Covid-19 Recognition in CT Scans using Artificial Intelligence (AI) guided tools

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Abstract- In this study, AI-guided algorithms will be utilized to screen CT scans for Covid-19 analysis. We have developed AI-guided tools to detect, localize and segment Covid-19 cases which are still limited to training and testing. Artificial intelligence has been built to examine whether the patient has Covid-19 or not. A total of $1,810$ CT scan datasets have been collected for this project where $1,267$ Covid-19 patients' and 543 healthy patients' CT Scans. The pre-trained models InceptionNet V3 and U-net have been used for training purposes. K-fold cross-validation has been used to verify a better model. To measure the performance, we have performed accuracy and AUC (area-under-the-curve) evaluation metrics. We have achieved 97.58% of accuracy and 0.9756 of AUC from the Inception V3 and 70.24% of accuracy and 0.71 of AUC from the U-net. Our main goal is to show which model can perform better to detect, localize and segment Covid-19 cases using CT scan images so that we can use one or two globalized models for Covid-19 analysis.

Keywords: Artificial Intelligence · CT Scan · Covid-19 · InceptionV3 · U-net.

1 Introduction

According to WHO [1], Coronavirus is an infectious disease that was originally found in Wuhan, China, in 2019 and has since spread throughout the world, culminating in the Coronavirus outbreak of 2019–2022. It is regarded as a key health crisis that occurred at the time and spread around the world. Border limitations, flight limits, social isolation, and increased hygiene awareness have all been implemented by governments around the world. However, the infection continues to spread at a breakneck speed. While most persons infected with Covid-19 got mild to moderate respiratory illness, a few people acquired pneumonia, which was fatal. Elderly adults with underlying medical conditions such as cardiovascular disease, diabetes, chronic respiratory disease, renal or hepatic disease, and cancer are thought to be more likely to acquire serious illness [2]. Different kinds of variants like Delta, Omicron are still affecting people and it is not over yet. In the fields of healthcare and medical imaging, Artificial Intelligence (AI) has made numerous advances. So, AI-guided tools can help us to detect Covid-19 way early. Figure 1 represents the CT Scan images for both Covid-19 patients and healthy patients.

The rest of the paper is organized as follows. In Section 2, we describe the motivation behind this research. Next in the section 3 we have discussed about the literature review of other papers. The proposed methodology have been discussed in section 4. In section 5, the results have been showed. Then, section 6 is the conclusion of the work.

Fig. 1. Chest CT-scan image data: Covid and Healthy

2 Motivation

The virus infects people predominantly by respiratory droplets. SARS-CoV-2 continues to infect people all across the world, with over 504.53 million infections and 6.22 million deaths reported in two years and one month (as of April 17, 2022) [3]. The virus can persist on surfaces that have been encountered by an infected person, according to researchers. Coronavirus has a high spread rate by the end of March 2020 [3]. Furthermore, no forecast models are now accurate due to unprecedented events [4]. For identifying and detecting Covid-19 patients, the polymerase chain reaction (PCR) is the gold standard. Using nasopharyngeal or oropharyngeal swabs, SARS-CoV-2 RNA can be identified in respiratory materials. Because of its high precision and sensitivity, the PCR process takes a long time and requires a lot of resources. For Covid-19 screening, radiography techniques such as CXRs have been recommended as an alternative to the traditional PCR approach. Furthermore, researchers in [5] provided a statistical analysis of the increase in radiographic clues in Covid-19 confirmed cases, as well as the chronological phases of the disease's evolution in the host's body. The authors of [6] also talked about the size of dataset needed to produce reliable Covid-19 imaging tools and procedures. For all of these reasons, AI-driven methods for mass screening must be adopted internationally.

3 Literature Review

In the literature, numerous AI-guided tools has been used to classify and identify COVID-19 using CT scans images. In [7] authors demonstrates the analysis of Corona Virus Disease based on a probabilistic model. Four image filters are used in conjunction with the proposed composite hybrid feature extraction to extract features from CT images using a combination of traditional statistics and machine learning approaches (CHFS). The stack hybrid classification approach was used to classify the selected features (SHC). Their findings demonstrate the feasibility of employing artificial intelligence to extract radiological parameters for the diagnosis of COVID-19 in a timely and exact manner.

