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COVID-19 infection prediction from CT scan images of lungs using Iterative Convolution Neural Network model

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ABSTRACT

World Health Organization has defined COVID-19 as a contagious, communicable and fast spreading disease engendered by the Corona virus, SARS-CoV-2, is a respirational microorganism. Computerized Tomography (CT) scan images of the chest helps in detecting COVID 19 infection in a fast way with much reliability. In this paper, chest CT scan images of COVID and Non-COVID categories are considered to train the supervised classifier, Iterative convolution Neural Network. The training process is done with six different training data size. The trained models are iterated for the fixed size of testing data (20 images). The same set of training and testing processes are done with two different Iterative Convolutional Neural Network architectures, one with two hidden layers (CNN1) and another with three hidden layers (CNN2). The iterations are extended up to 7, but the model performance is degraded after the 6th iteration, which makes to fix the iteration level as 5 for both CNN models. Six different training sets with five iterations have led into 30 CNN models. For two different CNN architectures, which lead to 60 different models. The model designed with 100 training sets in both CNN1 and CNN2, have produced the high accuracy in COVID classification than any other models. The better classification accuracy 89% is achieved from CNN2 model with its 5th iteration.

1. Introduction

The new Corona virus is the major reason for the current epidemic of lung-fever which is started at early December 2019. Corona virus identified during December 2019 is initiated to have the name COVID-19 (Corona Virus December 2019) commonly referred as COVID-19. The virus has given more challenges in human health, world economic level, social activities, education, business etc. With respect to the human health, the diagnosis of the COVID-19 is not as easy as like other diseases. Symptoms of the infection are dyspnea, fever and cough and it also leads to diseases such as pneumonia, Severe Acute Respiratory Syndrome (SARS), organ failure and in more critical situations this infection leads to death. And it is also reported that men are highly affected by this infection when compared with women. This is because of more exposure and another report says that there is no death in the children of age below 9 years. While comparing people affected by COVID-19, patients having pneumonia are highly affected with respiratory problems and it spread faster than the normal people affected by COVID-19. Around 82% of the total infected patients does not show any symptoms or mild symptoms and the remaining patients affected are in critical conditions. Statistics of current status of infected patients provides the probability that 5% is the mortality rate and the chances of recovery is 95%. This pandemic disease spread very rapidly even though the preventive measures are taken all over the world. Since this pandemic disease is a biggest challenge around the world, many researchers in every area of science have started studying the issue to manage the problems. One among such problem is the automatic diagnosis of the disease. To find covid-19 positive cases, testing relies completely on Reverse Transcription-Polymerase Chain Reaction (RT-PCR) and this testing is a time-consuming process and it also has false-negative error. Thus, it is essential to develop new approaches for detecting the infection in patient’s body with more accuracy and at a faster rate. X-Ray images or Computed Tomography (CT) scan images are more easily accessible techniques for detecting the virus in a patient. And it is also possible to detect the infection by processing these images even though the patients affected by this virus does not show any symptoms like cold, fever or cough. Since the main impact of COVID-19 virus is reflected on lung with fever, the researchers started to concentrate on the CT scan image of lungs for early identification of the deadly COVID-19 infection. Both chest X-ray and CT scan images have quickly
generates an enormous amount of data on COVID-19 among all the leading diagnostic imaging techniques, which helps in the growth of new machine learning algorithms, a form of artificial intelligence (AI). Researchers have shown more interest on computational automation with Artificial Intelligence for detecting COVID19 positive cases with high reliability. Recently, AI-based tools for solving image classification problems are highly recommended in all areas of research especially in the field of healthcare by training CT scan images, X-ray images, etc. For understanding complex, cognitive problems deep learning is considered as an eminently strong tool, and the onestep of their use and interpretation in different problems is expanding. In this paper, we have made use of iterative convolutional neural network (ICNN), a deep learning algorithm that can effectively detect COVID-19 infection from CT scan images of lungs for fast diagnosis.

1.1. Image classification

From computer vision perspective there are few challenges which are trivial for a human to perform are variations in the images. These include scale variation, viewpoint variation, deformation of the image, background clutter, occlusion, illumination conditions and intra-class variation. Moreover, there are about 10,000 to 30,000 distinct object categories that could be recognized. Therefore, a continuous work and research in this field are attempting to expose a good image classifier that is uniform to all these variations by enforcing and formulating different machine learning techniques and architectures. Since one of the most dominant approaches in Artificial Intelligence is machine learning using supervised models. When the supervised model is considered, then, the training set data are to be selected carefully. Many classification techniques such as K-Nearest Neighbors, Support Vector Machine (SVM), Bayes’ etc. are preferred by the researchers to make the classification. In the same way, Artificial Neural Network is another model for classification under the concept of Convolution Neural Network for performing the classification process.

