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A Convolutional Neural Network for Detecting COVID-19 from Chest X-ray Images

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Abstract**—** *since the global pandemic of COVID-19 has spread out, the use of Artificial Intelligence to analyze Chest X-Ray (CXR) image for COVID-19 diagnosis and patient treatment is becoming more important. This research hypothesized that using COVID19 radiographic changes in the X-Ray images. Artificial Intelligence (AI) systems may extract certain graphical elements regarding COVID-19 and offer a clinical diagnosis ahead of pathogenic test; therefore, saving vital time for disease prevention. Employing 2614 CXR radiographs from Kaggle data collection of verified COVID-19 cases and healthy persons, a new Convolutional Neural Network (CNN) model that is inspired by the Xception architecture was presented for the diagnosis of coronavirus pneumonia infected patients. The suggested technique reached an average validation accuracy of 0.99, precision of 0.95, recall of 0.92, and F1-score of 0. 95. Finally, such findings revealed that the Deep Learning (DL) technique has the potential to decrease frontline radiologists' stress, enhance early diagnosis, treatment, and isolation; therefore, aid in epidemic control.*

Index Terms— *Chest X-ray images, Convolutional Neural Network, COVID-19, Detection.*

I. INTRODUCTION

COVID-19 is a new virus, which was never diagnosed or seen in humans. Coronavirus is also responsible for Middle Eastern Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) [1]. Coronavirus types are a broad family of viruses, which are transmitted from animals to humans. The outbreak began in Wuhan, China, in Dec 2019 and had since spread over the world and causing a total of 201502 deaths till 26 April 2020. Subsequently, the World Health Organization (WHO) has declared this ongoing outbreak as a global public health emergency. COVID-19 mainly affects the respiratory system of human and damages the alveoli of lungs. Although COVID-19 infection cases are mild in general, it causes severe disease with 2% fatality rate [2]. Polymerase Chain Reaction (PCR) tests are commonly applied for diagnosing COVID-19 disease. PCR can be defined as a gold standard procedure, even though it does have significant drawbacks. It has high sensitivity, and any sample contamination, even small amounts of DNA, might cause erroneous results. Prior sequencing information is also required for creating its primers. Therefore, it can determine whether known pathogens or genes are present [3]. The Computer Aided Diagnostics (CAD) concept had shown to be a reliable tool for supporting medical practitioners in the field. Because of its non-invasiveness, convenience of use and accuracy, it is used in practically each area of a medical healthcare unit, and its demand is growing by the day [4].

The first stage involves detecting the disease, recognizing the symptoms, and using distinguishing signs to accurately detect the disease. Depending on the disease, symptoms may include shortness of breath, cough, acute respiratory problems, and common cold or fever, while patients may also have a cough for no apparent reason for a few days. COVID-19, unlike SARS, affects not only the respiratory system but also other organs in the body, such as the liver and kidneys. COVID-19 typically causes symptoms to appear a few days after an individual becomes infected, although symptoms may appear later in some cases. It is assumed that elderly people suffering from basic clinical issues such as diabetes,

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cardiovascular disease, hepatic or renal disease, persistent respiratory infection were bound to develop genuine disease. [5].

AI combined with image processing can be an accurate and quick way to distinguish between affected and normal CXR images. It might increase the speed with which the cases of COVID-19 are identified and decrease its spread, especially in resource-constrained environments in which high-end medical equipment and expert's radiologist are not provided for patient management and early diagnosis. Convolutional Neural Network (CNN) is a powerful AI technique for detecting diseases in medical images [6] [7].

This work suggested multi-layer convolution neural network trained on CXR images to accomplish detection COVID-19 disease. A total of 2614 images have been acquired for this project from the X-ray dataset in Kaggle repository.

The following is a summary of the study's primary contribution:

- Given the drawbacks of PCR technique, the architectures of CNN were investigated for addressing the issue, and a model for COVID-19 detection has been suggested avoiding the tiresome feature extraction process and learns (automatically) features from images since the suggested model has an end-to-end structure that eliminates any needs for manual feature selection and extraction techniques.
- A method of data augmentation has been used for boosting the suggested model's performance.

The remainder of this work has been organized in the following way: In Section (II) explain related works, Section (III) explains the techniques and material, including the dataset utilized in this work, preprocessing, image data augmentation, and the suggested architecture of CNN. The results and discussion are presented in section (III) and summarized in the conclusion.

II. RELATED WORKS

AI-assisted approaches for COVID-19 classification from CT or chest X-ray images have been increasingly popular in recent years. Many authors have tackled the advancement of neural network and their latest breakthrough deep learning architecture. The advancement of machine learning has made it possible to acquire accurate results in image classification in general and in medical image recognition to be specific. Linda et al. [8] have created a ResNet architecture and a CNN architecture to detect COVID-19 infection from 76 and 50 confirmed chest X-ray images, respectively. In both experiments, the feature extraction and classification processes were applied directly to the raw images, with no segmentation or artifact removal, where the fact that both of these steps are critical in reducing false COVID-19 alarms.

