COVID-19 Detection in X-ray Images using CNN Algorithm

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***Abstract*—Based on the best published research from Stanford University, the CheXNet algorithm was developed to diagnose and detect pneumonia from chest X-rays. To achieve better performance than experienced radiologists from the same university, simple changes were made to the algorithm to diagnose 14 pathological condition in the chest X-ray with a performance that exceeds all Previously developed deep learning [1]. In this paper, we experimented with applying a convolutional neural networks (CNN) algorithm in a similar way to the mechanism of work in CheXNet algorithm by using a dataset of 550 Chest X-ray images collected from Kaggle website, some of them are infected with Covid-19 virus. We had an acceptable prediction accuracy of 89.7% which is closed to the results of CheXNet algorithm.**

Keywords—Covid-19, CNN, CheXNet, Classification

I. INTRODUCTION

The rapid spread of COVID-19 as a result to the new SARS-COV-2 virus is the biggest problem facing humanity today, and about one half million patients die from Covid-19 this year (2020) in the world [2]. Therefore, it has become imperative in order to detect positive cases as quickly as possible to prevent the further spread of this epidemic. AI-based X-ray screening is considered as a promising approach in order to test COVID-19 in asymptomatic patients. In addition, detection of Covid-19 in chest X-ray images is a challenging task depending on the presence of the experienced radiologists. Having a radiologist does not solve the problem to some extent, since the appearance is not specific and often ambiguous, which leads to significant differences between the radiologist during diagnosis.

For example, an expert radiologist diagnoses the pathology correctly while a less experienced radiologist diagnoses it with abnormalities. By developing CheXNet algorithm which is more efficient than expert X-ray specialist, the diagnostic problem will be solved and the most important is that the algorithm can be relied upon for diagnosis in institutions which lose out to diagnostic imaging specialist. CheXNet algorithm consists of a (121) layer convolutional neural network (CNN) which is trained on 14 ChestX-ray [1].

The performance of the CheXNet algorithm was compared to the performance of a group of radiologists consisting of four radiologists and the results showed that the CheXNet algorithm exceeded the average performance of the radiologist on the F1- score. The F1-score, or F1-scale, is used in the statistical analysis of the binary classification to measure the accuracy of the test, since when its value is equal to 1, its best value while its worst degree is 0. It is computed from the accuracy of the test and retrieved, where the accuracy is the number of results Correctly identified positivity divided by the number of all positive outcomes, including those that were not correctly identified, and the recall is the number of correctly identified positive results divided by the number of all samples that should have been identified as positive [3]. The formula for the F1 score is described in (1) as follows:

$$F1 = \frac{2\times Precision \times Recall}{Precision + Recall} \qquad (1)$$

Table I shows the results of the performance comparison between a group of 4 radiologists and the CheXNet algorithm [1]. CheXNet achieved higher F1 score by 95% Confidence Interval (CI) compared to the radiologist as shown in Table I. As a result of the rapid spread of the Covid-19 pandemic among people and since the result of a laboratory examination of Covid-19 using an RT-PCR device takes no less than two days, chest x-rays are the best way to diagnose Covid-19 infection [4],[5],[6].

Table I: performance results of 4 radiologists and CheXNet [1].

F1 Score (95% Confidence Interval CI)	
Radiologist1	0.383
Radiologist2	0.356
Radiologist3	0.365
Radiologist4	0.442
Radiologist Avg.	0.387
CheXNet	0.435

With the development of the CheXNet algorithm, the diagnosis of the disease became more efficiently than the performance of specialists. Accordingly, a unique challenge for algorithms is the ability to distinguish COVID-19 from other lower respiratory diseases that may appear similar on X-ray images.

Our study proved the feasibility of adopting a deep learning approach to help clinicians discover patients with COVID-19 through X-ray images. Depending on deep learning's high performance in the task of detecting people with Covid-19, the proposed prediction model is now able to rapidly identify the patient.

In this paper, we used a CNN algorithm [8] that is trained on a set of X-ray images to determine whether a person is suspected of being infected with Covid-19 virus or not. The Chest X-ray images dataset which contains about 550 X-ray images was collected from the Kaggle website [9], [10].

