A Deep Learning Application for COVID-19 Detection

An Efficient & Robust Model

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Abstract

Detection of the disease is a major challenge in the field of medical science. It is important to accurately identify the disease. To reduce the misidentification of the disease, several traditional diagnostic techniques are used. These diagnostic techniques take a long time to deliver. And the cost is very high.

In this study the different deep learning model are examined which are introduced to solve the problem and the no of trainable parameter along the accuracy of the models respectively

Convolutional neural network (CNN) has established benchmark results for many challenging problems in the field of image processing and computer vision. In this article, a new model for automatic detection of Corona Virus Disease (COVID-19) is presented using raw chest X-ray images. We design and implemented a five-layer Convolution Neutral network and two Dense layers for COVID-19 disease detection.

Our model is trained on covid-19 dataset to provide an accurate diagnosis for the classification of binary classes (COVID-19 vs No-findings) and produced an accuracy of 95.20%. Batch Normalization Layers after every convolution and dropout after fully connected layers made the model immune from overfitting.

We conclude that many deep learning and machine learning models have been introduced to identify the disease. We also conclude that this model handles large amounts of data and produces a balanced level of accuracy. However, it is not possible to manage the number of parameters and require a high-end processor to run them.

Keywords:

Batch Normalization, Computer-aided system, Dropout, Image-classification, Neural Network, X-ray images

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List of acronyms

Acronym	Unfolding
CNN	Convoluted Neural Networks
COVID-19	Corona Virus Disease
CT	Computed Tomography
GAN	Generative Adversarial Network
MERS	Middle East Respiratory Syndrome
RT-PCR	Reverse Transcription Polymerase Chain Reaction
ReLU	Rectified Linear Unit
RES-NET-18	Residual Network
SARS-Cov-2	Severe Acute Respiratory Syndrome Coronavirus
VGG-19	Visual Geometry Group

1 Chapter: Introduction

An unknown disease with a homogenous symptom of pneumonia was first appeared in Wuhan, China, and subsequently spread to all parts of the world by the end of March 2020, becoming the global pandemic. The disease is named COVID-19 and the virus is termed Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2) [7]. The University of Hong Kong, China found evidence of human-to-human transmission of Corona Virus Disease (COVID-19) for the first time[5] Most coronaviruses affect animals, but they can also be transmitted to humans because of their zoonotic nature[1]. With more than 5.92 million substantiated cases of infection and 364,000 cases of death by the fifth month of its revelation(as on May 30,2020) [2].The typical clinical features of COVID-19 include pyrexia, cough, sore throat, headache, fatigue, muscle pain, and shortness of breath [8].

Coronavirus spreading all over the world in an exponential ratio it became the most consequential to have the expeditious screening implement to identify the coronavirus disease. The most common test technique currently used for COVID-19 diagnosis is a real-time Reverse Transcription-Polymerase Chain Reaction (RT-PCR) [1]. Chest radiological imaging such as computed tomography (CT) and X-ray have vital roles in early diagnosis and treatment of this disease [9]. Although the diagnosis has become a relatively expeditious process, the financial issues arising from the cost of diagnostic tests concern both states and patients, especially in countries with private health systems, or restricted access health systems due to prohibitive prices [6].

To minimize the cost and the time of identification of disease some of the deep learning models are introduced like Alex net, Google net, Inception Net, Resnet-18 with different number of Convoluted Neural Network(CNN) layers and these models achieved a good accuracy with sizably voluminous data sets. In this article we introduced a 7 layered CNN architecture in which the feature extraction is inbuilt advantage where Batch normalisation and dropout layer are used to overcome the overfitting problem and achieved an accuracy of 95.02% with smaller number of trainable parameters.

2 Chapter: Survey of related work

This section gives the information about sundry method for detecting the coronavirus disease. Precise diagnosis of coronavirus disease became of the research area in the field of Deep Learning, Transfer learning and Machine learning. Coronaviruses are enveloped positive sense Ribonucleic Acid (RNA) viruses ranging from 60nm to 140nm in diameter with spike like projections on its surface giving it a crown like appearance under the electron microscope. Hence the name coronavirus [8].

The current COVID-19 outbreak is both similar and different to the prior severe acute respiratory syndrome (SARS; 2002-2003) and Middle East respiratory syndrome (MERS; 2012-ongoing) outbreaks [7]. COVID-19 infection causes a severe lower respiratory tract infection with bilateral, basal, and peripheral predominant ground-glass opacity, consolidation, or both as the most common reported CT findings-features typical of an organizing pneumonia pattern of lung injury [9].