A COVID-19 disease classification model is provided in this paper [8] to classify infected patients from chest CT scans. On the training data, the suggested MODE-based CNN and competitive classification models. The combination of deep learning of extracted features with Q-deformed entropy handmade features for discriminating between COVID-19 coronavirus, pneumonia, and healthy computed tomography (CT) lung scans is presented in this study [9]. Pre-processing is employed in this work to lessen the impact of intensity differences between CT slices. The maximum accuracy achieved for classifying the 321 patients in the dataset was 99.68%. Authors suggested a weakly supervised deep learning technique for detecting and classifying COVID-19 infection from CT scans in [10]. The suggested method reduces the need for manual CT image labeling while still detecting infections accurately and distinguishing COVID-19 patients from non-COVID-19 cases. Using 3D CT volumes for COVID-19 classification and lesion localization, another weakly-supervised deep learning framework was constructed on [11]. The lung region was segmented for each patient using a pre-trained U-net, and the segmented 3D lung region was then fed into a 3D deep neural network to predict the likelihood of COVID-19 infection. The authors of [12] gathered 495 chest CT images from three Chinese hospitals retrospectively. They used a deep learning network to construct a multi-view fusion model to screen patients for COVID-19 utilizing CT images with the maximum lung areas in axial, coronal, and sagittal views. Using deep learning techniques, the authors of [13] attempted to develop an early screening model to identify COVID-19 from influenza-A viral pneumonia (IAVP) and healthy cases using lung CT images. There were a total of 618 CT samples taken. Using a 3D deep learning algorithm, the candidate infection areas were first segregated out of the pulmonary CT picture collection. Using a location-attention classification model, these separated images were divided into the COVID-19, IAVP, and irrelevant to infection (ITI) groups, along with the accompanying confidence scores. Finally, the Noisy-OR Bayesian function was used to calculate the infection type and overall confidence score for each CT case. The benchmark dataset's experimental results revealed that the overall accuracy rate was 86.7%.

Overall, we observed from the literature review that numerous machine learning, deep features have been used individually to identify or classify COVID-19 patients with healthy patients using CT scans images and we can easily identify that AI-guided tools are best in this area. But, none of these research has been compared with several deep features in together. Our goal was to compare the performance of two pre-trained deep learning models InceptionNet V3 and U-net, which have been described briefly in the next part of our paper.

4 Proposed Methodology

4.1 Inception V3

Inception-v3 [14] is an extended version of the popular GoogLeNet [15], which has demonstrated strong classification performance in a variety of biomedical applications by employing transfer learning [16,17]. Inception-v3 suggested an inception model that concatenates multiple different sized convolutional filters into a new filter, similar to GoogLeNet. The number of parameters that must be taught is reduced as a result of this architecture, and the computational complexity is reduced. The architecture of Inception V3 [18] is in Figure 2. An Inception v3 network's architecture is developed one step at a time, as described below:

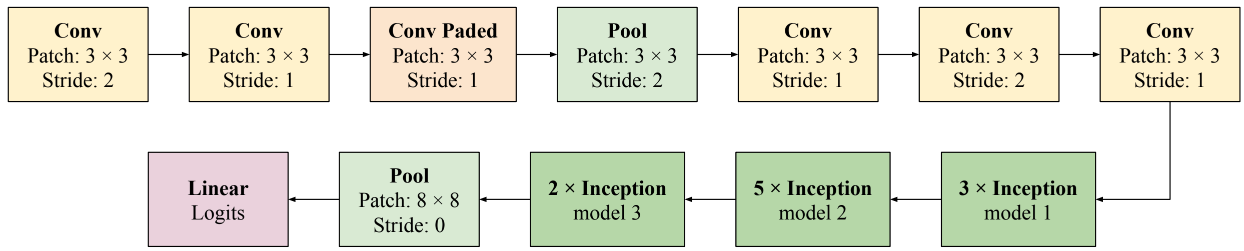

Fig. 2. The architecture of Inception V3.

Factorized Convolutions: This reduces the number of parameters in a network, which improves computational efficiency. It also monitors the network's efficiency.

Smaller convolutions: substituting smaller convolutions for larger convolutions results in significantly faster training. A 5×5 filter, for example, has 25 parameters; two 3×3 filters, in place of a 5×5 convolution, have just 18 (3*3 + 3*3) parameters.

