An Effective Deep Learning Approach Based On CNN to Predict COVID-19 Rapidly Using Chest Images

Ranjit Kumar Shing, Sohel Rana, Md. Rakibul Basher, Md. Sazzad Hossain, Md. Hasibul Hasnat, Faisal Ahahmmad

Department of Computer Science and Engineering, Bangladesh University of Business and Technology, Dhaka, Bangladesh

***Abstract*: In December 2019 the novel coronavirus which first appeared in Wuhan City of China spread rapidly around the world and became a pandemic. It has caused a devastating effect on daily lives, public health, and the global economy. As soon as possible we have to detect the affected patient and quickly treat them. There are no accurate automated toolkits available so the need for auxiliary diagnostic tools has increased. Modern outcomes attained using radiology imaging systems recommend that such images have salient evidence about the COVID-19 virus. Real-time reverse transcription-polymerase chain reaction (RT-PCR) is the most common test technique currently used for COVID-19 diagnosis that is too much time-consuming. Using artificial intelligence (AI) techniques associated with radiological imaging can be helpful for the accurate detection of this disease and can also be assistive to overcome the problem of an absence of specialized doctors in remote communities. In this paper, a new model based on Convolutional Neural Network (CNN) that automatically detects COVID-19 using chest images is presented. The proposed model is designed to provide accurate diagnostics for binary classification. A computer vision is rapidly relieved day by day. During our study, we observed that most of the affected people have no common symptoms before checkup COVID-19. If the detection results are incorrect, the patient will not be able to understand that he or she has Covid-19. The proposed model is evaluated by Python libraries namely TensorFlow and Keras. In the proposed model, we got 95% accuracy as well as the detection of COVID-19 is fast.**

***Keywords:* CNN, Covid-19 affected dataset, Chest Images, Python, TensorFlow.**

I. INTRODUCTION

At present Covid-19 is the most dangerous name. Covid-19 is a large family of viruses that start to cause illness beginning from the common cold to more severe diseases such as the Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV). The major problem of Covid-19 is identification because it is a new strain that has not been previously identified in the human body or animals. A new model for Convolution Neural Network (CNN) that automatically detects COVID-19 using raw chest images is presented. The proposed model is designed to provide accurate diagnostics for binary classification. Computer vision is expressing rapidly day-by-day. Our main target to identify Covid-19 easily.

A. Problem Statement

We know at present Covid-19 is the main issue the entire world. Many researchers work hard to find out the strain of Covid-19. We use CNN in chest x-ray images to find easily a covid-19 person. Many researchers work on new technique algorithms. CNN is among them. It is challenging for us to get better results in this dataset. We know Covid-19 change his action day by day so this is difficult for us to identify the common pattern of this virus . However, if we can success to find out the Covid-19 action then we overcome this disease. There are some common challenges to identify Covid-19 like lack of awareness, difficult to find out strain, geographic separation etc. In this paper, A CNN based model is proposed to classify the early stage of Covid-19 using chest x-ray images.

B. Motivation

Now the whole world is facing the most dangerous situation. Many people die early Covid-19 because we cannot identify this in the early stage. So we think we research Covid-19 and trying to identify it in the early stage. We know many researchers already work in this field. We are motivated by them and want to research this field. We add some features and try to hard solve this problem

C. Significance of the research

We focus on chest image because Clinical setups and population surveillance employ serology for the detection of antibodies. The limited availability of the test kits makes it challenging to detect every individual affected by the virus. Our research can help the medical site by deciding and give treatment to patients. A doctor can easily find out a Covid-19 person by using chest X-ray images.

D. Research Contribution

The contributions of our research:

- We focus on early detection of Covid-19 which is a good solution to save lives of people.
- We modified an existing method to achieve the best accuracy to detect COVID-19.
- We used the some mathematical primitives which increase performance of the proposed CNN model.

E. Paper Organization

The rest part of this paper organized as follows: Chapter II highlights the background and literature review on the field of the speaker recognition system. Chapter III contains the proposed architecture of the speaker recognition system, along with a detailed walkthrough of the overall procedures. Chapter IV includes the details of the tests and evaluations that were performed to evaluate our proposed architecture. Chapter V illustrates the analysis of the result. Finally, chapter VI contains the overall conclusion of proposed model.

II. Literature Riview

We studied more than thirty related popular CNN based classification algorithms like K-nearest, Native bays, CNN, KNN,BP, XGBoost, BPNN, LR, etc. Also, there have many datasets for the research purpose. By using deep learning manner, researchers acquire more exactness and most of them focus on CNN. They got a better outcome by using CNN manner. Most researchers used chest images for their experiments.

