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COVID-19 RADIOGRAPHIC IMAGE DETECTOR USING CNN

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ABSTRACT— Automatic disease identification has turned into a crucial area of study in medical science as a result of the current rapid population growth. A method for automatically recognizing diseases aids in medical diagnosis, generates reliable data quickly, and lowers the death rate. As a result of its recent global expansion, the COVID-19 is currently one of the utmost severe and critical infections. The quickest means of diagnosis should be developed in the form of an automated detection system to stop the spread of COVID-19. The international community works to identify and treat COVID-19 patients as soon as feasible by looking for, implementing, or developing novel strategies. In order to effectively diagnose and identify sick tissues in Covid-19 patients based on pulmonary medical imaging, we apply deep learning algorithms. The suggested technique predicts output labels using a Convolutional Neural Network (CNN) architecture. We try to use classification and feature extraction based on CNN techniques in order to assess the sensitivity and accuracy of the strategy. We try to use classification and feature extraction based on CNN techniques in order to assess the sensitivity and accuracy of the strategy. In order to achieve high efficiency and accuracy, we implement various pre-existing models and suggest an application using DenseNet201, VGG16, and Xception architectures that uses radiographic pictures to detect and classify the potential existence of SARS-CoV-2.

Keywords — covid-19, coronavirus, convolutional neural network, DenseNet201 , VGG16, Xception.

1. INTRODUCTION

Covid-19 has been brought on by the SARS-CoV-2 coronavirus. World Health Organization (WHO) announced COVID-19 a pandemic on February 11, 2020. According to statistics from the World Health Organization, the disease has spread to practically every country since the discovery of the first case and will have claimed the lives of over 4 million individuals among the roughly 180 million verified cases by June 2021.

Although the final identification of COVID-19 still mostly depends on transcription-polymerase chain reaction (PCR) testing, screening patients at primary health centres or hospitals is the first step in therapy. Medical imaging is becoming a mainstay of hospital election procedures due to its simplicity and speed, which enables doctors to immediately identify infection and their effects. Computed tomography scans and X-ray pictures are increasingly commonly used in clinics as alternative diagnostic procedures to identify Covid-19 and determine the effects of the coronavirus.

The RT-PCR (Reverse transcription polymerase chain reaction) testing, which is used to detect SARS CoV-2 RNA from respiratory material such as nasopharyngeal or oropharyngeal swabs, is the gold standard in the diagnoses of COVID-19 patients. More important limitations of RT-PCR testing than its high sensitivity is the less or limited accessibility of resources, such as kits used for testing, and the time duration it takes to get a result, albeit being shorter now than in the past. In order to save time and valuable resources during a pandemic, we propose in our work to employ a convolutional neural network to quickly identify and categorize contemporary x-rays/CT scans of a patient for potential detection of the COVID-19 virus.

This paper describes the approach we took to create a system of three CNN architectures that classifies whether the Radiographic image of lungs is of a patient suffering from COVID19 or not. To accomplish this, we perform (1) comparative study between pre-trained CNN architectures, (2) identify three top performing models, (3) develop a web application for ease of use.

2. LITERATURE REVIEW

In order to diagnose and identify COVID-19 disease using CNN, a few study frameworks on the COVID-19 pandemic are briefly addressed in this part. Several studies [1-3] have sought to build automatic classification scheme for COVID-19 classification, largely by CNN (convolutional neural networks), since highlighting the benefits of human-centred diagnosis and the potential of X-ray images and CT scans in detecting COVID-19 (CNNs). Xu et al. [4] employed a 3D CNN pre-trained model to extract potentially sick area from

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the CT data. After that, a second CNN is supplied with these candidates to divide them into three categories. With an overall accuracy of 86.7%, influenza-A-viral-pneumonia, COVID-19, and irrelevant-to-infection In Reference [5], CT scans are also used to detect positive for COVID-19. All slices are supplied into the developed model independently, and then its outputs are combined together using a Max-pooling method. By this the model has been able to achieve 90% sensitivity. Similar work has been proposed Sethy and Behera [6], the authors has trained different CNN models over X-ray image datasets, followed by a SVM (Support Vector Machine) as a classifier to classify positive COVID-19 cases. Using this proposed scheme, the authors has been able to reach at an accuracy of 95.38%.