The rest of the paper reviews some related works. Then, Installation of CNN algorithm used in this study is described. After that, the methodology is explained. In section 5 demonstrates the experimental results and discussion. The conclusions and future works are described in the last section.

II. Related work

Knowledge extraction from medical data can help in detecting diseases in the early stages [11]. Many researchers worked on medical images using CNN algorithm. Gulshan et al. [12] developed a deep learning algorithm by using large datasets to exceed the performance of medical professionals, in a wide set of medical imaging tasks, with the aim of automatically detecting diabetic retinopathy and diabetic macular edema in retinal fundus images where a definite type of an improved neural network to image classification which is called deep convolutional neural.

In this research, we seek to prove the feasibility of applying a deep learning algorithm in early detection of infection with the Coronavirus and to determine whether using the algorithm could lead to the development of an accurate computer-based method to help doctors to identify COVID-19 patients by using x-ray images.

Apostolopoulos and Mpesiana [13] used pre-trained models (learning to transfer) using convolutional neural networks with a dataset of 1,427 X-ray images, (700) from patients with pneumonia, (224) COVID-19 disease, and 504 normal. The purpose of the study is to evaluate the performance of convolutional neural network architectures proposed for medical image classification. The results of the Deep Learning with X-ray imaging to Covid-19 disease were the best accuracy (98.66%). The aim of the study is to evaluate the performance of the proposed convolutional neural network architectures for classifying medical images. Deep learning results using X-ray imaging of Covid-19 showed better accuracy (98.66%), while in this paper, the CNN was constructed and trained from scratch, rather than using a pre- trained model for applying transfer learning.

Cohen et al. [14] provided a neural network model for predicting and measuring the severity of pneumonia in general and covid-19 chest X-ray images for use in escalation and de-escalation in care and to monitor the effectiveness of treatment used in the intensive care unit.

Barstugan et al. [15] provided early detection of coronavirus using machine learning methods through computerized tomography (CT) images. The feature extraction process has been applied for corrections to increase classification performance, and the wavelet transformation algorithm has been used to extract and classify features by SVM and obtain a 99.68% rating accuracy. Ying et al. [16] The study was conducted on a sample of images from a CT scan of 88 patients who were infected with Covid-19, 86 healthy people for modeling and comparison, and 101 patients with pneumonia that were taken from hospitals in China, where the results showed high accuracy in identifying Covid-19 patients, reaching 99%. The patient can be diagnosed within 30 seconds, and thus the model achieves accurate and rapid identification of Covid-19 in human samples.

We apply and evaluate a Convolutional Neural Network (CNN) model that was built on a dataset of chest X-ray images collected from Kaggle [9], so that it can accurately detect the effects of COVID-19 and demystify these uninfected people.

III. CheXNet

CheXNet is a 121-layer condensed model [13] trained in the ChestXray14 dataset [14] containing 100.000 front chest images. Training the model was based on categorizing X-ray images into 14 different categories of chest diseases. As a result of CheXNet training on a more specific dataset, it became more efficient to classify x-rays. Fig. 1 shows the CheXNet building structure, which consists of an input shape 224 * 224 * 3, then more than a bypass layer and ends with the fully connected layer with Relu activation function, and the output has a layer to classify the image.

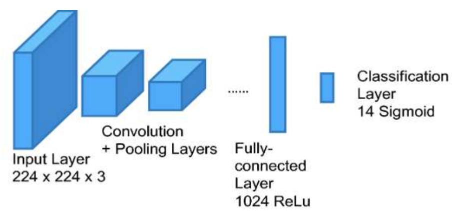

Fig. 1. CheXNet constructed based on DenseNet-121 [7]

IV. Methodology

This section describes the CNN model which includes the phases used for covid-19 detection. The phases are shown in Fig. 2 and discussed hereafter.

