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Deep Learning Assisted Covid-19 Detection using full CT-scans

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Abstract The ongoing pandemic of COVID-19 has shown the limitations of our current medical institutions. There is a need for research in the field of automated diagnosis for speeding up the process while maintaining accuracy and reducing computational requirements. In this work, an automatic diagnosis of COVID-19 infection from CT scans of the patients using Deep Learning technique is proposed. The proposed model, *ReCOV-101* uses full chest CT scans to detect varying degrees of COVID-19 infection, and requires less computational power. Moreover, in order to improve the detection accuracy the CT-scans were preprocessed by employing segmentation and interpolation. The proposed scheme is based on the residual network, taking advantage of skip connection, allowing the model to go deeper. Moreover, the model was trained on a single enterprise-level GPU such that it can easily be provided on the edge of the network, reducing communication with the cloud often required for processing the data. The objective of this work is to demonstrate a less hardware-intensive approach for

COVID-19 detection with excellent performance that can be combined with medical equipment and help ease the examination procedure. Moreover, with the proposed model an accuracy of 94.9% was achieved.

Keywords Covid-19 · Medical Imaging · Deep Learning · CT-scan · Convolutional Neural Networks · Supervised Learning.

1 INTRODUCTION

An outbreak of pneumonia caused by a novel coronavirus was first believed to be originated in December 2019, in Wuhan, China [1]. The virus was then officially named as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) by the World Health Organisation (WHO). The WHO, further declared this outbreak a pandemic on March 11, 2020. Transmission capacity of the SARS-CoV-2 is much stronger [2] as compared with the SARS-CoV outbreak in 2003. The rapid increase in confirmed cases makes the prevention and control of COVID-19 extremely serious. More than 27.3 million cases have been reported across 188 countries and territories with more than 893,000 deaths; more than 18.3 million people have also recovered.

The COVID-19 spreads mainly through the medium of air and contact, transmitted in the form of small droplets produced by an infected person while sneezing and coughing. These droplets can land on the hands/cloths of nearby people, from there to eyes, nose or mouth and eventually reach the lungs. Touching the nose, mouth or eyes after making a contact with the surface exposed to virus can result in an infection [3]. Although, risk of the virus spreading from an animal to a human is quite low, it can still spread in some situations, as reported by a few pet owners [4]. The people infected with the COVID-19 display symptoms similar to influenza like illness and other

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respiratory ailments. The reported symptoms range from mild to the severe symptoms. Fever, cough, shortness of breath, headache, diarrhea are a few that occur in the people having the COVID-19 virus. These symptoms may take up to 2-14 days to appear after exposure to the virus [5].

Presently, there are several methods for the diagnosis of COVID-19. The standard procedure for testing is the real-time reverse transcription-polymerase chain reaction (rRT-PCR). Along with this laboratory testing, scans of the chest area in the form of X-rays and CT scans are proven to be helpful in its diagnosis [6]. Chest imaging in the patients have the multilobar involvements and rounded as well as peripheral airspace opacities. The chest CT scans are more sensitive to the ground-glass opacities, which could be missed in the X-ray scans [7].

Since there is no known cure for the COVID-19, the number of people infected is rising day by day. The increasing number of infected people poses a problem for the current screening procedures as they are overwhelmed by the number of people being tested. Huge queues are formed to get a CT scan. Moreover, evaluation of the scan is also time consuming and puts extra load on the doctors involved in quarantining and treating the infected patients. To overcome this problem, the process of diagnosis through CT scans can be fastened through state-of-the-art (SOTA) computer vision and deep learning techniques. These algorithms can be used for the evaluation of COVID-19 as they can identify the lesions and the varied opacities at a faster rate than the existing methods.

The proposed work considers Convolutional Neural Networks (CNN), a specific class of neural network having grid-like structure for processing the data. Data could be a one-dimensional time series or a two-dimensional array of pixels, as found in the images. This type of neural net employs the convolution operation, which is a kind of linear operation. CNN uses convolution instead of standard matrix multiplication for calculation in at least one layer of the network [8]. CNN forms the basic building block of most of the deep and complex image based deep learning algorithms. For training and maintaining such large algorithms, cloud based architectures provide an efficient solution as they possess greater horsepower than average desktops, but it increases the communication overhead and computational latency considerably.