Additionally, Ali et al. [9] have implemented 3 CNN-based models (InceptionV3, ResNet50, and InceptionResNetV2) to detect coronavirus pneumonia infected patients using CXR radiographs. Taking the obtained performance results into account, the pre-trained ResNet50 model achieved the best classification performance with 98 percent accuracy among the other two suggested models (accuracy of 97 percent regarding InceptionV3 and accuracy of 87 percent regarding Inception-ResNetV2). The limitations of the suggested algorithm are working with limited data therefore they used transfer learning method because it allows the training of data with datasets that contain few pictures and requires less calculation costs.

Alternatively, Li et al. [10] developed ResNet50 to distinguish COVID-19 from non-pneumonia or community-acquired pneumonia. A total of 618 CT samples have been used in the present work with an accuracy of 86.7 percent. The drawbacks of this study were the number of model samples was limited. The number of training and test samples should be expanded to improve the accuracy.

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furthermore, Ghulam et al. [4] proposed using CNNs to detect COVID-19 in an automatic manner. The dataset used included CT and X-Ray images (7021 images of both pneumonia and normal, whereas there have been 1066 images with COVID-19 infection). The model achieved an average specificity (95.65%), accuracy (96.68%), and sensitivity (96.24 %).

In the same manner, Ioannis et al [11] assessed the effectiveness of the state-of-art CNN models for medical image classification. The dataset used in the study included 1427 X-Ray images, 700 of which confirmed common pneumonia, 224 with confirmed COVID-19, and 504 with normal conditions. The detection of COVID-19 has achieved a general accuracy of 97.82 percent.

Lastly, Kishore et al. [3] used a deep CNN approach to reliably and quickly identify COVID-19 from patient CXR images. The typical workflow for such a system includes five major phases: 1. data acquisition, 2. preprocessing, 3. segmentation, 4. feature extraction, and 5. classification model. The model was able to achieve an accuracy of around 93 percent.

It is noticeable that the implementation of various models of machine learning and deep learning in the previous works mentioned above achieved good accuracy, yet the main difference lies in the methods applied to the data and the type of the data. As some of the authors used X-Ray images and others using CXR-radiographs. The collected datasets were from different subjects in different conditions and geological distributions. Some of the related work applied preprocessing and manual feature extraction techniques and others have relied on the automation of CNN to achieve the require results. In Table I, a summary shows the method of comparison with the results of previous work to increase the reliability of the proposed research model.

TABLE I. REVIEW DETAILS OF LITERATURE SURVEY

Study	YEAR	TECHNIQUES	Accuracy (%)
Ali Narin et ai [9]	2019	3 CNN-based models (InceptionV3, ResNet50, and InceptionResNetV2)	98%
Linda et al. [8]	2020	COVID-Net	93%
Li et al. [10]	2020	Deep Convolutional Neural Network (CNN) ResNet50	86.7%
Ghulam et al. [4]	2021	CNNs	96%
Ioannis et al [11]	2020	CNN models	97.82%
Kishore Medhi et al [2]	2020	Deep Convolutional Neural Network	93%
PROPOSED CNN	2021	New technique that is inspired by the Xception architecture	99%

III. MATERIAL AND METHODS

Machine learning algorithms have been used by many researchers in order to diagnose many diseases. The majority of them employs conventional methods for detecting, classifying, and grading various abnormalities, such as feature selection, reduction, extraction and classification based on such characteristics. The biggest disadvantage of such solutions is the long time required for feature engineering. Furthermore, conventional approaches have poor performance measures. DL architectures were investigated to deal with such challenges. The possibility of deep features prompted us to look at the architectures of CNN.

A. Dataset

This study involved the training and testing of a COVID-19 recognition model from chest x-ray images. To train the model, a suitable image dataset is needed. For this purpose, Kaggle repository was used as the source of a recent dataset. The dataset contains 2614 images and the reason for choose that number of images for the preference of computer that we had, where 1307 images include a healthy

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(normal) chest condition and the remaining 1307 images have confirmed COVID-19 cases. The proposed data set can be seen in *Fig. 1*, where label 0 is healthy "Negative" and label 1 is "Positive". The positive image data exhibits a white patchy region shadowing the lungs that can be diagnosed by radiologists. The dataset is downloaded remotely as one compressed file and processed immediately in Google Colab, no local machine downloads has taken place.