1.2. Convolution neural network

In recent years, CNN have evolved as the principal algorithm in computer vision. They have persuaded to attain superhuman performance on complicated visual tasks with the improvement in computational power. CNN works in a way such that it automatically extracts features from the given image. In a pixel vector algorithm, the possibility of the loss of spatial interaction between pixels could be more, whereas CNN effectively uses all adjacent pixel information from the image. Initially this model down sample the given image by convolution layer and finally uses a prediction layer. This concept was first presented by LeCun [1] where he used a single convolution layer or digit classification. In 2012, Alex net became more popular where multiple convolution layers are used to achieve state of the art on image net. Convolutional neural networks cannot learn relevant features from an image. The implementation of CNNs is stimulated by the fact that they can capture or learn relevant features from an image at different levels. This capturing of relevant features is similar to a human brain which is referred as feature learning. Weight sharing is another main feature of convolutional neural network. It is highly efficient in terms of complexity and memory. When we compare neural network and CNN with billions of neurons, then CNN would be less complex and saves more memory than the Neural Network. When performance is measured, CNN outperform conventional image recognition tasks and also many other tasks than that of neural network. And it is also a very good feature extractor for a completely new task or a problem. This means that useful attributes can be extracted from an already designed CNN with its trained weights by giving the data on each and every level of the model and modify the CNN a bit for the particular task. For example, appending a classifier after the final layer with labels specific to the problem or task which is said to be pre-training. CNN are very effective in these types of tasks when compared to the other neural network. The main advantage of pre-training is to avoid training of CNN so that memory and time could be saved. Though we have more advantages when compared to neural network, there is a small drawback from practical perspective. Both the models are easy to implement but the code for CNN is bit longer than a Neural Network. This is because of additional max-pooling layer and also it consists of fully-connected layers at the end for image classification.

In this paper, the CT scan images of lungs by Yang et al. [2] are considered for the COVID-19 positive cases classification. COVID-19 data are sensitive, people are finding very difficult in data collection. Almost all data are available as open, getting the entire data set for scientific research is very difficult. Yang et al. [2] collected the highly reliable CT scan images of 349 COVID-19 positive cases and 463 non-COVID cases (classes) for their research purpose. Two different Convolution Neural Networks (CNN1 & CNN2), CNN1 with two hidden layers and CNN2 with three hidden layers are designed for the classification process. The training image sets are considered as 100 (50 images from each class) to 600 (300 images from each class) with the increment of 100 images (50 images from each class) for both the models.

This paper is organized in the following way where Section 2 is about Literature survey after Introduction, Section 3 is about System Description followed by the Results and Discussions in Section 4. Section 5 is about Conclusion and Future work.

2. Literature survey

Fong et al. [3] and Huang et al. [4] described as COVID-19 virus spread into more than 150 countries around the world, including India, US, Italy, China etc. Due to its long existence on various objects the spreading level is in an exponential form. The rapid speed makes WHO (World Health Organization) to declare it as pandemic one. Almost all countries are facing the issues on human health, finance, business, employment, the technological support to come across the situation in a safe way such as CCTV information to find the existence of COVID-19 affected persons are close by or not, accessing the bio information such as temperature, heart beat etc. to be observed from a remote location. The authors also suggested about the IoT based wearables, chatbots for communication etc. Authors were explaining about the virus from origination, impacts by comparing with other flues, protection by applying the technologies. Nabavi et al. [5] and Aï et al. [6] described that the COVID-19 results generated by Real Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) and NAAT (Nucleic Acid Amplification Test) are not reliable. Most of the people who are getting negative are identified as infected. They have suggested that the medical images can be used to get a highly reliable infection status. Yang et al. [2] collected the CT scan images of lungs from both the COVID-19 infected and non-infected categories. To make their research as a highly reliable one, the collected images were verified by the radiologist to ensure quality of their collection. Multitasking learning with self-supervised learning methods are approached to achieve the accuracy as 89%. Images from the data collection are considered to make the supervised learning to classify the infected status. Chen et al. [7] developed a system for detecting COVID-19 pneumonia based on deep learning on high resolution CT, to relieve work pressure of radiologists and contribute to the control of the epidemic. Gozes et al. [8] conducted multiple retrospective experiments in which the system performance is analysed. In his experiment, suspected COVID-19 thoracic CT features are identified and progression of the disease is evaluated in each patient over time. This is done by using a 3D volume review, which generates a Corona score. Chowdhury et al. [9] proposed a strong technique in which a pre-trained deep-learning algorithm is applied on digital chest X-ray images for automatic detection of COVID-19 pneumonia. This algorithm is applied for maximizing the accuracy of the detection. To train and evaluate several pre-trained deep Convolutional Neural Networks, Transfer learning technique was used with the help of image.
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3. System description