It is clear from the aforementioned studies that CNN techniques may be able to predict the event with trustworthy outcomes based on learning and experience processes. The experimental results in the literature show the value of using CNNs with one or more layers.

3. SCOPE OF THE WORK

Given the widespread use of chest diagnostic imaging systems in today's medical systems, the portability of portable machines allows radiography examinations to be conducted more rapidly and with better accessibility, making them an excellent complement to RT-PCR testing. especially given that Chest X-ray scan and Computed tomography are routinely performed on patients with respiratory complaints as part of routine care. Additionally, after getting initial negative findings from RT-PCR testing, patients who return to the emergency room with clinical worsening are advised to have CXR imaging. Therefore, chest X-rays and CT scans are an essential part of the different screening techniques that have been proposed [7]. The necessity for qualified radiologists to interpret the radiography images, however, is one of the largest obstacles encountered, as the visual indicators can be subtle.

3.1 CNN Architectures - A brief overview

Convolutional neural networks (CNNs) and deep learning algorithms in general have recently made significant advances, including segmentation, recognition, and object detection. It has been demonstrated that deep learning techniques are effective at automating the arduous process of manually creating features for feature representation learning. By using a hierarchical layer of feature representation, convolutional neural networks (CNNs) and deep learning attempt to mimic the composition and operation of the human visual cortex system.

The CNN architectures that were used here will all be briefly discussed in the sections that follow, along with their unique characteristics. To go into depth about each of these CNN models would be outside the scope of this paper, hence we request readers to read papers such as [8] [9].

ResNet50 - The ResNet designs were submitted by Microsoft's He et al. [10], and they won the 2015 ILSVRC. The main development in ResNet topologies is indeed the usage of residual layers along with skip connections to address the issue related to vanishing gradient, which may prohibit the network's weights from further updating or changing. Deep networks are particularly susceptible to this problem since repeatedly applying chain rules may result in the gradient value disappearing or becoming zero. Gradians will be able to skip connections and flow immediately backward from the last layers to begin layer filters. CNN models can become more complicated with 152 levels.

The acronym ResNet50 stands for residual network with 50 layers. ResNet50 and VGG-16 are comparable, however ResNet50 has an additional identity mapping feature. Fig. 1 shows this. ResNet foresees the change that will be required from one layer to the consecutive layer to arrive at the concluding estimation [20]. The disappearing gradient issue is solved by ResNet by enabling gradients to follow a different shortcut path. If the current layer is not required, the model can bypass a CNN weight layer thanks to ResNet's identity mapping. This helps to solve the overfitting issue with the training set. ResNet50 has 50 layers in total.

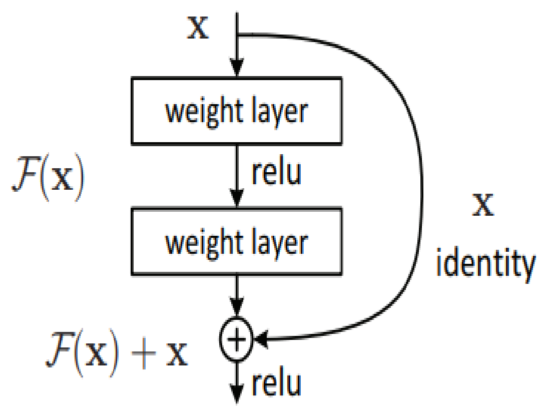

Figure 1. Residual Learning: A building block

VGG16 - The visual geometry group at Oxford University [13], hence the acronym VGG, developed this architecture and demonstrated that utilizing modest 3-by-3 filters in all of the network's convolutional layers enhances performance. The fundamental idea behind VGG architectures is that a number of modest filters can simulate the impact of more substantial ones. VGG architectures are widely utilized owing to their design simplicity and classification

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capability.