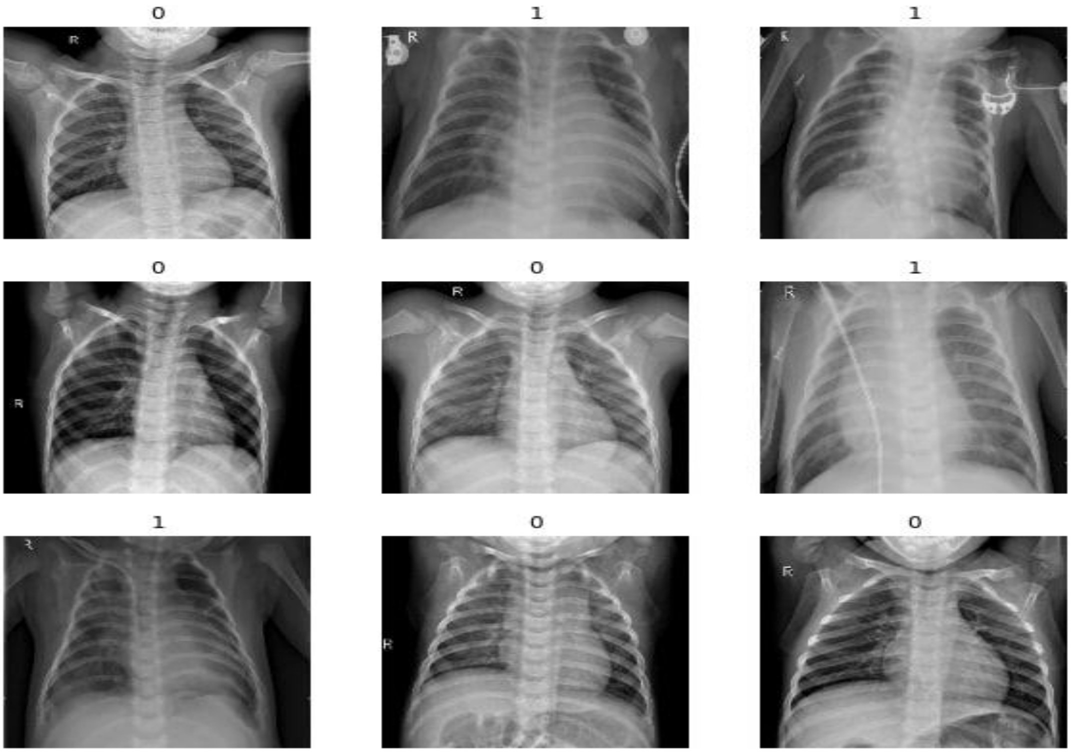

FIG. 1. PROPOSED COVID19 DATASET (LABEL 1 IS "POSITIVE" AND 0 IS "NEGATIVE").

B. Preprocessing

This step is necessary to ensure that all images are valid for training. Since the image data is downloaded from online sources, an additional image corruption check is included to filter out damaged or corrupted images. Moreover, the images are rescaled to (180,180) pixels in order to be consistent with the model's input size. After checking the quality of the samples in the data set, it was found that all the images are valid for processing and training

C. Using Image Data Augmentation

Data augmentation enhances the performance of CNN, slows overfitting, and is simple to implement before training a model. Overfitting usually occurs, in the case of limited data and features where the model limits its capacity for generalizing results to new data. This is usually seen when the testing accuracy of unseen data is much lower than the training accuracy. To overcome this issue using random, however, realistic modifications to training images, like random horizontal flipping or minor random rotations, is helpful for the exposure of the model to new features of training data, when data augmentation is used the number of data increases. This step is applied when the sample set is small in the data set or the quality of some data is low. It is used to increase the accuracy extracted, but it also causes slow results in obtaining the results as *Fig. 2.*