Asymmetric convolutions: Instead of a 3×3 convolution, a 1×3 convolution followed by a 3×1 convolution might be used. The number of parameters would be significantly higher than the asymmetric convolution described if a 3×3 convolution was replaced with a 2×2 convolution.

Auxiliary classifier: an auxiliary classifier is a tiny CNN that is introduced between layers during training and adds the loss to the main network loss. Auxiliary classifiers were utilized for a deeper network in GoogLeNet, whereas an auxiliary classifier works as a regularizer in Inception v3.

Grid size reduction: Pooling techniques are commonly used to reduce grid size. However, a more effective strategy is proposed to overcome the computational cost barriers.

4.2 U-net

Figure 3 illustrates the network design. It is made up of a contracting path (on the left) and an expansive path (on the right). The convolutional network's contracting path follows the standard architecture. It comprises of two 3×3 convolutions (unpadded convolutions) that are applied repeatedly, each followed by a rectified linear unit (ReLU) and a 2×2 max pooling operation with stride 2 for downsampling. We quadruple the number of feature channels with each downsampling step. An upsampling of the feature map is followed by a 2×2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the proportionally cropped feature map from the contracting path, and two 3×3 convolutions, each followed by a ReLU in the expansive path [19].

5 Results

5.1 Dataset

To collect the dataset of Covid-19 is not easy even now. Though more dataset are becoming available day-by-day. A total of $1,810$ CT scans datasets have been collected for this project where $1,267$ of Covid-19 patients and 543 of Healthy patients CT Scans. Table 1 represents the summary of the dataset. The dataset is publicly avaialable in Kaggle [20].

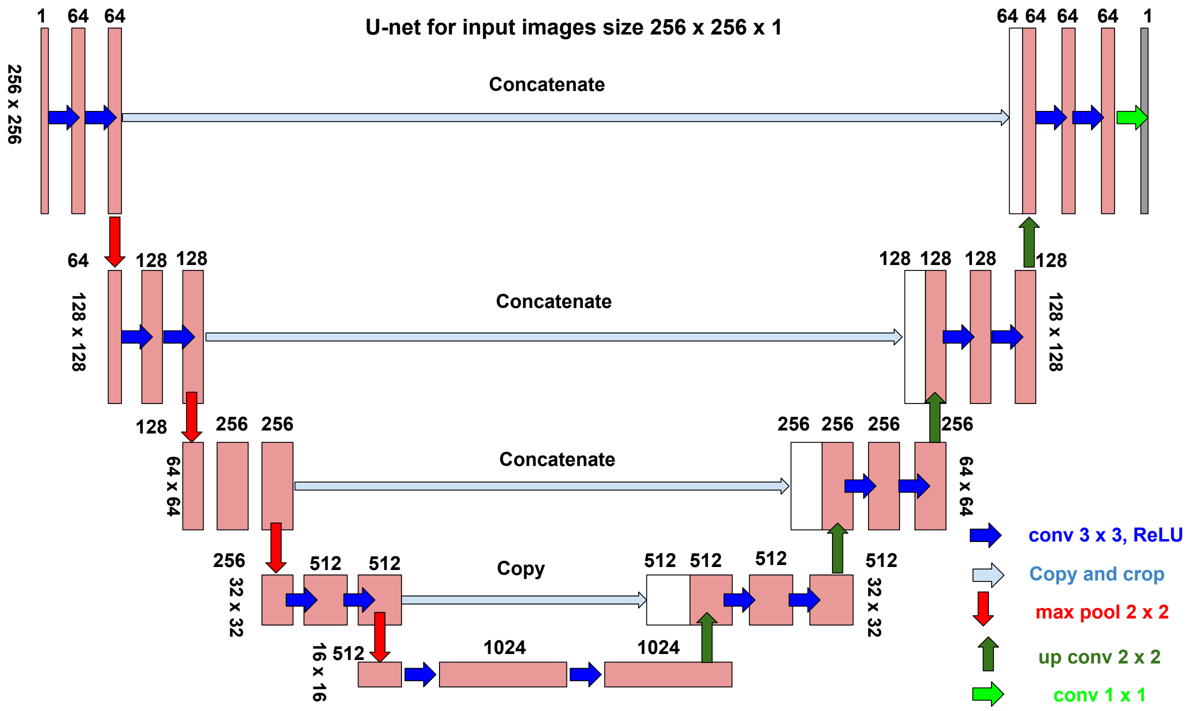

Fig. 3. The architecture of U-net.