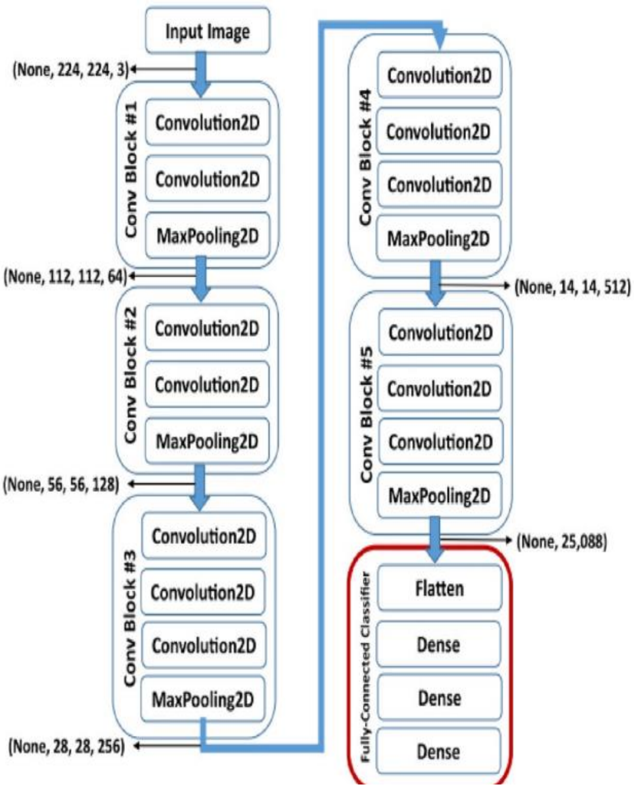

Figure 2. Block diagram of VGG16 Network

The VGG-16 network was trained using the ImageNet database [17, 18]. The VGG-16 network achieves excellent accuracy even with tiny sets of images because of the extensive training it has received. A 33-pixel receptive field and sixteen convolution layers make up the VGG-16 network. There are a total of 5 such levels, including a Max pooling layer of magnitude 22. There are three fully linked layers after the last Max pooling layer. It uses the softmax classifier as the last layer. ReLu turns on all concealed layers. Figure 4 [19] shows the VGG-16 architecture's design.

DenseNet201 - According to Huang et al. from Cornell University, who presented ResNet in 2018[11], this architecture can be seen as a natural extension of that architecture. In DenseNet, each CNN layer is attached with every single other layer present in the network model in a feed-forward manner, it minimizes the threat of gradient vanishing, requiring lesser training parameters, and permitting for the reuse of feature maps. Every layer accepts the inputs from all features from layers before it. Furthermore, the novelists also noted that DenseNet is less prone to overfitting issues when datasets are utilized without any additional data.

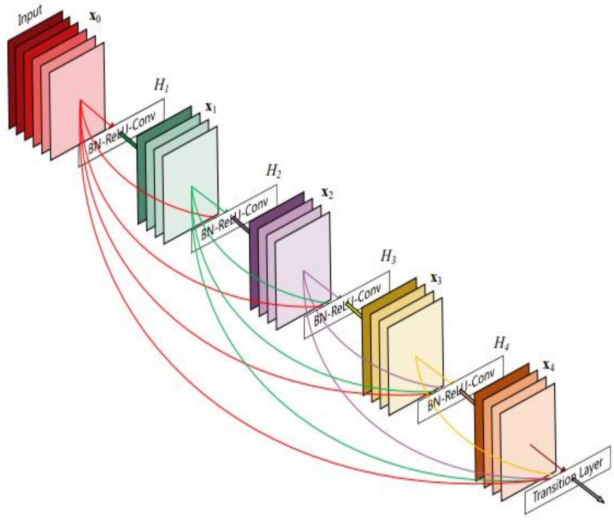

Figure 3. A 5-Layer Dense block with a growth rate of k= 4

InceptionV3 - It is the third generation of Inception convolutional neural network architectures, and it is notable for its use of batch normalisation. Szegedy et al [19] at Google proposed this architecture.

InceptionV1 and InceptionV2 had flaws that were addressed by their successors. InceptionV2 employs the RMSprop optimizer. Batch normalization is performed in the Auxiliary classifiers' fully connected layer. 77% factorized Convolutional instead of 55% in V1 and 23% in V2. Smoothing of Labels Regularization is carried out, which is a technique for regularizing the classifier by estimating the effect of label dropout during training. It prevents the classifier from overly confidently predicting a class. The addition of label smoothing improves the error rate by 0.2%.