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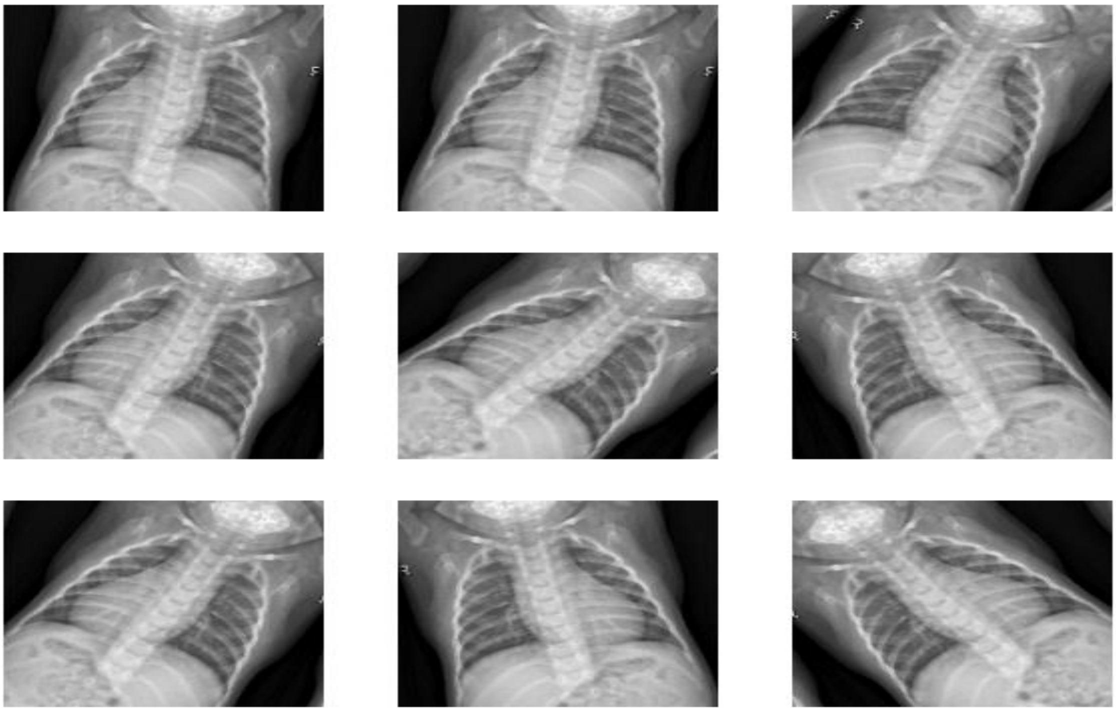

FIG. 2. DATASET AUGMENTATION.

D. The Proposed CNN Architecture

CNN was selected in this study for classifying images into normal, and COVID19. Since it is a multistage trainable neural network architecture, it is sophisticated for classification problems and is advanced technique to ML inspired by the human brain. CNN works similarly to the human visual system and has been built on the concept that raw data is made up of 2D images, allowing specific characteristics to be encoded. Generally, CNN generates feature maps through convolving images with kernels. In addition, kernel weights connect units to tweaked layers in a feature map, and such weights are modified throughout training via a back propagation process. Table II will show how the CNN proposed algorithm works.

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TABLE II. ALGORITHM OF PROPOSED CNN MODEL

Input: dataset, E= number of epoch, input shape =IS
Output: The accuracy measurements

1. Preprocessing the images dataset using rescaling
2. Initialize a random value for all parameters
   learning-rate = 0.0001
   Max_No._epoch = E (batch's size = 64, IS= (image size,3), K=2 for each epoch)S = 2,
   P= 1, padding=" same"
3. Split data into training / test sets data by 70% to 30%
4. Call CNN: Apply network layers
   A. Conv 1, with 32 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   B. Conv 2, with 64 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   C. Conv 3, with 128 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   D. Conv 4, with 256 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   E. Conv 5, with 512 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   F. Conv 6, with 728 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   G. Conv 7, with 1024 filter, AF = ReLU,Max_pool, with P=2, k=3, Batch normalization
   H. Conv 8, with 1024 filter, AF = ReLU, avareage_pool, with pool_size= 1
   I. If number of class ==2
      then activate using sigmoid, unit=1
      else
      then activate using softmax, unit= number of class
   J. Dropout (0.5)
   K. Fully connected layer with Dense layer, number of class
   L. Classify the outcome for a give dataset
   M. update weight using ADAM
5. Return to Step 4
6. Class of dataset
7. CNN performance measures by confusion matrix
8. **Classifier Results = Best (Accuracy. Results)**