Zhao et al. [1] not only found ground-glass opacities (GGO) or mixed GGO in most of the patients, but they also observed a consolidation, and vascular dilation in the lesion.

Li and Xia [2] reported GGO and consolidation, interlobular septal thickening and air bronchogram sign, with or without vascular expansion, as common CT features of COVID-19 patients. Peripheral focal or multifocal GGO affecting both lungs in 50%–75% of patients is another observation.

Zu et al. [3] and Chung et al. [4] discovered that 33% of chest CTs can have rounded lung opacities..

Narin et al. [6] achieved a 98% COVID-19 detection accuracy using chest X-ray imagescoupled with the ResNet50 model.

Sun et al.[7] concluded that the CNN represented higher performance than deep belief network (DBN) and stacked denoising autoencoder (SDAE) in diagnosing malignant lung nodules with an area under the curve (AUC) of 0.899

Barbosa et al.[8] compared the quantitative CT (qCT), pulmonary function testing (PFT), and semi-quantitative image scores (SQS) metrics and found that pul - monary function testing and qCT metrics demonstrated the highest ac - curacy for monitoring bi- and unilateral lung transplantation with an AUC of 0.771 and 0.817

M. Alhanahnah [9] They focused on two model, Back Propagation Neural Network (BPNN) model and the Logistic Regression (LR) model. LR model give a result with the value between zero to one which indicate the risk factor of this disease. They get higher accuracy in LR algorithm.

Bolei at el[10] Worked with histopathological image. Worked with deep learning algorithms, they used DeNet and SaNet approach where DeNet is used to find out the most useful patches from images and it is use for classification. Using BreakHis dataset and they get 98 percent accuracy.

Wang at el[11] worked with mammography images. Used CNN in detection phase and US_ELM for feature extraction and clustering. In diagnosis phase they use deep feature set of each mammogram as a input of ELM for classification. The output indicates benign or a breast tumor.

TingSim[12] worked with self-regulated multilayer perceptron neural network (ML-NN). This algorithm can help medical experts in diagnosis of breast cancer. This algorithm can classified the input medical images as benign, malignant or normal patient with accuracy, specificity, sensitivity and AUC of 90.59%, 90.67%, 90.53%, and 0.906 ± 0.0227 respectively.

XiaofeErik at el[13] worked with the 2D mammograms and 3D tomosynthesis images. Used CNN for classification. They get better result in 3D tomosynthesis images.

PinarSelma at el[14] worked with mammogram images. Used CNN for classification. Worked with MIAS and BCDR database. Get 87% accuracy with MIAS database and 88% accuracy with BCDR database.

Burak Akbugday [15] analyzes different machine classifiers like k-Nearest Neighbors (k-NN), Naïve Bayes(NB) and Support Vector Machine (SVM) with Weka software. The dataset contains 699

Xiaofei Zhamg'[16] el at developing and evaluated a number of CNN models for whole image classification mammogram. He showed that CNN model he had built and optimized via data augmentation and transfer learning have a great potential for automatic breast cancer detection.

Erwin Halim [17] applied on the different models for early detection of breast cancer like DWT- based multi-resolution MRF (MMRF) segmentation for mammography, MLP for histologic examination, and k-– SVMRFE method for gene identification.he expected to increase the accuracy in early detection of breast cancer.

Hanij et al [18] work with thermal image. Use LSVM and CNN for processing the images. Implement random walks algorithm. Dataset contain 200 images. Get 90.5% accuracy.

khanAroma[19] work with thermal image. Use SVM classifier. Work with 50 image. Get 84.5% accuracy.

NanKrzysztof at el[20] In this paper they worked with Breast density classification which is an essential part of breast cancer screening. They apply CNN. Get 88% accuracy.

TasleemWang at el[21] Worked with histology images. Apply CNN for classification. Worked with ICIAR 2018 breast histology dataset. Get 94.3% accuracy on 4-class and 97.5% 2-class histology image.

Some research papers reviewed above, especially CNN, SVM, ML, XGBOOST algorithms designed to detect Covid-19 disease. The researcher obtained better accomplishment with the use of Convolution Neural Network which is flourished on deep learning. In this paper we modified existing CNN based approach to achieve highest accuracy to detect COVID -19 using chest images.

III. PROPOSED MODEL

This chapter illustrates the action-ability of the Covid-19 system and the acceptance of demand for the proposed model. Ultimately this chapter clarifies the models of all-inclusive architecture which is elaborated in details.

A. Requirement Analysis

We implemented the proposed architecture with the following tools and software

- High-performance computing Device.
- Google Colab.
- Open source software libraries for scientific computations like *TensorFlow* of Python.
- Open source software libraries for machine learning models.