Inception-ResNetV2 - This architecture combines the concepts of inception blocks and residual layers, as presented by Szegedy et al. [12] in 2016. Utilizing residual connections has the dual goals of avoiding the degradation issue brought on by deep networks and speeding up training. We employ the pre-trained weights in these 164 layers of the inceptionresnetV2 architecture, which has 20 inception-resnet blocks, to help us achieve our goal of detecting COVID-19 in X-Ray images.

Xception - Xception means extreme inception It brings Inception's guiding concepts to a logical conclusion. Chollet et al [14] proposed a deep convolutional neural network architecture involving Depth Wise Separable Convolutions. According to Google, the inception stages of convolutional neural networks represent a transition between the depthwise separable convolution operation and traditional convolution.

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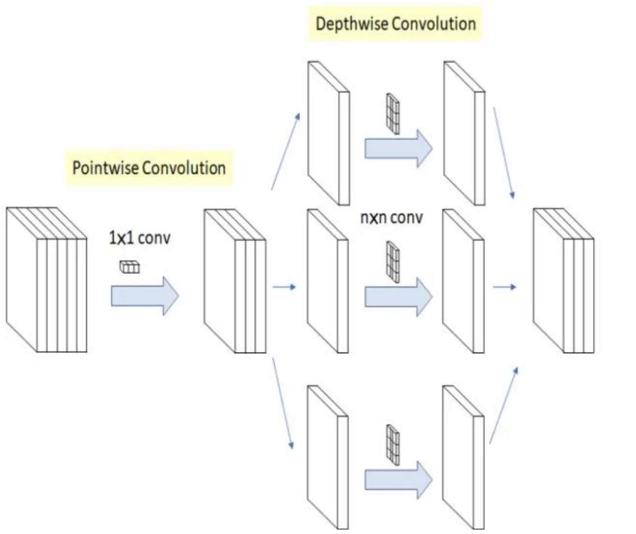

Figure 4. The Modified Depthwise Separable Convolution used as an Inception Module in Xception

In Inception, the initial input was compressed using 1x1 convolutions, and each of the depth spaces was then generated from each of the input spaces and subjected to a number of filters. With Xception, the opposite occurs. Instead, it first applies the filters independently to every depth map before using 1X1 convolution to ultimately reduce the input space. This technique is virtually exactly the same as a depthwise separable convolution, which was first applied to build neural networks in 2014. Between Inception and Xception, there is yet another distinction. whether or whether there is a non-linearity following the initial process. However, Xception does not add any nonlinearity, whereas both processes in the Inception model are followed by a ReLU nonlinearity.

EfficientNet - In order to scale up CNNs in a more organized way, the research publication [20] suggests a unique model scaling technique that makes use of a straightforward but incredibly powerful compound coefficient. The recommended approach employs a predetermined set of scaling coefficients to scale each dimension evenly, in contrast to existing approaches that scale network dimensions like depth, width, resolution, and width. The development of a class of models known as EfficientNets, that surpasses contemporary accuracy with up to 10 times higher efficiency, is enabled by this unique scaling strategy and recent advancements in Auto ML (smaller and faster).

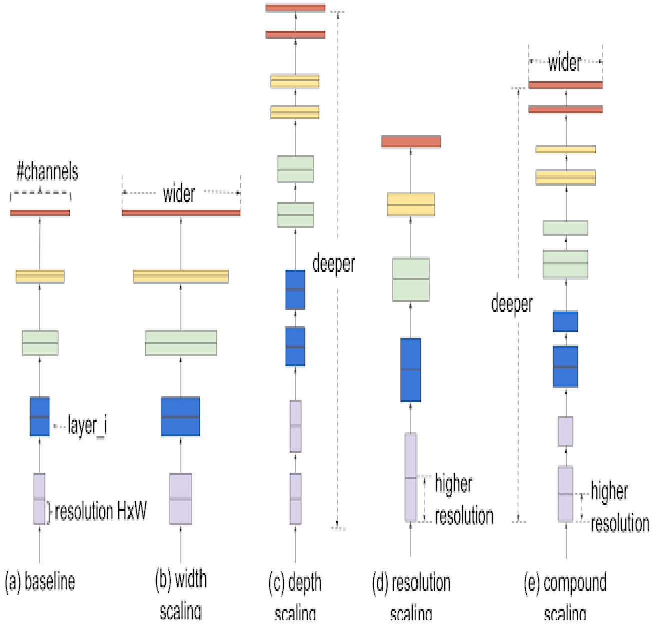

Figure 5: An examination of several scaling techniques. Our compound scaling mechanism consistently scales up all network dimensions, unlike traditional scaling procedures (b)-(d), which arbitrarily raise a single dimension.