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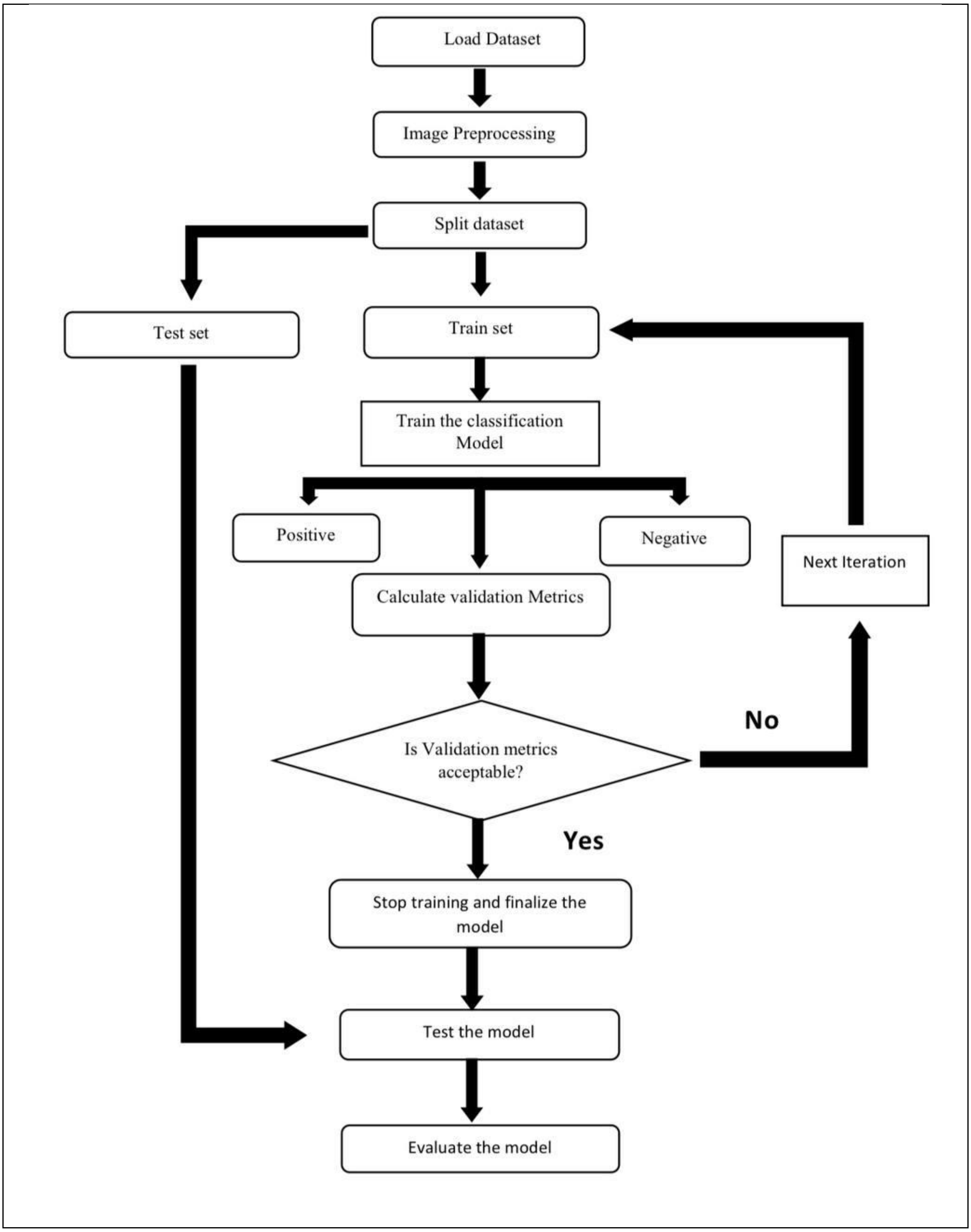

FIG. 3. FLOW DIAGRAM OF THE PROPOSED SYSTEM.

Since the same kernels were utilized by all units, the convolutional layer had to learn less weight. *Fig. 3* shows the needed steps with CNN for achieving the goal of chest image classification. The proposed neural network architecture is shown in Table III, where 20 layers is implemented including the convolutional, activation, and pooling layers followed by a fully connected layer at the end to classify between the two classes. Where Conv refers to convolutional layers, SConv refers to separable

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convolution layer, BN refers Batch Normalization layer, ReLU refers Rectified Linear Unit as an activation function, FC refers to fully connected layer. Each of the layers is explained in the following section.

TABLE III. THE PROPOSED MODEL'S ARCHITECTURE

Layer #	Type of Layer	Kernel Size and Stride	Output Size
1	Input layer	-	180×180×3
2	Conv2D, BN, RelU	Kernel size=3×3, stride=2	90x90x32
3	Conv1, BN1, RelU1	Kernel size=3×3, stride=2	90x90x64
4	SConv1/Conv2, BN2, RelU2, Max Pooling	Kernel size=3×3, stride=2	90x90x128/ 45x45x128
5	Add1	Addition of two inputs	45x45x128
6	Activation: RelU2	Activation Function	45x45x128
7	SConv2/Conv3, BN3, RelU3, Max Pooling	Kernel size=3×3, stride=2	45x45x256/23x23x256
8	Add2	Addition of two inputs	23x23x256
9	Activation: RelU3	Activation Function	23x23x256
10	SConv3/Conv4, BN4, RelU4, Max Pooling	Kernel size=3×3, stride=2	23x23x512/12x12x512
11	Add3	Addition of two inputs	12x12x512
12	Activation: RelU4	Activation Function	12x12x256
13	SConv4/Conv5, BN5, RelU5, Max Pooling	Kernel size=3×3, stride=2	12x12x728/6x6x728
14	Add4	Addition of two inputs	6x6x728
15	Activation: RelU5	Activation Function	6x6x728
16	SConv5 BN6, RelU6, Max Pooling	Kernel size=3×3, stride=2	6x6x1024
17	Activation: Relu7	Activation Function	6x6x1024
18	Average Pool	Gloabal Average Pooling	1x1x1024
19	Dropout	Drop with 0.5 learning rate	1x1x1024
20	FC	Fully Connected	1