Transfer learning is adopted to evaluate the performance of state-of-the-art convolution neural network for medical image classification [6]. Deep transfer learning technique is used to identify COVID-19 infection on large datasets and performance is analysed based on two evolution metrics: sensitivity and specificity [4]. The fact that X-ray imaging systems are more common and cheaper than CT scanning systems, a deep learning-based CNN (Convolutional Neural Network) model is proposed from which COVID-19 positive CXRs are screened for, other non-COVID and / or non-COVID healthy cases [2].

The Dark Net model with 17 convolutional layers and introduced different filters on each layer was trained on raw chest X-ray images of various patients to detect COVID-19 [1]. Multiple CNN models were acclimated to relegate CT image datasets and calculate the infection probability of COVID-19. These findings might greatly avail in the early screening of patients with COVID-19 [5]. A transfer of deep learning models to classify COVID-19 X-ray images by embedding the medical X-ray images using Generative Adversarial Network (GAN) to generate X-ray images [3].

3 Chapter: Problem statement, objectives, and main contribution

In this study, we will discover the presence of the Corona virus by examining the chest X-ray images of the person. Comparing the user issued X-ray scan with the dataset in the model categorizes whether a person is COVID -19 positive or not.

But, for implementation of the project we need an efficient and robust approach. With the poor choice of the algorithm, disruptions may occur in the results. Thus, causing the model failure. So, the primary objective of this project is to choose an algorithm for the image classification. There are wide varieties of architectures in CNN. Our next challenge is to select an architecture which gives the optimal result. There are many architectures with variant Convolution and Dense layers. There are some with Batch Normalizations, dropout, and Checkpoints. Right combination of these layers may bring out the best output. So, the next objective is to select an architecture that best fits into the model for accurate and robust result.

Implementation of this model in the real world will be very fruitful. There are several contributions this model can provide, e.g., a very fast and accurate COVID-19 diagnosis system with lowest cost, less human intervention, Automated decision-making system. Using this model one can reduce the cost for diagnosis significantly, when compared to other processes and can achieve accurate result within five minutes.

4 Chapter: Solution

We selected five layered CNN architecture to implement this model.

4.1 Modeling

4.1

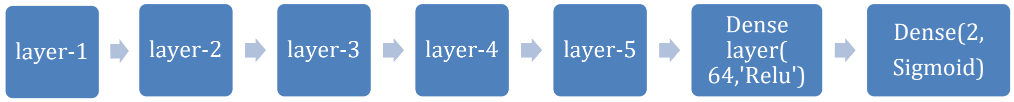

Figure 4-1. Proposed Architecture

We layout a Convolution Neural Network structure and trained it with scanned X-ray image. Our proposed CNN structure has five convolution layers, every layer followed by Batch Normalization and Max pooling layers. We used 32 kernels of size (3 X 3) for all convolution layer and Max pooling layer of window (2 X 2) is utilized after all convolution layers. Rectified Linear Unit (ReLU) activation function is applied to acquire the feature maps. All the features maps after the five convolution layers are passed to flatten layer to convert them into 1-Dimensional array.

A Dense layer with 64 units and ReLU activation function is added after Flatten layer which learns information from the feature maps. A Dropout layer with 0.2 rate is integrated after the Dense layer to avert model from overfitting. Conclusively, another Dense layer with 2 units and sigmoid activation function is integrated at the end of the network for classification of X-ray image. *Figure 4-1*gives the overview of the proposed architecture where all the layer represents the convolution layer followed by batch normalization and then max pooling layer

4.2 Implementation

4.2.1 X-ray image dataset

Labelled x-ray images of 2 different classes (COVID-19 vs no-findings) had been acquired from git hub repository. The size of the data set is 625 images wherein 500 are no -findings and 125 are covid-19 effected x-rays has been 43 female and 82 male x-rays located to be positive. *Figure 4-2* represents the sample images