This proposed research aims to provide the state-of-the-art solutions to evaluate CT scans combined with the techniques such as data augmentation and transfer learning to refine the results and reduce the overall bias that may occur in data-sets that are comparatively smaller in size. The proposed work overall aims to reduce computational requirements and still achieve good performance such that resources can be provided on the edge of the network itself.

Rest of the paper is organized as follows. Section 2 discusses the recent works done in the literature related to the Covid-19 detection using CT scan images. Section 3 presents the proposed scheme to evaluate CT scan images. In Section 4 various methods used in CNN which helped in detecting the Covid 19 are discussed, followed by the performance evaluation of the proposed scheme and conclusions.

2 Related Work

Recently, after the Covid-19 outbreak, few researchers have worked on Covid-19 detection using CT-scan images. Zhao et al. [9] prepared a data set of the CT-scan images of the Covid-19 patients. To address the problem of overfitting due to small dataset size, the authors used data augmentation and transfer learning methods, along with their deep learning model. Later, Morozov et al. [10] published an extensive dataset of the full chest CT-scans of the patients with varying degree of the COVID-19 infection aimed at facilitating research in this field. Further, this dataset is also used in our proposed approach. Wang et al. in [11] proposed a deep CNN named as COVID-Net, for detection of the COVID-19 using the chest X-ray images. The authors constructed an initial network prototype based on human-driven design principles. However, for the ease of training, the authors only considered four densely connected 1×1 convolution layers, which slightly reduces the accuracy.

The authors in [12] considered a simple CNN and applied a pre-trained AlexNet model on the X-rays and CT scan images dataset where the learned weights, bias and features are transferred to the proposed approach. The authors considered a CNN model consisting of only one convolutional layer and constitutes 16 filters where each filter was constructed based on 5×5 filter size, batch normalization, rectified linear unit (ReLU) and few other connected layers. Further, preprocessing like cropping and resizing is also performed on the images. Asmaa et al. in [13] adapted a deep CNN, called as Decompose, Transfer, and Compose (DeTraC), for classification of the COVID-19 chest X-ray images. The authors proposed to add a class decomposition layer to the already trained models. This added layer partitioned each class into various subclasses within the image dataset. Then, new created sets were assigned new labels, and each subset was treated as an independent class. At last, these subsets were assembled back to produce the final predictions. However, it also suffered with unavailability of the large dataset. The authors in [14–16], also used the CNN for the Covid-19 cases detection using the X-ray or CT-Scan images.

Majority of the works in computer-aided diagnosis of the COVID-19 infection, focused on using the X-ray images of the infected patients as a primary dataset. Islam et al. in [17],

Fig. 1 ReCOV-101 Architecture

presented a combination of CNN with Long Short Term Memory network (LSTM) for the detection of COVID-19. Their novel approach made it possible for them to achieve an AUC score of 99.9%. Similarly, Nour et al. [18] were able to achieve an accuracy of 98.97% using a deep CNN model combined with Bayesian optimisation algorithm for hyperparameter tuning. These works primarily focused on differentiation between pneumonia, and COVID-19, but not the infected patients. On the other hand, this proposed work focuses on detection of varying degrees of the COVID-19 infection for easy patient segregation and monitoring. Both the above works served as inspiration for our approach in terms of model architecture and parameter tuning. Polsinelli et al. in [19] proposed a light CNN model based on SqueezeNet, a SOTA model, for the efficient discrimination of the COVID-19 CT scan images with the other CT scan images. Their light and efficient method helped transform the initial concept of the presented model to a more robust yet memory efficient model. Moreover, the common shortage of large dataset among the works directed us to incorporate techniques like transfer learning and Synthetic Minority Over-sampling Technique (SMOTE) to compensate for the size of datasets.

Unlike other works, this proposed work analyzed full chest CT scan in one go for a much better analysis, emulating the way a physician would perform the diagnosis. Moreover, most of the above mentioned works require high computational resources, which may only be available at the cloud servers. The proposed work uses a single SOTA model as its backbone to increase the overall robustness without increasing hardware needs. Further, transfer learning, segmentation, efficient preprocessing and hyperparameter tuning are combined with a unique

architecture for classification of the scans. The framework used in this work along with the CNN architecture are explained in the following section.