1. Convolutional layer

A convolutional layer has been made up of a set of filters, every filters have their own group of the parameters that must be learned. The filters' weight and height are less than that of the input volume. Every one of the filters is convolved with input volume for the production of a neuron-based activation map. To put it another way, the filter has been slid across the input's height and width, while the dot products between filter and input are evaluated at each one of the spatial positions. Also, stacking the activation maps regarding all the filters along depth dimension yields the convolutional layer's output volume. Because each filter's height and width are small compared to input, each one of the neurons in activation map has been just connected to a small local input volume region, and because the activation map is created by doing convolution between input and filter, while filter parameters have been shared across all of the local positions. Weight sharing minimizes the number of the parameters that are required for effective expression, generalization and learning [12], [13]. There are two differences between the convolutional layers and the separable convolution model as follows:

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- The order of the operations: separable convolutions as usually implemented (e.g. in TensorFlow) perform first channel-wise spatial convolution and then perform 1x1 convolution, whereas convolutional layers the 1x1 convolution first.
- The presence or absence of a non-linearity after the first operation. Convolutional layers are followed by a ReLU non-linearity, however, separable convolutions are usually implemented without non-linearities [14].

2. Activation Function

The data was transformed into non-linear form using this function. The rectifier linear unit (ReLU) is the activation function used in the proposed framework, and it has been represented by Eq (1).

$$f(x) = \begin{cases} 0, if\ x\ < 0 \\ x, if\ x \geq 0 \end{cases} \tag{1}$$

where x = an input value.

Softmax and Sigmoid are the two activation function types which are commonly utilized. Another activation function type utilized in neural computing is Softmax function. It is utilized to make a probability distribution out of a set of real numbers. The output of the Softmax function is a range of the values in the range from 0 to 1, with summation of probabilities being equal to 1.

Sigmoid function is widely used in classification problems, particularly in output layer regarding a binary classification, in which the results are either 1 or 0. Due to the fact that the value of the sigmoid function is only in the range from 0 to 1, the result might be simply predicted to be 1 in the case where the value is higher than 0.50 and 0 otherwise.

Softmax and Sigmoid functions vary primarily in that the Sigmoid is utilized for binary classification, whereas the Softmax is utilized for multivariate classification.

3. Pooling Layer

This layer was created to merge spatially neighbor features in feature maps. To join features, max-pooling or average-pooling is utilized. Pooling can be implemented using a variety of non-linear functions, the major one is max pooling. It divides input image to a collection of non-overlapping rectangles and produces the maximum for every one of these sub-regions; the precise placement of a feature is less significant compared to its approximate location relative to other features. Pooling in CNN has been based on this concept. The pooling layer results in the reductio of spatial size of representation as well as the number of the parameters, amount of computation in a network, and memory footprint allowing for better fitting control. Also, a pooling layer is frequently inserted between subsequent convolutional layers in the architecture of CNN. Another translation invariance type is provided by the pooling procedure. The pooling layer resizes each depth slice regarding the input spatially and functions independently on each one [15]. *Fig. 4* shows a simple example of average and maximum pooling.

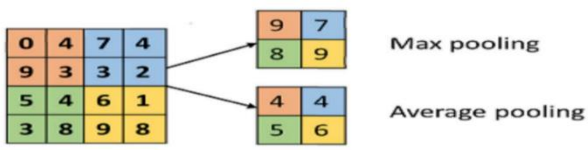

FIG. 4. EXAMPLE OF MAX AND AVERAGE POOLING. [15].