COVID-19 positive and negative cases are classified from CT scan images of lungs by constructing two different architectures of CNN. These models are considered as an Iterative Convolutional Neural Network. The first CNN model is represented as CNN1 with two hidden layers and the second CNN model is constructed with three hidden layers which is represented as CNN2. The classification of positive and negative cases is done with the following processing steps: image collection, data augmentation, models construction, iteratively training the models, testing the models and evaluate the model performance.

The processing steps are described as follows. The images are selected into different size of dataset for variable volume size. These images are trained in both the CNN models. Since the images are augmented into six different datasets, each model is trained with five epochs which gives the maximum accuracy, yields 30 models in each CNN which leads to 60 models. The training dataset images size varies with equal number of positive and negative cases whereas the testing image dataset size is fixed as 20. It is shown in the above Fig. 2.

3.1. Image collection

In a human body, the major target region of COVID-19 virus is Lung. The description of Lung can be visualized using the chest CT scans. CT scan images gathered for the computational research by Xingyi Yang et al., 2020, are considered for the classification process. The authors collected the images in two categories, COVID and Non-COVID images. The sample set of images of both positive and negative cases images are shown in Fig. 3(a) and 3(b), respectively.

Since the training process is done for variable data set sizes, varying from 100 to 600 with the increment of 100 images, the data are organized as six different datasets. In each dataset equal number of positive and negative cases are trained and a fixed size dataset of 20 images are used for testing the model. The dataset organization is represented in Table 1.

3.1.1. Image augmentation

Artificial expansion of the size of a training set by creating modified data from the existing one is data augmentation which is a technique where size of the data is increased for training a model. To avoid over fitting, it is advisable to use data augmentation. Not only for the problem of over fitting, instead if the initial dataset size is too small to train on, and also for the better performance of the model. In general, having a huge dataset is complex for the performance of both Machine Learning and Deep Learning models. But, by augmenting the data which we already have, the performance of the model can be improved, so that the performance of the model could be enhanced. Therefore, augmentation of the existing data helps in order to make a much better generalized model. Data augmentation can be applied in various domains, especially in the field of computer vision. An approach of applying various transformations on to the original images is referred as Image augmentation. Most widely used data augmentation techniques for images are: 1. Geometric transformations – randomly flip, crop, rotate or translate images, 2. Color space transformations – change RGB color channels, intensify any color, 3. Kernel filters – sharpen or blur an image, 4. Random Erasing – delete a part of the initial image, 5. Mixing images – basically, mix images with one another.

3.1.2. Augmentor

Moving on to the libraries, Augmentor is a Python package that aims to be both a data augmentation tool and a library of fundamental image pre-processing functions. In general, Augmentor consists of various classes for standard image transformation functions, such as Crop, Rotate, Flip, and many more. Augmentor allows the user to pick a probability parameter for every transformation operation. This

Fig. 1. Architectural representation of the CNN Model.
parameter controls how often the operation is applied. Thus, Augmenter allows forming an augmenting pipeline that chains together a number of operations that are applied stochastically. This means that each time an image is passed through the pipeline, a completely different image is returned. Depending on the number of operations in the pipeline and the probability parameter, a very large amount of new image data can be created. Augmenter is more focused on geometric transformation though it has other augmentations too. The main features of Augmenter package are: 1. Perspective skewing – look at an image from a different angle, 2. Elastic distortions – add distortions to an image, 3. Rotating – simply, rotate an image, 4. Shearing – tilt an image along with one of its sides, 5. Cropping – crop an image and 6. Mirroring – apply different types of flips. In this process, the basic transformation operations such as rotation, scaling and shearing are applied on the images. The augmentation process is applied for both training and testing data set.