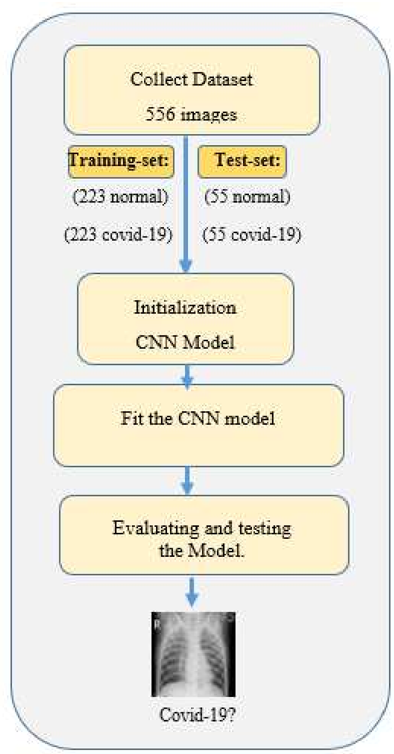

Fig. 2. The proposed CNN prediction model for covid-19

A. Dataset

The collected Chest X-ray images dataset contains 556 X-ray images divided into 446 images for training (80%) and 110 (20%) for testing. The X-ray images were collected from the kaggle website [9], [10] and importing the Keras libraries in [17].

B. Initialization

- Add first layer (Convolution 2D): We use 64 output filters in the convolution 3*3 filter matrix that wi ll multiply to input RGB size image 64*64 and use activation = relu.
- Apply (MaxPooling2D), Processing, Hidden Layer 1 (2*2 matrix rotates, tilts) to all the images. The step 1 and 2 are repeated twice.
- Adding Flattening: converts the matrix in a single array.
- Adding full connection (128 final layer of outputs, activation= relu &Dense layer, activation= sigmoid).

Fig. 3 represents the layer of CNN architecture and Fig. 4 shows the summary of CNN.

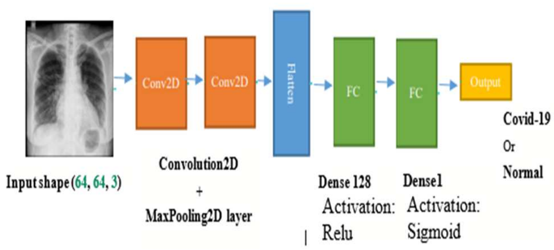

Fig. 3. The layer of CNN architecture

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 21, 21, 64)        1792
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 10, 10, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 1, 1, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               8320
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 47,169
Trainable params: 47,169
Non-trainable params: 0
```

Fig. 4. CNN model summary.

C. Fit the CNN model

In the field of deep learning, a popular Adam algorithm is used because it delivers good results quickly, and it is an optimization algorithm to update iterative network weights based on training data instead of the classic random gradient descent procedure [18].