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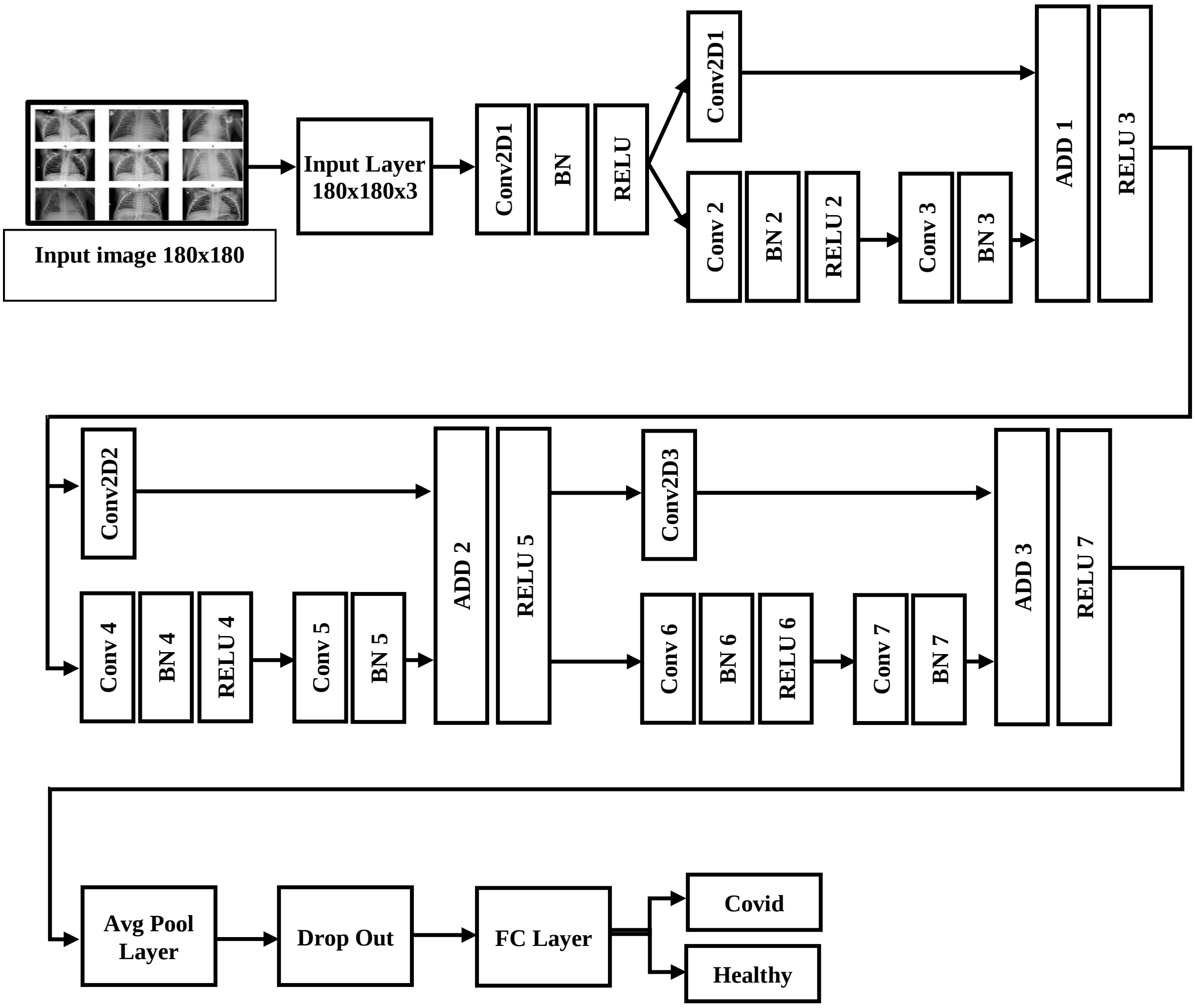
4. Dropout Layer

Then, a dropout layer is used with a likelihood of 0.5 and finally, features have been passed on to fully connected layer, which has a 3 output size for the classification of input CXRs as one of 2 classes, which are: normal, or COVID-19.



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5. Fully connected layer

A multilayer perceptron on top of last convolutional layer will be used for eventually classifying the image into a category. The previous convolution and pooling techniques drastically decreased the size of input image while preserving the classification's distinctive qualities. The output feature map must be flattened since feeding an MLP needs input vectors (1D arrays). As a result, MLP receives small-sized feature maps as a 1-D array and selects the appropriate class for the feature maps [16] [17]. The specifics of the suggested architecture for normal and Covid19 classifications are provided in Table III, which includes layer type and filter size is "Kernel" or "feature detector" achieving the greatest results in testing and training process in the case when utilizing 3x3 filter size. Stride: Moves the filter matrix over the input matrix by a certain number of pixels. Stride equal to 2 is chosen, which means moving the filters 2 pixels at a time, while the value 2 rather than 1 since it creates smaller, more significant feature maps. *Fig. 5* shows the structure of the proposed model. In our proposed model, the layered structure of the model was inspired by the approach used in the Xception model, the original

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model has 36 convolutional layers while the proposed model has 20 layers. The number of samples in the data set is not large. Low performance devices are used to perform this work with lower resource requirements (CPU and memory). And it was enough to get out with high accuracy in order to save time and resources. The same principle applies to depth-separable convolution layers, except that Xception uses a slower learning rate than the proposed model. in our model.

After all the layers have been defined and prepare, the data is fetched, and the training process is executed followed by a validation and testing step.

6. Model Training and Validation

After the development of the suggested CNN model, we trained it for 30 epochs while employing data augmentation for preventing overfitting. Then, evaluation metrics was used to indicate the performance which was recorded on the validation set, and reaching high system accuracy comes from the system's high efficiency with few errors. The accuracy, precision, recall, and f-score metric scales that were employed are listed below [18] [19].