3.2. CNN model construction

To solve image classification problems in the standard feed-forward neural networks, inputs are image pixels. But even very small images may have more number of pixels, which results in very large number of connection weight parameters. All these weighted parameters have to be trained and this results in more complex systems. To avoid over-fitting problem these complex systems, need large number of training samples. Whereas CNN models mixed weights into much smaller kernel filters such that the learning model is simplified dramatically. Also, when compared to the conventional fully-connected networks, CNN networks are more robust and much faster.

In case of image classification problems Convolutional Neural Network is considered to be one of the most successful models. CNN significantly improves its performance in every area of research for many image databases. Global and local structures from image data can be learned through CNN model. Hand written numbers or human faces are general image objects which has more evident local and global structures. Therefore, simple local features like curves and edges can be merged to become more complex features like shapes and corners and finally the objects. It could also be incorporated into medical imaging analysis. In the medical field, the lung image patches have no distinct structures because of its more texture-like, hence it is difficult to analyze deep layers in CNN on those data. Medical image database with only little number of samples while training large neural network with numerous parameters, over-fitting is the problem that has to be deal with. In this paper, we proposed Iterative CNN architecture particularly adapted for binary class image classification which is texture like. And also, the problem of over-fitting can be avoided by this model.

Input layer: Layer in which the input image to be fed into convolutional layer.

Convolutional layer: By convoluting the kernel over the image, this layer extracts the features from a given image. Hyper-parameters such as stride can be tuned over here.

ReLU (rectified linear unit) layer: A threshold value to the input is set in this layer. Any input value if it is less than zero is set to zero. It is not necessary to be a separate layer. Instead, we can also append it in the transfer function of the convolutional layer.

Pooling layer: Feature maps dimensions are reduced in this layer and thereby it avoids over fitting.

Dense layer: Flattening of the feature maps are done in this layer to create feature vector, which is then fed into the last classification layer.

Classification layer: Prediction of the class of the input image is done in this layer. The number of neurons in classification layer is equivalent to the number of classes in the final output.

Training parameters for a given CNN are the number of
convolutional layers, filter size, number of max-pooling layers, size of stride, number of hidden neurons in dense layer, and transfer function.

The CNN model is designed with two different set of hidden layers. The Model with two hidden layers which are defined with CNN1 model and the other one with three hidden layers are defined with CNN2 model. The model summary generated by the system for CNN1 and CNN2 is shown in Fig. 4. Both the architecture is tested on different volume of dataset and the maximum accuracy are obtained when the CNN model is trained with 5th iteration. For best performance of classification, more number of iterations with different volume of dataset training has been done. But the performance of the model is decreased. Thus, the saturation level for best performance is fixed as 5th iteration of the model.

CNN1 and CNN2 architectural description of layers and the parameters are represented in Table 2. In both the models, the filter size is fixed as $3 \times 3$. The number of neurons in CNN1 and CNN2 is 32 in the first convolutional layer. In the second convolutional layer, the number of neurons is increased to 75 and in the third layer it is reduced to 32. The maxpooling size is fixed as $2 \times 2$ in all layers in both the models. Relu is the activation function used in both the models. Dense and Dropout layers are set to be 75 in both the models. For the final output sigmoid function is used as an activation function.

### Table 1

Division of original images into training and validation datasets.

| S.No | Total Images | Training dataset | Testing dataset |
|------|-------------|------------------|----------------|
|      |             | Positive cases   | Negative cases |
| 1    | 812         | 349              | 463            |
| 2    | 100         | 50               | 50             |
| 3    | 200         | 100              | 100            |
| 4    | 300         | 150              | 150            |
| 5    | 400         | 200              | 200            |
| 6    | 500         | 250              | 250            |
| 7    | 600         | 300              | 300            |

The training process is done with six different data sets varying from 100 to 600 of 6 level with the increment of 100 images. Data set is considered in such a way 50% from COVID (C) and 50% from Non-COVID (NC) images. Data are considered for the training as given in formula (1) and (2).

$$T_i = C_{Li} + NC_{Li}$$  
$$L_i = \frac{i \times 100}{2}$$

where,

- $T_i$ = $i$th Training set
- $C_{Li}$ = $i$th Level COVID training set
- $NC_{Li}$ = $i$th Level Non-COVID training set
- $L_i$ = $i$th Level Data set length $i$ = 1,2,3,...,6

3.3. Iterative training

Training process is done with six different data sets varying from 100 to 600 of 6 level with the increment of 100 images. Data set is considered in such a way 50% from COVID (C) and 50% from Non-COVID (NC) images. Data are considered for the training as given in formula (1) and (2). Iteration is nothing but performing a set of tasks in a repeated way. In Machine Learning, there are many different iteration methods are supported in machine learning such as parameter iteration, data iteration, model iteration and human iteration.