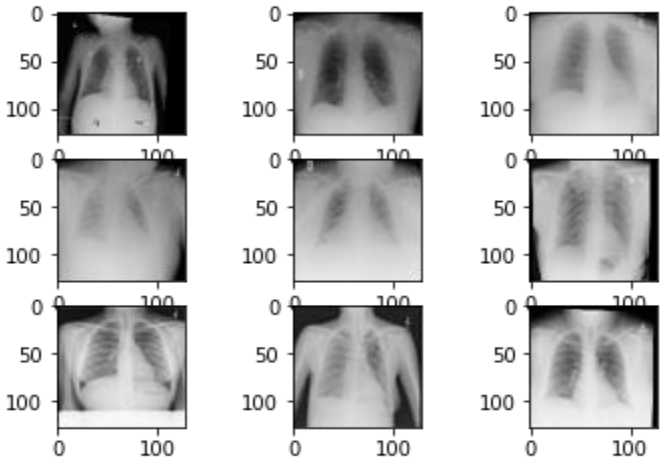

Figure 4-2. Sample images[10]

Table 4-1 Describes the dataset summary with both COVID-19 positive and negative scans.

Table 4-1. Summary of Dataset

Category	**#Images**	**#Train**	**#Test**
No-findings	500	437	188
Covid-19	125		

4.2.2 Training details

Labelled 625 X-ray images are inputted to CNN structure in which 70 percent are applied in training phase and remaining are applied in testing phase. As it is multi label relegation binary cross entropy loss function is utilized ADAM optimizer is applied to optimize the error. Every time data batch of 16 is loaded into the structure in the course of training to decrease the burden on the memory. Model is executed till 50 *epochs*, using *Model checkpointing mechanism* best weights and minimum validation loss is preserved. The Conv2d, Flatten, Dense layers are imported from the *keras.model module*. A clear description of number of parameters utilized by the proposed model is given in the *Table 4-2.*

Table 4-2. Layers and layer parameters of the proposed architecture

#Layers	**Type of layer**	**Output shape**	**#parameters**
1	Conv2d	[126,126,32]	896
2	Conv2d	[61,61,32]	9248
3	Conv2d	[28,28,32]	9248
4	Conv2d	[12,12,32]	9248
5	Conv2d	[4,4,32]	9248
6	Flatten	[128]	0
7	Dense	[64]	8256
8	Output(dense)	[2]	65

4.3 Validation

Different performance evolution metrics like accuracy, precision, recall, f1 scores are used to measure the efficiency of the proposed model on test data.

$$recall = \frac{true\ positive}{true\ positive + false\ negative}$$

$$precision = \frac{true\ positive}{true\ positive + false\ positive}$$

$$F1\ scores = \frac{2 * (recall * percision)}{(recall + percision)}$$

These measures can be computed from confusion matrix. Performance of the CNN is analysed in the *Table 4-3.*

Table 4-3. Performance of proposed CNN

Measurement metrics	**Performance [%]**
Accuracy	95.20
Precision	80.00
Recall	100
F1-scores	89.05

Error! Reference source not found. shows the distributed plot of train and test data accuracies, where the x-axis and y-axis indicate accuracy and epochs, respectively. In this figure the accuracy of the train data with respect to the epoch is represented with an orange line and the test data with a blue line

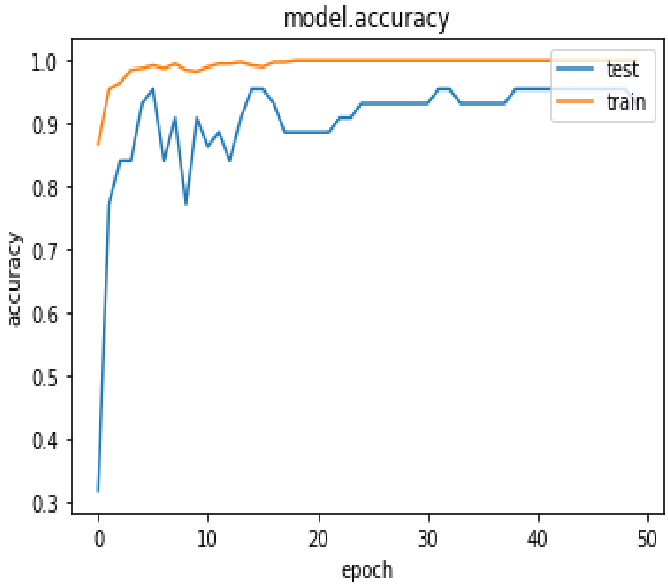

Figure 4-3. Distributed plot of train and test data accuracies

From *Table 4-4* , it is clear our proposed CNN model is superior with all existing model in term of number of parameter and it crossed the accuracy of *Alex net, Google Net, Visual Geometry Group (VGG-19), Residual Network (RES-NET-18).*