```
Epoch 1/10
14/14 [==============================] - 10s 719ms/step - loss: 0.3289 - accuracy: 0.8430 -
Epoch 2/10
14/14 [==============================] - 10s 709ms/step - loss: 0.3099 - accuracy: 0.8610 -
Epoch 3/10
14/14 [==============================] - 10s 702ms/step - loss: 0.3538 - accuracy: 0.8453 -
Epoch 4/10
14/14 [==============================] - 10s 701ms/step - loss: 0.3111 - accuracy: 0.8632 -
Epoch 5/10
14/14 [==============================] - 9s 675ms/step - loss: 0.3072 - accuracy: 0.8498 -
Epoch 6/10
14/14 [==============================] - 10s 699ms/step - loss: 0.2645 - accuracy: 0.8969 -
Epoch 7/10
14/14 [==============================] - 10s 694ms/step - loss: 0.2979 - accuracy: 0.8744 -
Epoch 8/10
14/14 [==============================] - 10s 704ms/step - loss: 0.3345 - accuracy: 0.8274 -
Epoch 9/10
14/14 [==============================] - 10s 685ms/step - loss: 0.2591 - accuracy: 0.9013 -
Epoch 10/10
14/14 [==============================] - 10s 697ms/step - loss: 0.2477 - accuracy: 0.8969
<tensorflow.python.keras.callbacks.History at 0x7f1d8ce08240>
```

Fig. 5. Result of model training in 10 Epoch

The optimizer which is called Adam, is an efficient variant of gradient descent which generally does not require hand-tuning of the learning rate. Throughout training, the optimizer uses the gradients of the loss to try reducing the error ("optimize") of the model output by adjusting the parameters. According to Kingma et al. [19], "the method is computationally efficient, has little memory requirement, invariant to diagonal rescaling of gradients, and is well suited for problems that are large in terms of data/parameters".

Apply fitting to the training set (steps_per_epoch:100, no. epoch: 10, Validation data: test-set, nb.val.samples (60), callbacks= [early_stop]). Fig. 5 shows the results of model training in10 Epochs.

D. Evaluating and testing the Model.

For evaluation the CNN model, loss (binary_crossentropy) and accuracy metrics are used. The Loss Function which is known as a prediction error of Neural Net, is one of the most important components of Neural Networks, and it is also considered as the method to calculate the loss.

Simply, we can describe the way that a Neural Net is trained as following: The Loss is used to calculate the gradients and then, gradients are used to update the weights of the Neural Net [20].

While binary Crossentropy (BCE) loss is used for the binary classification tasks. We use BCE loss function just when we need one output node and this for classifying the data into two classes, hence the output value should be passed through a sigmoid activation function and the range of output should be (0 – 1). The Cross-Entropy (CE) loss can be expressed in (2) as explained by [21]:

$$\frac{\partial}{\partial s_i}\left(CE(f(s_i))\right)=\begin{cases} f(s_i)-1 & if\ \ t_i=1 \\ f(s_i) & if\ t_i=0 \end{cases} \quad (2)$$

Where f is the sigmoid activation function, t_i is the ground-truth, and s_i is the CNN score for each class i in C classes.

In order to verify our Model, some samples of cell are given to detect covid-19. The pictures were loaded and converted into array, then the model can predict if the image is covid-19 or normal. Fig. 6 shows a model of testing for new X-Ray images.

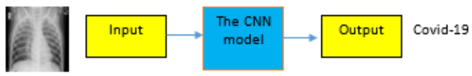

Fig. 6. New prediction

V. Result and Discussion

In the first experiment, 276 Chest X-ray images dataset [9] was used for training and testing, 220 images for training (80%) and 56 for testing (20%). The model was trained with a set of 110 x-rays of people with Covid-19 and 110 normal, and a test set containing 56 chest radiographs divided between people with Covid-19 and people without infection. The complete data set must pass multiple times to the same Neural Network to improve the learning process. Then, 10 periods are used to update the weights of the CNN model. The results showed 84% accuracy and 45% loss.

In the second experiment, a group of 280 images were collected from [10] and added to the previous data set to be 556 images then passed to the model again (80% training and 20% testing), where the results showed 89.7% accuracy and 24.8% loss. Table II shows the difference between the results of applying the CNN model to the input datasets. Fig. 7 is a graph of the amount of error ratio (loss ratio) for the data during training.

Through experience, it has been shown that with an increase in the training sample, certain models can achieve a more accurate identification of COVID-19 in human samples, allowing the identification of the patient.

Table II: Results of CNN model

No.images	No. epoch	loos	accuracy
276	10	45%	84%
500	10	24.8%	89.7%

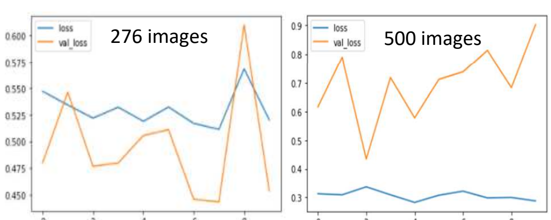

Fig. 7: loss ratio during training

VI. Conclusion and Future Works:

In conclusion, the results of this unique research show a potential role of a very accurate Artificial Intelligence algorithm to quickly identify patients, which could be useful and effective in combating the current outbreak of Covid-19. We are almost certain that it is possible for the proposed CNN model, which shows the equivalent of the highest score for the accuracy of a specialized chest radiologist, represents a very effective examination tool for the rapid diagnosis of many infectious diseases such as the COVID-19 epidemic that do not require the introduction of a radiologist or physical examinations.

In future studies, we recommend addressing other topics such as outbreak escalates [22], as well as trying to explore different approaches to convolutional neural networks, including deep learning models and improved interpretation of CNN models.

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