MobileNetV3 - This model was created by Howard et al [21] and other Google researchers. MobileNet was one of the first projects to develop CNN architectures that could be easily implemented in smartphone platforms. One of the major technologies is depthwise abstraction layers, as depicted below. A form of convolution known as a separable convolution divides a standard convolution kernel into two kernels. Instead of a 3x3 kernel, for instance, we get a 3x1 and a 1x3 kernel. This division decreases the number of processes required to carry out the convolution, seeking to make it significantly productive. Separation on the spatial dimension is not always feasible, therefore it is more prevalent to separate on the depth (channel) dimension.

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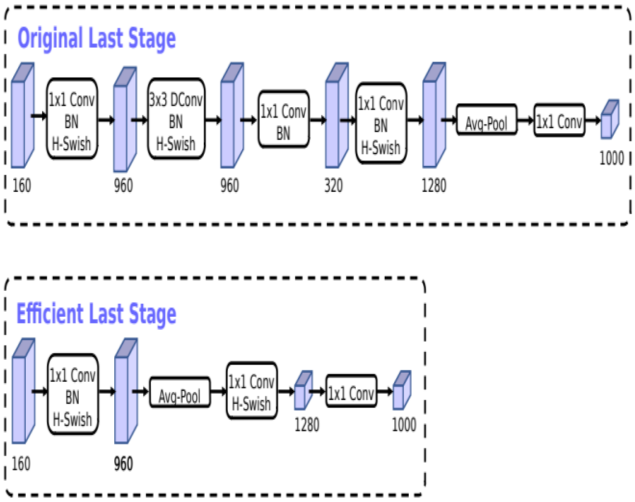

Figure 6: The original last stage and the effective last stage are contrasted. With no loss in accuracy, this more effective last stage can eliminate three pricy layers at the network's end.

NASNetMobile - Zoph et al [22] published research aimed at finding the best CNN architecture using reinforcement learning. The term NAS refers to a methodology developed at Google Brain for scanning through an area of neural network combinations. NAS was used in combination with standard datasets such as CIFAR10 and ImageNet to enhance CNNs for various sizes.

In order to create a convolutional architecture, the researchers work to identify the finest cell or convolutional layer on the CIFAR-10 dataset and attempted to relate this cell to the Imagenet database through layering together many copies of this cell with different parameters named "NASNet architecture". The researchers also present Scheduled Drop Path, a new normalization technique that greatly enhances generalization in NASNet models. On CIFAR-10, NASNet achieves a state-of-the-art error rate of 2.4%. On ImageNet, NASNet achieves state-of-the-art accuracy that is 1.2% higher in top-1 accuracy than the greatest human architectures while using 9 billion fewer FLOPS - a 28% reduction in computational demand over the prior form prototype.

When assessed at multiple stages computation power, NASNets outperform existing designed models. For instance, a scaled-down version of NASNet achieves 74% top-1 accuracy, which is 3.1% better than equally advanced models for mobile platforms.

4. MATERIALS AND METHODS

The entire COVID-19 detection method involves a number of phases. The preprocessing approach was used to initially process the raw X-ray images. In the preprocessing pipeline, data resizing, shuffling, and normalisation were carried out. We trained the DenseNet201, Xception, and VGG16 architectures using the training data after partitioning the preprocessed data set into training and testing sets. After each period, the training accuracy and loss were calculated.