3 Proposed Approach

This section discusses the proposed CNN approaches used to identify COVID-19 cases through ct-scan images, and details of proposed CNN model implementations. The proposed work presents *ReCOV-101*, a deep CNN model with the ResNet-101 as its backbone. ResNet or residual network [20], which solves the problem of the vanishing/exploding gradient using a technique called skip connections. The skip connection skips training from a few layers and connects directly to the output. The advantage of adding this type of skip connection is that if any layer effects the performance of the architecture, then it is skipped by regularization. In the proposed work, the classification layer of the ResNet-101 backbone is removed. The backbone model can be understood by an analogy of a physician analyzing full CT scan at once, providing importance to slices with relevant information. This backbone model is presented with slices of a single scan and it outputs a 3D array with 2048 channels for each slice which are then passed through a 1×1 convolution network with 512 filters for down sampling the number of channels. For merging these arrays, an additional layer is also used. Before flattening this layer, a residual block of 3×3 convolution and 128 filters is added for more robustness. Finally, a 2D max pooling with 2×2 kernel size is added, and its output is flattened. For output, a softmax layer of four nodes is attached to the flattened nodes. The architecture of *ReCOV-101* is shown in Fig 1.

Fig. 2 Slices of a Scan from the Dataset

Recently Internet of Medical Things (IoMT) has made big impact into the health care system. Generally IoMT consists of the interconnected medical devices sharing the data like pacemakers, computerized tomography (CT) scan machines and Magnetic Resonance Imaging (MRI) [21]. Usually, a smart connected CT scanner sends scanned images of the lungs of the Covid-19 patients to the cloud server for further analysis and processing, because these images require high end GPUs to get the automatic results. However, transmitting data to the cloud and receiving the processed results is time consuming and hence, increases latency. One of the objective of this work is to design such a CNN that the models can be trained on a single enterprise-level GPU which can easily be provided on the edge of the network, on the path between the data sources and the cloud data centers. This will help in reducing communication overhead and latency.

4 Materials and Methods

The partitioning of the dataset used in the proposed work based on the degree of severity of the infection is explained in this section. The preprocessing methods used to highlight the region of interest in the CT-scan images, before feeding them to the network, are also explained here.

4.1 Dataset

The dataset considered in the proposed work is *MosMedData: Chest CT Scans with COVID-19 Related Findings*. The dataset contains full chest CT scans of the 1110 patients, annotated into the five classes. The classes are as follows [10]:

- CT-0:** Normal lung tissue, no CT-signs of viral pneumonia.
- CT-1:** Several ground-glass opacifications, involvement of the lung parenchyma is less than 25%.
- CT-2:** Ground-glass opacifications, involvement of the lung parenchyma is between 25 and 50%.
- CT-3:** Ground-glass opacifications and regions of consolidation, involvement of the lung parenchyma is between 50 and 75%.
- CT-4:** Diffuse ground-glass opacifications and consolidation as well as reticular changes in the lungs. Involvement of lung parenchyma exceeds 75%.

Some example scan slices are shown in Fig. 2. Each scan is a 3D array describing the patient's chest radiodensity in Hounsfield unit. Different scans contain different number of slices with 31 being the lowest and 71 being the highest number of slices. The width and length of the scans are consistent, both being 512 units. The varying number of slices pose an issue for the proposed model since the input shape is fixed. This problem is resolved in the next sub-section.

The classes contain 254, 684, 125, 45, 2 scans respectively. It is evident that the classes or categories are imbalanced, with CT-4 having the least number of occurrences. To tackle this issue, a combination of random oversampling and random undersampling is used in this work[22]. Since oversampling will not be fruitful for the category CT-4 as it contains only two instances which is 0.002 % of the CT-1 class, therefore this category is dropped for the sake of this research work. However, in future, the *ReCOV-101* can be modified to accommodate this class by using transfer learning when this class has enough instances. Before sampling the data, the data is distributed

Table 1 Data Distribution Between Splits and Classes

Class	CT-0	CT-1	CT-2	CT-3	Total
Train	163	438	80	29	710
Validation	40	109	20	7	176
Test	50	136	25	9	220

into training, validation and testing splits, where testing splits being 20% of the data from each class, validation being 20% of the remaining data and training being the rest. The sampling is only applied to the training split to maintain the imbalance and authenticity of the data during testing and validation. The detailed distribution of the data among classes and split is described in Table 1.