- **Accuracy:**

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{TN} + \text{FN}) \qquad (2)$$

Accuracy indicates the number of the correct classifications that have been made out of all classifications, i.e. the number of the TNs and TPs that have been performed out of FP + FNs + TP + TN. It indicates the ratio of the “True” cases to summation of “True” cases and “False” cases.

here [20] [21]:

- True positive (TP) represents number of the positive samples that had been correctly classified.
- False Negative (FN) represents number of positive samples that had been incorrectly classified.
- False Positive (FP) represents number of negative instances samples which that had been incorrectly classified.
- True negative (TN) represents number of negative instances samples which that had been correctly classified.

- **Precision:**

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \qquad (3)$$

Out of all that have been marked to be positive, the number of them that have been in fact truly positive.

- **Recall:**

$$\text{Recall} = \text{TP} / (\text{TN} + \text{FN}) \qquad (4)$$

Out of all actual real positives, how many have been identified to be positive.

- **F1-Score:**

$$\text{F1 score} = 2 \text{ x } (\text{Precision x Recall}) / (\text{Recall} + \text{Precision}) \qquad (5)$$

As was seen before, sometimes the weightage is given to FN and other times to FP. F1 score is considered as the weighted average of Precision and Recall, implying that FN and FP are given equal

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weight. In comparison to "Accuracy," this is an extremely significant metric. The issue with employing accuracy is that in the case of a highly unbalanced training data set (for instance, a training data-set with 5% negative class and 95% positive class), the model will learn the way of correctly predicting the positive class but not the way of identifying the negative class. However, the model will still have a high level of accuracy in test data-set since it will have a good understanding of how to recognize positives.

IV. THE OBTAINED RESULT

CXR imaged were used in this study to detect the existence of COVID19 infection. Python and Google Collaboratory environment were used to carry out the experiment. The existence of a white patchy region shadowing the lungs aids in the identifying process. All of the image were pre-processed using intensity normalization to ensure adequate detection, in which the grey pixels are clearly distinguished from white pixels. In comparison to normal lungs, the number of gray pixels in COVID19 affected lungs is significantly lower. The above-mentioned architecture of CNN was used for extracting features from images, and then all of the extracted features were passed into the SoftMax classifier for detection.

The dataset was split into 2 parts throughout the experiment, with 20% used for testing and 80% for training. The two tables (IV and V) show the outcomes of testing and training on the basis of average value of 50 epochs. Two per-trained models were used to benchmark our proposed model, namely the VGG net and the original Xception model. This work achieved accuracy of 98.7%, recall of 97.6%, precision of 98.2%, and F1-score of 97.8% throughout the process of training, and accuracy of 99%, recall of 96%, precision of 92.6%, and F1-score of 95% throughout the process of validation and testing. It is obvious that after 50 epochs, our model outperformed the other models and the experimental results have shown that the suggested approach for extracting radiological parameters for accurate and rapid COVID19 diagnosis is effective.

TABLE IV. ANALYSES OF A VARIETY OF THE PERFORMANCE MEASURES FOR TRAINING OF THE SUGGESTED MODEL UTILIZING DEEP LEARNING

CNN Model	Number of Epochs	Accuracy	Recall	precision	F1-score
VGG	50	96.6%	95.8%	95.4%	95%
Xception	50	97.7%	97%	97.3%	97.5%
Proposed Model	50	98.7%	97.6%	98.2%	97.8%

TABLE V. ANALYSIS OF VARIOUS MEASURES OF PERFORMANCE FOR VALIDATING THE PROPOSED MODEL WITH THE USE OF THE DEEP LEARNING

CNN Model	Number of Epochs	Accuracy	Recall	precision	F1-score
VGG	50	95.1%	95.8%	92.9%	94.6%
Xception	50	96%	93.6%	94.8%	95.5%
Proposed Model	50	99%	96%	93.6%	95%

V. CONCLUSIONS

It is important to predict that people will catch COVID19 early to prevent the disease from spreading to other people. In this paper, a proposed convolutional neural network trained on CXR images was used in the presented work. To automatically predict COVID19 patients, a total of 2,614 images were obtained from the Kaggle Repository X-ray dataset from both COVID19 and normal patients. A total of four measures were used to evaluate the performance of the model. The proposed classification model achieved an accuracy rate of 99% which is the best classification performance

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among the other two proposed models namely the VGG network and the original Xception model. Due to the impressive overall performance, it is widely assumed that our model will assist medical professionals in making the right and sound decisions in scientific practice. As doctors' time is constrained by the large number of patients receiving emergency or outpatient treatment, computer-assisted analysis can save lives with early detection and appropriate treatment.

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