B. Internal Architecture

This section illustrates the architecture of the proposed Covid-19 classification using the deep learning method. The overall architecture uses the CNN of the features as well. Also, the methodology of the proposed model is exhibited by back-to-back explanations comprehensively.

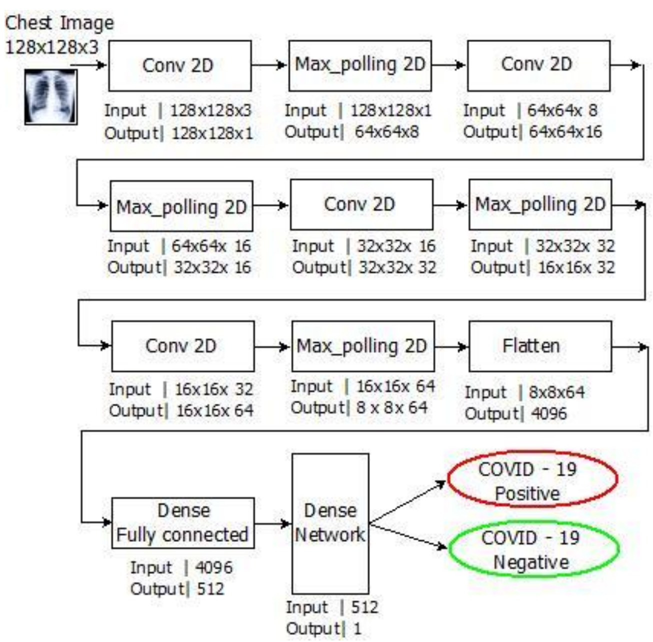

Fig. 1. Internal architecture

In the proposed approach, we used the CNN features to achieve better accuracy.The proposed model consists of four CNN layers namely Convo 2D, Max_pooling2D, Flatten, and Dense layer). We used four Convo2D and two Dense layers. These covo2D are (8,16,32,64) and Dense are (512,1).The size of Maxpooling2D used in the model is 2x2 with same padding . A flatten layer is used to create a single long feature vector size of 4096. The aactivation functions used in the dense layers are ReLu and Sigmoid. The activation function ReLu is applied to the final dense layer (512x1) to classify the Covid -19 in binary manner (positive or negative). For fully connected 4096x512 neural network, we used sigmoid function as the activation function.

The fully connected layer is passed to the ReLU layer so as to normalize the binary classification vector. After the output of the classification vector, two categories i.e. Covid-19 positive or Negative for evaluation. All the hidden layers use sigmoid as their activation function. The sigmoid function is more computationally efficient because it leads to faster learning and it also decreases the likelihood of vanishing gradient problem.

C. DFD of the model

This is the data flow diagram of the proposed model.

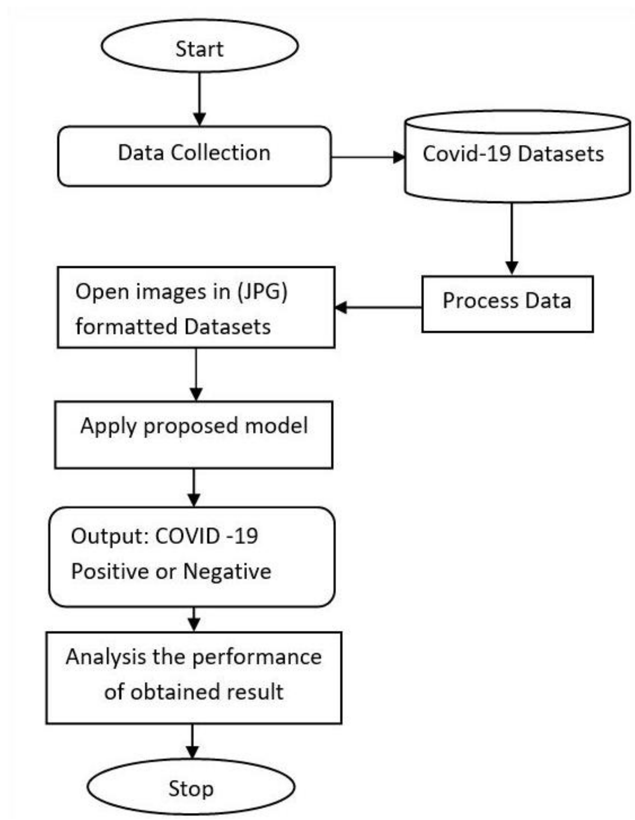

Fig. 2. DFD of the model

This section illustrates the Data Flow Diagram of the proposed models' working process. After collecting dataset, proposed model is trained to predict the Covid-19 virus from images. We used MINI-MIAS dataset to train the model. There is a performance evaluation process before making the final decision.