For sampling the training data, firstly, the dominant class is randomly undersampled i.e. CT-1 to 70%. Then, the remaining classes CT-0, CT-2 and CT-3 are randomly

Fig. 3 Process Flowchart

oversampled, to make them 75%, 65% and 55% of the dominant class respectively. Finally, after sampling, the training data consists of total 902 scans. The detailed distribution among the classes after sampling is given in Table 2. The oversampling percentages of classes CT-2 and CT-3 might seem like an issue which could potentially lead to the poor results due to presence of duplicate copies. Since the validation and the testing splits only contain unseen data, the accuracy achieved is justified. Moreover, in the next section the accuracy of the *ReCOV-101* between different classes is also studied to ensure the authenticity of the results.

Table 2 Sampling of training data

Class	Before Sampling	After Sampling	% change
CT-0	163	229	+40%
CT-1	438	307	-30%
CT-2	80	199	+148%
CT-3	29	168	+479%

4.2 Preprocessing pipeline

Each scan in the dataset was pre-processed before feeding into the model pipeline using various steps as shown in Fig. 3. The scans are in 3D NIfTI array format, with varying number of slices and have different pixel spacing. The presented procedure handles all these discrepancies and outputs a 4D array with (slices, length, width, channels) as dimensions. A scan may have a pixel spacing of [2.5, 0.5, 0.5], which means that the distance between slices is 2.5 millimeters. For a different scan this may be [1.5, 0.725, 0.725]. A method of dealing with this is resampling the full dataset to a certain isotropic resolution. For the proposed approach, the scans are resampled to [1, 1, 1] pixels. This helps in making the scans invariant to slice thickness.

After intensive research and analysis, it was found that the portion of the scans excluding the lung area

was not a determining factor of the degree of COVID-19 infection. Moreover, if present, the areas excluding the lungs caused the model to have bias and affected the overall reliability of model. To overcome this issue, segmentation is used. Lung masks are calculated for each scan using the hounsfield unit (HU) range of the lung tissue [23] as shown in Fig. 4a. Detailed segmentation process is discussed in the next sub-section. The masks are then applied onto the scans, removing the unnecessary portions. However, dataset segmenting raises another issue. The segmented scan contains considerably large portions of no information or null pixel value. To reduce these portions, the scans are cropped. First, bounding box dimensions are obtained from the slice having the largest lung portion. Then, all the slices are cropped using those dimensions. This helps in centre positioning of the scan while also reducing the areas with no information.

ReCOV-101 requires each scan to be of a consistent dimension. The backbone of the model, ResNet-101, requires each slice to be of the shape 224×224 pixels with 3 channels. To achieve this, each slice of the scan is resized and repeated three times since they only contain a single channel. The values (in HU) of the scan are also mapped to 8-bit pixel range and then normalization is performed. Further, the number of slices in each scan are limited to 20. These slices are randomly sampled from the full scan while maintaining their order, excluding a few slices from top and bottom which do not contain any significant lung information. The final shape of each scan is (20, 224, 224, 3). Since there are 902 scans for training, each having 20 slices, the total number of images that the ResNet-101 backbone receives amounts to be 18,040.

4.3 Segmentation

Many datasets may contain various images with very less lung portion. Maguolo et al. in [24] critically evaluate existing methods of COVID-19 detection. They discussed the possibility of achieving high accuracy scores with images that do not contain most of the lungs. Although the paper only considered X-ray images, similar pattern

Fig. 4 Segmentation using HU Range of Tissues

can creep into CT scans also. To avoid such behavior, the lung portions are segmented from the CT scans using HU range of lung tissue, region growing and morphological operations. Typical HU value for lung tissue is about -700 and air is -1000. Only separating lung tissue does not help since air is contained between the lungs. To differentiate between the air inside and outside the lungs, the lung tissue provides a boundary. Then, using region growing algorithm the air pocket inside the lungs is labeled. During this process, it is possible to label multiple air pockets since there can be a few present inside the body. The final step in segmentation is to choose the largest region since lung is the largest air pocket. The results of this process are shown in Fig. 4.

4.4 Transfer Learning

Owing to the depth of *ReCOV-101*, convergence of the gradient posed a problem. Convergence took a very long time or would plateau at a local minima. This issue is removed by using transfer learning on the ResNet-101 model. It was pre-trained on the same dataset with the slices as raw input before inserting it in *ReCOV-101*. The slices were sampled from the middle portion of the scans to ensure maximum lung presence. The preprocessing procedure was kept the same to ensure consistency between trainings. In comparison, *ReCOV-101* performed much better with transfer weights than with randomly initialized weights. The pre-trained ResNet-101 achieved an accuracy of 92.4% on its testing.