- Parameter based – The parameters in the model are executed multiple times until reaching the best state
- Data based – Various data are put into the system to check the parameter adjusted model is working better or not.
- Model based – Running the same model for multiple times with the same parameters and the data set.
• Human based – Induced by human being by combining different models for form a complete smart model.

In this paper, the model based iteration is applied on the CNN1 and CNN2 models to generate the better result. The iteration has repeated up to 6 levels. At the 6th iteration, in all models, the accuracy has come down than the 5th iteration. This makes to finalize the iteration level as 5 for all the models. Total models constructed for the classification is totally, 6 various data set sizes with 5 different iterations yields 30 models. Classification has done on two different CNN architectures brings the model count 60 (30 + 30).

3.4. Testing the model

The test data are augmented and applied on the trained model. The testing has been done with the images of fixed dataset size which is set as 20. Though we have increased the volume of the dataset from 100 to 600 with an increase of 100 in each dataset, the testing dataset size is fixed. The outcome of the test data is considered for measuring the performance of the model. In our work, both the accuracy and loss values are generated as outcome which is used to measure the model’s performance. In general, inverse proportional relation exists among the two parameters accuracy and loss. When accuracy is high, the related loss value should be less. Thus, the accuracy and loss in each iteration is considered for the performance of the model.

4. Results and discussion

Convolution Neural Network models CNN1 and CNN2 are trained with 6 different size of data sets. Training outcome at each iteration for the entire 6 data set size are shown as a bar representation from Figs. 5-9. From the bar chart it is clear that overall performance of CNN2 (3 hidden layers) is looking better than CNN1 (2 hidden layers). Starting from iteration 1 to iteration 5, the charts are making the result as transparent, as iteration 5 results are comparatively high than any other iterations.
Accuracy of CNN2 is better than CNN1, makes to consider the 6th iteration accuracy values of various data sets of CNN2 to compare with all other iterations of the same models, shown in Fig. 10. After the 5th iteration, the accuracy values are falling down, this helps to fix the iteration level as 5.

Already it is described about the relation among the loss values and accuracy values. When the accuracy looks high, the loss would be less in the specific level. This is considered for the 5th iteration alone, shown in Table 3. The values are represented in the form of line chart, shown in Fig. 11.

5. Conclusion and future work

Supervised classifier models are constructed for the major task of classifying the COVID-19 cases. This is achieved with the help of iterative convolution models. In this paper, two layered and three-layered CNN architectures are designed for classification. The training tasks are done with variable size data set with the images of 100 (50 from COVID-19 & 50 from non-COVID patients) to 600 (300 from COVID-19 & 300 from non-COVID patients) total of 6 data sets. In each class with the minimum of 50 to the maximum of 300 are considered for the process. Image augmentation is applied on the selected image training set. Augmentation is done to generate the transformed images for the classification process. Transformed objects are applied for training the models, CNN1 and CNN2. Variable training set under two different iterative CNN architectures have produced 60 models. Accuracy values of the models are compared to find the better CNN architectural model. Finally, it is identified that, CNN2 under the size of 100 training set at the 5th iteration has generated the better accuracy as 89%. Loss values are also used to evaluate the model performance. When the loss value is less, the model’s performance looks high. Accuracy and loss values comparison is also done to show the model which is having high accuracy has very less loss when compared to other models. From this paper, it is clear that, once the chest CT scan images are used to train the model, then, the model can be used to classify the newly arrived images with high reliability, which is assured by the accuracy. The emerging technology of explainable artificial intelligence can be done as a future work in which the feature responsible for the prediction can be identified. The explain ability and causality for the prediction and classification is more important in the field of medicine.
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Author statement

Madhavi. M: He performed the analysis, the overall concept, writing and editing. Supraja P: He participated in the methodology, Conceptualization, Data collection and writing the study.

Declaration of Competing Interest

The authors declare that we have no conflict of interest.

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