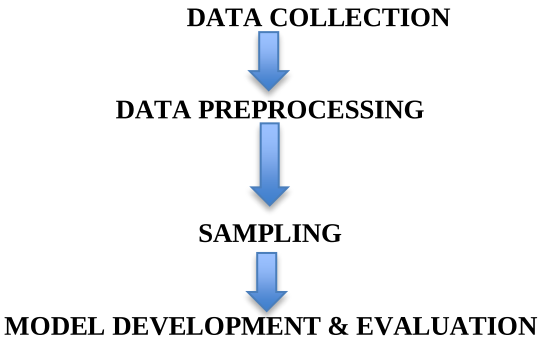

Figure 7: Steps involved in Model Implementation

A simple neural network cannot learn complex characteristics, in contrast to a deep learning architecture, even if a CNN is a particular type of multilayer perceptron. CNNs have proven to perform exceptionally well in a variety of applications, including image classification, object recognition, and medical image analysis. A CNN works on the essential tenet that it can take local features from inputs at high layers and deliver them to lower layers for more complex features. A CNN is made up of three layers: convolutional, pooling, and fully connected (FC).

This paper uses the concept of transfer learning on aforementioned pre-trained models. 2 Dense layers are added over each model to train the model to identify if the patient is affected with covid-19 or not.

Each image category (Pneumonia/Normal) has its own subfolder within the dataset's two main folders (train and test). There are 2 categories (Pneumonia/Normal) and 5,863 X-Ray images in JPEG format.

Chest X-ray of pediatric patients aged between one and five at the Guangzhou Women and Children's Medical Center in Guangzhou were selected. All chest X-ray imaging was performed as a routine component of the clinical care given to patients.

Dataset:https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

A total of 2482 CT scans make up the dataset for SARS-CoV-19, including 1253 scans of infected individuals (COVID-19) and 1230 scans of healthy individuals. These specifics were obtained from real patients who underwent medical treatment in hospitals in Sao Paulo, Brazil. This dataset is intended to advance research into and the development of artificial intelligence tools that can analyses a person's CT scan to determine whether they are infected with the SARS-CoV-2 virus. Using an eXplainable Deep Learning technique (xDNN), we were able to achieve an F1 score of 97.31% as a baseline result for this dataset, which is adequate. The data set is accessible at: www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset

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Table 1: Dataset Distribution

Class	Data/Cases
Infected	1252
Non-infected	1230
Total	**2482**

5. RESULTS AND DISCUSSIONS

In this paper we have successfully implemented several existing CNN architectures such as DenseNet201, InceptionResNetV2, MobileNetLarge, Resnet50, Xception, VGG16, NASNetMobile, EfficientNet. Radiographic image data has been used to train and validate the models and to measure the efficiency accuracy and losses has been calculated and compared. then to compare their accuracy and loss against each other. The results obtained by training the above listed models has been presented in table 2. It has been observed that DenseNet201, Xception, and VGG16 are the most efficient models for the prediction about the person is covid-19 infected or not in the most efficient and precise manner. With the minimum loss of 4.13 when trained over 20.8M parameters offers an accuracy of 98.71%. hence we can use these convolutional neural network (CNN) architectures to the early-stage problem-solving of the pandemic and to determine the covid-19 positive cases.

Model	Parameters	Accuracy	Loss
DenseNet201	**20.8M**	**98.71%**	**4.13**
InceptionResNetV2	56.4M	94.14%	15.5
InceptionV3	24.4M	94.14%	14.33
MobileNetV3Large	4.5M	86.14%	31.96
ResNet50	26.2M	90.29%	24.28
Xception	**23.5M**	**97.29%**	**6.97**
VGG16	**15.7M**	**97.43%**	**9.2**
NASNetMobile	5.8M	96%	11.41
EfficientNet	55M	51.71%	88.56

Table 2: Calculated Accuracy and Loss for the models.

6. Conclusions

As COVID-19 instances frequently rise, resources are currently becoming scarce in many countries. Finding every single positive example is so essential during this health emergency. CNN is utilised as a feature extractor to find COVID-19 in CT-scanned & X-Ray pictures using a variety of architectures, including DenseNet201, Xception, VGG16, and others.dataset The results showed that DenseNet201 (98.71%), Xception (97.29%), and VGG16 (97.43%) were the most accurate architectures. In order to differentiate among infected patients and non-infected patients with accuracy, a Django web application with a Drag & Drop feature has also been developed.

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