4.5 Hyperparameter Tuning

ReCOV-101 on itself performed better than many approaches aimed at COVID-19 detection from CT scans. To further enhance the model various hyperparameters were tuned such as the learning rate, optimiser, backbone model, merge layer and the number of additional residual layers. For learning rate, exponential learning rate schedule [25] is used, which keeps the initial learning rate constant for 10 epochs and then decreases it exponentially. Pre-trained ResNet-50, ResNet-101, DenseNet-169 and DenseNet-201 were tested as the backbone models in which ResNet-101 performed the best. Optimum number of additional residual blocks, optimiser and batch size for training were selected using grid search and cross-validation which came out to be 1, Adam [26] and 64 respectively.

For the merge layer, addition, average and concatenation were considered. The addition layer and average layer are similar in implementation since they do not change the array dimension. The concatenation layer, however, altered the dimension which needed slight modification in the architecture as considered in DenseNet. Out of the three, the addition layer outperformed others in terms of accuracy and efficiency.

5 Performance Evaluation

The dataset considered for measuring the performance of the proposed approach with accuracy, as the metric, and categorical cross-entropy, as the loss, is *MosMedData* [10]. For deeper understanding, model's performance between

Class	With Segmentation			Without Segmentation		
	Training	Validation	Testing	Training	Validation	Testing
CT-0	99.8	97.5	96.2	100	96.2	94.6
CT-1	100	96.9	98.6	100	94.8	92.4
CT-2	99.8	94.2	93.1	99.9	92.3	88.3
CT-3	99.6	92.2	91.7	100	90.7	85.1
Overall	99.8	95.2	94.9	99.9	93.5	90.1

Table 3 Experimental Results (Accuracy in %)

different classes is also analysed. To ensure that *ReCOV-101* does not overfit, regularisation and early stopping are used during training. Training is also carried out separately for segmented and non-segmented data.

As shown in Fig. 5, for the segmented data, after about 50 epochs, the model achieved an accuracy of 88.7% on the testing data. Continuing the training, the testing accuracy kept on increasing upto about 80th epoch. Further training increased the training accuracy to about 100%. The training was complete in about 100 epochs which is quite early for such a large network. This anomaly could be understood by analysing the dataset. A single example in the dataset consists of 20 images which are all used to train the backbone model. Moreover, the backbone model was pre-trained on the same dataset separately. Hence, the overall convergence took a small number of epochs. The final accuracy achieved on the training, validation and testing data were 99.8%, 95.2% and 94.9% respectively. The performance of the model in different classes is shown in Table 3 (rounded to nearest decimal). Comparatively, the model performs poorly in the CT-3 class with about 91.7% accuracy which could be due to the lesser number of examples present in this class. The model was only shown about 30 scans from this class although they were oversampled to about 168. Oversampling ensured that the model did not have bias towards a particular class but the lack of distinguishable examples hampered its performance. Similar pattern can be seen in the class CT-2, which also had comparatively less number of examples. Moreover, this pattern is non-existent during training since class imbalance was compensated using sampling.

On the other hand, *ReCOV-101* with non-segmented data was less stable during the training. It achieved an accuracy of 90.1% and similar accuracy distribution among classes. In this particular use case, detection without using segmentation can produce destructive results even if it seems to achieve decent results because the model could be fitting to patterns outside the lung area which do not indicate COVID-19 presence (small but considerable probability)[7]. Still, for the sake of research, the results from both the

Fig. 5 Comparison of Training Process

approaches are included and the training process as shown in Fig. 5.

6 Conclusions

In this work, *ReCOV-101*, a convolution based model has been presented and analysed for the detection of COVID-19 from CT scan images. The work also proposes methods to preprocess full CT scans using combination of techniques and later use them for development of a robust model. *ReCOV-101* was trained on a single enterprise-level GPU and is not hardware intensive as compared to other approaches. Further, other techniques such as data augmentation can also be incorporated to artificially increase the size of the dataset with consultancy from a radiology specialist. Moreover, unsupervised Visual Representation, such as *Momentum Contrast* [27] can be used to further increase the models' performance. However, it is hardware intensive and requires two or more GPUs to run, which inhibits its usage to a few individuals and enterprises. For any deep learning model, the more the data, the better the performance. In future, when the database for COVID-19 research grows big enough, *ReCOV-101* has potential and is expected to outperform its currently presented form.

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