IV. Experimental Setup

The proposed model is implemented by using Python language and Google collaborator platform. The Convolutional neural network models are implemented using python. Also, we used *NumPy* and Pandas for additional calculation and implementation purpose. The visual evolution reports were produced using Matplotlib in python. At the same time, this section illustrates the evaluation metrics used to measure the accuracy of the results and the detailed analysis of the results.

A. Configuration of dataset for the model

In the proposed model, we used the batch size of the dataset as 64. Size of chest image is 128x128 as height and width. The image batch of our dataset is (“64”, “128”, “128”, and “3”). There are two important methods namely *cache*, *prefetch* which are used to load the datasets for the proposed model.

B. Data Pre-processing

Data pre-processing in any machine learning process is the step where data is converted or encoded, bringing it to the point where the machine can now easily parse. In other words, the data properties can be easily explained by algorithms. For training and evaluation, we used the MINI-MIAS dataset. We use two classes for trains and validation. After pre-processing chest images is shown below.

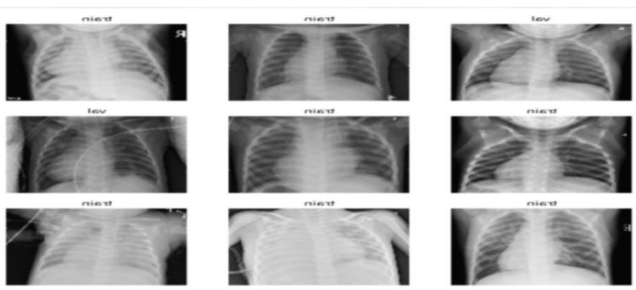

Fig. 3. Data visualization after pre-processing

C. Data Augmentation

Data augmentation creates new training data from existing training data. Cropping, padding, and horizontal flipping are commonly used to train large neural networks for data augmentation techniques. Using the augmentation, the model gets the better performance to finding accuracy.

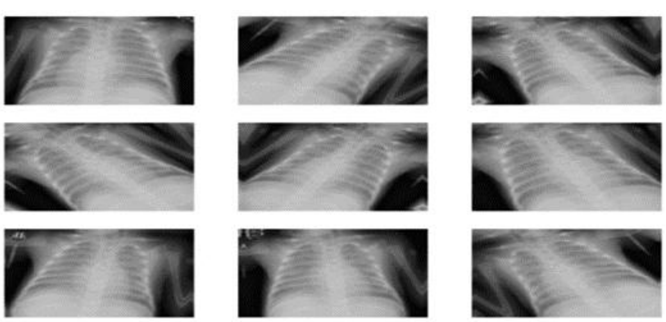

Fig. 4. Data visualization after augmentation

D. Result of the model

We designed the different layers of the proposed model as shown below.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 128, 128, 8)       224
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 64, 64, 8)         0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 64, 64, 16)        1168
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 32, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 32)        4640
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        18496
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 4096)              0
_________________________________________________________________
dense (Dense)                (None, 512)               2097664
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 2,122,705
Trainable params: 2,122,705
Non-trainable params: 0
```

Fig. 5. Proposed CNN Mode

E. Epoch’s Result

We got the following result for the proposed model.

```
Epoch 90/100
78/78 [==============================] - 97s 1s/step - loss: 0.1087 - accuracy: 0.9564 - precision_1: 0.9733 - recall_1: 0.9708
Epoch 91/100
78/78 [==============================] - 98s 1s/step - loss: 0.1107 - accuracy: 0.9550 - precision_1: 0.9740 - recall_1: 0.9685
Epoch 92/100
78/78 [==============================] - 99s 1s/step - loss: 0.1035 - accuracy: 0.9562 - precision_1: 0.9761 - recall_1: 0.9678
Epoch 93/100
78/78 [==============================] - 98s 1s/step - loss: 0.1085 - accuracy: 0.9568 - precision_1: 0.9763 - recall_1: 0.9688
Epoch 94/100
78/78 [==============================] - 98s 1s/step - loss: 0.1449 - accuracy: 0.9407 - precision_1: 0.9627 - recall_1: 0.9620
Epoch 95/100
78/78 [==============================] - 97s 1s/step - loss: 0.1129 - accuracy: 0.9555 - precision_1: 0.9750 - recall_1: 0.9679
Epoch 96/100
78/78 [==============================] - 96s 1s/step - loss: 0.1097 - accuracy: 0.9583 - precision_1: 0.9749 - recall_1: 0.9725
Epoch 97/100
78/78 [==============================] - 96s 1s/step - loss: 0.1124 - accuracy: 0.9569 - precision_1: 0.9722 - recall_1: 0.9727
Epoch 98/100
78/78 [==============================] - 96s 1s/step - loss: 0.1135 - accuracy: 0.9510 - precision_1: 0.9686 - recall_1: 0.9679
Epoch 99/100
78/78 [==============================] - 97s 1s/step - loss: 0.1153 - accuracy: 0.9546 - precision_1: 0.9714 - recall_1: 0.9704
Epoch 100/100
78/78 [==============================] - 96s 1s/step - loss: 0.1350 - accuracy: 0.9459 - precision_1: 0.9689 - recall_1: 0.9612
```

Fig. 6. Epoch’s Result_1