Table 4-4. Parameter and accuracy comparison of various models

Models	**Accuracy [%]**	**#parameters**
Darknet[1]	98.08	65 million
Inception net[2]	99.02	5 million
Alex net[3]	85.02	61 million
Google net[3]	80.06	7 million
VGG-19[4]	93.06	138 million
RES-NET-18[5]	86.07	11 million
Proposed CNN**	95.20	46 thousand

5 Chapter: Conclusion and future work

The detection of Covid-19 is one of the major challenges today. It is very important to identify the disease accurately. In this article, our proposed CNN architecture, can identify and classify the covid-19 positive cases from X-ray images. When compared to the existing model, our approach is simple and robust in terms of parameters and obtained an accuracy of 95.20%. This study can be extended to the multiclass classification.

Furthermore, this project can be extended by implementing this model in a mobile application. This can also be made a web application and be used by the people whenever necessary.

Reference

[1] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, “Automated detection of COVID-19 cases using deep neural networks with X-ray images,” Comput. Biol. Med., p. 103792,2020.

[2] D. Das, K. C. Santosh, and U. Pal, “Truncated inception net: COVID-19 outbreak screening using chest X-rays,” Phys. Eng. Sci. Med., pp. 1–11, 2020.

[3] M. Loey, F. Smarandache, and N. E. M Khalifa, “Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning,” Symmetry, vol. 12, no. 4, p. 651, 2020.

[4] M. S. Boudrioua, “COVID-19 detection from chest X-ray images using CNNs models: Further evidence from Deep Transfer Learning,” Available SSRN 3630150, 2020.

[5] X. Xu et al., “A deep learning system to screen novel coronavirus disease 2019 pneumonia,” Engineering, 2020.

[6] I. D. Apostolopoulos and T. A. Mpesiana, “Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks,” Phys. Eng. Sci. Med., p. 1, 2020.

[7] Z. Wu and J. M. McGoogan, “Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention,” Jama, vol. 323, no. 13, pp. 1239–1242, 2020.

[8] “Singhal, Tanu. "A review of coronavirus disease-2019... - Google Scholar.” https://scholar.google.co.in/scholar?hl=en&as_sdt=0%2C5&q=Singhal%2C+Tanu.+%22A+review+of+coronavirus+disease-2019+%28COVID-19%29.%22+The+Indian+Journal+of+Pediatrics+%282020%29%3A+1-6.&btnG= (accessed Oct. 20, 2020).

[9] J. P. Kanne, B. P. Little, J. H. Chung, B. M. Elicker, and L. H. Ketai, Essentials for radiologists on COVID-19: an update—radiology scientific expert panel. Radiological Society of North America, 2020.

[10] M. Talo, *muhammedtalo/COVID-19*. 2020.

Appendix 1:
Feature maps Code snippet 1

The function of the following code snippet is to take images of size (128,128,3) as input, processes those in 5 convolution layers and gives feature maps as output.

COVID-19_Prediction_CNN.ipynb

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

```
from keras.callbacks import ModelCheckpoint
filename = '/content/drive/My Drive/transferlearning/best_model.h5'
checkpoint = ModelCheckpoint(filename, monitor='val_loss', verbose=1, save_best_only=True, mode='min')
```

```
model = Sequential()
model.add(Conv2D(32,(3,3),activation='relu',input_shape=(128,128,3)))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
#model.add(BatchNormalization())
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
#model.add(BatchNormalization())
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
#model.add(BatchNormalization())
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
#model.add(BatchNormalization())
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D((2,2)))
model.add(Flatten())
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_6"
```

Appendix 2:
Output Code snippet 2

The following code snippet takes y_test data and y_prediction data as input and results classification report i.e. confusion_matrix.

```
y_pred=np.argmax(predictions,axis=1)
```

```
from sklearn.metrics import classification_report,confusion_matrix

print(confusion_matrix(y_test,y_pred))
print("-"*70)
print(classification_report(y_test,y_pred))
```

```
[[150   0]
 [ 38   0]]
----------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.80      1.00      0.89       150
           1       0.00      0.00      0.00        38

    accuracy                           0.80       188
   macro avg       0.40      0.50      0.44       188
weighted avg       0.64      0.80      0.71       188

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no p
  _warn_prf(average, modifier, msg_start, len(result))
```