
[26]	Ensemble Bootstrap aggregating training and Multiple NN methods	93%	Need to increase Accuracy
[27]	Capsule Networks	95.7%	New versions of covid not detected
Proposed	XCOVNet	99.51%	By doing experiments on CT scan image data of Chest for finding of COVID-19 and mixing both models to recognize the severity level

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