```
true_positives_1: 1957.5696 - true_negatives_1: 495.2911 - false_positives_1: 43.3797 - false_negatives_1: 52.8354
true_positives_1: 1926.3924 - true_negatives_1: 500.8228 - false_positives_1: 49.6835 - false_negatives_1: 57.8987
true_positives_1: 1926.2785 - true_negatives_1: 491.6962 - false_positives_1: 56.1013 - false_negatives_1: 64.8861
true_positives_1: 1917.1646 - true_negatives_1: 506.0000 - false_positives_1: 47.2785 - false_negatives_1: 64.3544
true_positives_1: 1925.0506 - true_negatives_1: 494.1266 - false_positives_1: 51.5570 - false_negatives_1: 62.8734
true_positives_1: 1929.9241 - true_negatives_1: 481.8861 - false_positives_1: 64.1772 - false_negatives_1: 72.4937
true_positives_1: 1905.0380 - true_negatives_1: 502.4557 - false_positives_1: 49.9494 - false_negatives_1: 61.8861
true_positives_1: 1951.1899 - true_negatives_1: 483.7595 - false_positives_1: 50.9241 - false_negatives_1: 55.4684
true_positives_1: 1923.0633 - true_negatives_1: 496.5696 - false_positives_1: 54.9367 - false_negatives_1: 57.8481
true_positives_1: 1923.9367 - true_negatives_1: 501.4304 - false_positives_1: 55.7848 - false_negatives_1: 63.1646
true_positives_1: 1918.6582 - true_negatives_1: 494.5443 - false_positives_1: 51.9367 - false_negatives_1: 60.7342
true_positives_1: 1910.7975 - true_negatives_1: 502.0253 - false_positives_1: 60.0759 - false_negatives_1: 74.9873
```

Fig. 7. Epoch’s result_2

V. PERFORMANCE ANALYSIS AND DISCUSSION

Accuracy, Recall and Precision are the core metrics for evaluating a classification model in CNN. Informally, accuracy is a fraction of what our model accurately estimates. In general, accuracy has the following definitions.

$$\text{Accuracy} = \frac{Number of correct predictions}{Total number of predictions}$$

For binary classification, accuracy can also be calculated in terms of positives and negatives as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Recall} = \frac{TP}{FN+TP} \quad (2)$$

And

$$\text{Precision} = \frac{TP}{FP+TP} \quad (3)$$

where *TP* = True Positives, *TN* = True Negatives, *FP* = False Positives, and *FN* = False Negatives.

A. Now Accuracy for proposed model $= \frac{TP+TN}{TP+TN+FP+FN}$

$= \frac{1910.7975+502.0253}{1910.7975+502.0253+60.0759+74.9873}$

=0.95*100

=95%

B. Matrix of the Recall for proposed model $= \frac{TP}{FN+TP}$

$= \frac{1910.7975}{74.9873+1910.7975}$

= 0.96*100

=96%

C. Matrix of the precession $= \frac{TP}{FP+TP}$

$= \frac{1910.7975}{60.0759+1910.7975}$

= 0.97*100

=97%

D. Matrix of the F1 Score $= \frac{2*(0.97*0.96)}{0.97+0.96}$

= 0.96*100

= 96%

TABLE I. PERFORMANCE METRICS

Accuracy (%)	Recall (%)	Precision (%)	FI Score (%)
95	96	97	96

From the evaluation reports, it is evident that this CNN architecture performs the most satisfying accuracy on Covid-19 detection tasks.

VI. CONCLUSION AND FUTURE WORKS

Nowadays COVID-19 classification with chest images using CNN is going to rapidly popular. This work is helpful because this work's performance is much better than the others. Our work has 95% accuracy. Hope that this work will be efficient in diagnosis in medical. It will be faster to identify COVID-19 virus and helps peoples to save lives.

In future, we will test the model for more datasets to increase the performance using the most powerful hardware.

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