Table 1. The summary of the dataset

Cases	Dataset (size)
Covid-19	$1,267$
Healthy	543
Total	$1,810$

5.2 Performance metrics

In our experiment, we have measured the performance metrics of accuracy, area under curve (AUC). The number of correct CT scan images divided by the total number of guesses, multiplied by 100, is possibly the most straightforward metric one can imagine.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}$$

The AUC is a total measure of a binary classifier's performance over all potential threshold settings. The area under the ROC curve is calculated by AUC, which is between 0 and 1. The likelihood that the model ranks a random positive example higher than a random negative example is one approach to analyze AUC. On a broad level, the higher a model's AUC, the better it is. The performance results of Inception V3 are discussed in Table 2 and Table 3 shows the results for the U-net architecture.

Table 2. Performance result of Inception V3

Folds	Accuracy	AUC
Fold-1	0.5103	0.5071
Fold-2	0.9655	0.9655
Fold-3	0.9517	0.9581
Fold-4	0.9862	0.9862
Fold-5	0.9758	0.9756
Mean (μ)	0.8779	0.8785
σ	0.2059	0.2079

Table 3. Performance result of U-net

Folds	Accuracy	AUC
Fold-1	0.6862	0.6862
Fold-2	0.7207	0.7252
Fold-3	0.687	0.718
Fold-4	0.692	0.759
Fold-5	0.7024	0.71
Mean (μ)	0.6977	0.7197
σ	0.0144	0.0264

5.3 Comparative Results

We have collected each folds results to compare the performance. The graphical representation of the results are shown in the Fig. 4. From these representations, we understand that how each fold is performing in each performance metrics.

6 Conclusions

AI-driven technologies must be integrated from the start of data collection, in collaboration with experts in the field. The necessity of AI-driven tools for future Covid-19 epidemics has been discussed in this study. We have employed Inception V3 and U-net in CT scan images of healthy and Covid-19 patients for the evidence of Covid-19 on a dataset size of $1,810$. We have achieved an accuracy of 97.58% and AUC of 0.97 in Inception V3 and

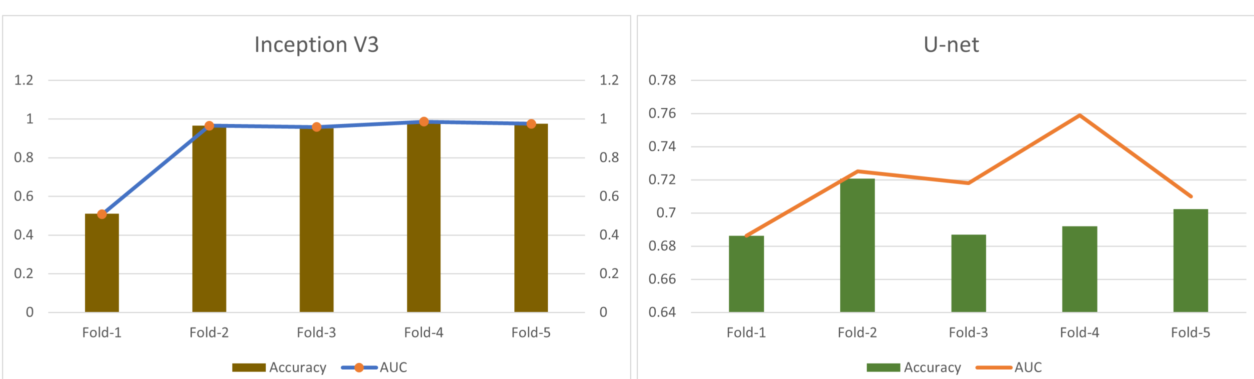

Fig. 4. Graphical representation of performance result of Inception V3 and U-net

accuracy of 70.24% and AUC of 0.71 in U-net. Between these two models, Inception V3 is performing well. Our future plan is to work on the explainable artificial intelligence in CT scan images to screen Covid-19.

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