Deep Learning and Classification Algorithms for COVID-19 Detection

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***Abstract*—The imaging modalities of chest X-rays and computed tomography (CT) are commonly utilized to quickly and accurately diagnose COVID-19. Due to time and human error, it is exceedingly difficult to manually identify the infection using radio imaging. COVID-19 identification is being mechanized and improved with the use of artificial intelligence (AI) tools that have already showed promise. This study employs the following methodology: The chest footage was pre-processed by setting equalizing the histogram, sharpening it, and so on. The transformed chest images are then retrieved through shallow and high-level feature mapping over the backbone network. To further improve the classification performance of the convolutional neural network, the model uses self-attained mechanism through feature maps. Numerous simulations show that CT image classification and augmentation may be accomplished with higher efficiency and flexibility using the Inception-Resnet convolutional neural network than with traditional segmentation methods. The experiment illustrates the association between model accuracy, model loss, and epoch. Inception-statistical Resnet's measurement results are 98%, 91%, 91%.**

Keywords—Deep Learning; COVID-19; classification; artificial intelligence

I. INTRODUCTION

COVID-19, a new strain of the Coronavirus, was initially discovered in Wuhan, China in December of this year and has since spread rapidly over the globe [1, 2]. SARS-CoV-2, the virus that causes the disease, has infected millions of individuals throughout the globe. After infecting throat mucosa, COVID-19 may move to lungs through respiratory tract. In order to stop the spread of COVID-19 and expedite treatment, it is critical to quickly screen, identify, and isolate people who have the illness. Medical imaging, such as CXR and CT scans, have been shown to accurately diagnose COVID-19 infection and are now frequently utilized in disease screening [3–5]. However, owing to the disease's recent origins and resemblances to other respiratory conditions such as pneumonia, proper interpretation of findings via pictures presents various difficulties. Achieving a reliable diagnosis of COVID-19 is difficult and time consuming because of its complexity [6-10]. Only radiologists are qualified to conduct this work. Healthcare personnel all throughout the globe have a difficult task as a result of this epidemic. Many patients' test findings must be analyzed over a period of time. In recent years, there has been a growth in the need for clinical assistance for COVID-19 patients' treatment [11,12]. In order to meet the needs of a large number of patients, image analysis on medical pictures combined with decision support systems may give an accurate and speedy diagnosis of illness. While radiologists can spend up to 10 minutes reviewing CT scans manually, decision support systems can do the same in less than a minute. Although COVID-19 may induce major organ malfunction, such as pneumonia and renal failure, it can also lead to mortality (Fleuren, Tonutti et al., 2021). As a result, early detection of COVID-19 patients is critical. The illness continues to spread since the patient is not isolated after the PCR test, which was used to diagnose COVID-19.

The rest of the paper is organized as follows; Section II describes about the related work; Section III describes proposed model; Section IV describes about the deep residual networks; Section V describes about results and discussions; Section VI describes about conclusions.

II. RELATED WORK

Deep learning may be classified into unsupervised, supervised, and semi-supervised learning depending on the training dataset's labels. Images are all tagged via supervised learning, and the model is tuned using these image-label pairings. A probability score will be generated for each testing picture based on the model's optimum parameters [15]. It's possible to use unsupervised learning to discover patterns or hidden data structures without providing any labels to the model beforehand. In this case, the model learns input-output relationships from the labelled data and is enhanced by the unlabeled data, which contains more semantic and fine-grained information. Semi-supervised learning is a term for this sort of learning method [13]. We'll cover the most popular frameworks for each of these learning paradigms. The three broad methodologies mentioned here may be integrated with other learning standards for enhanced medical image processing performance. The general classification of the radiography image is represented in Fig. 1. The chest X-Ray images of various formats are represented in Fig. 2.

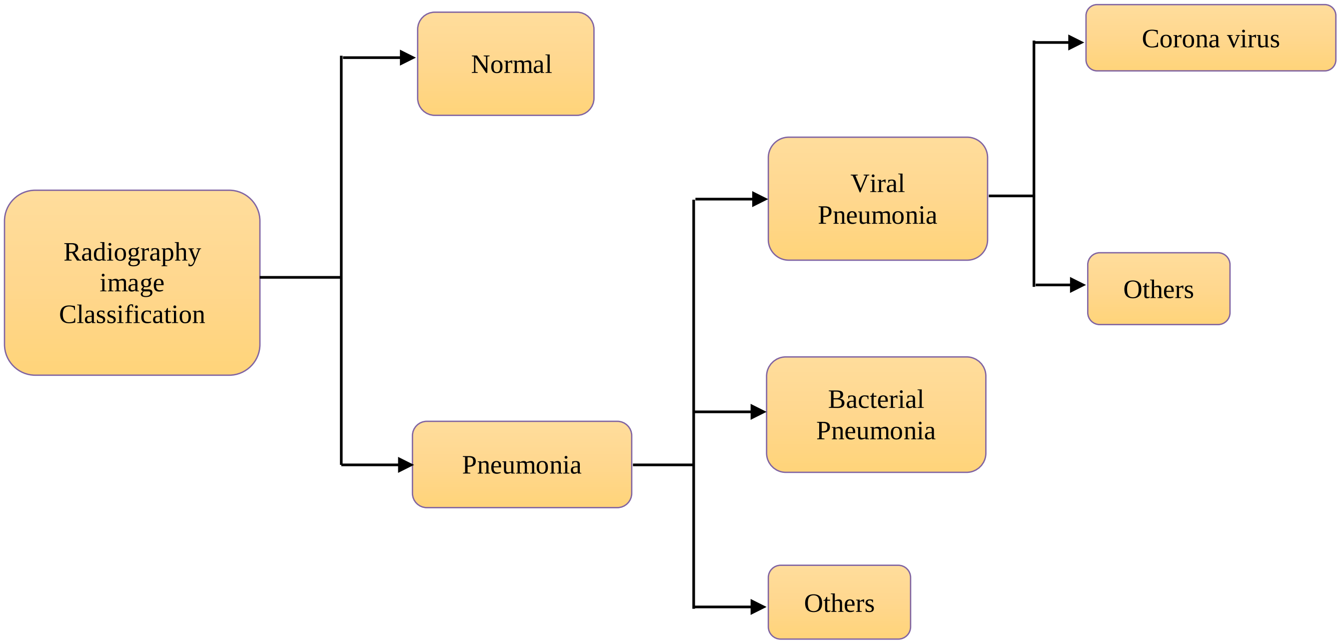


Fig. 1. General Classification of Radiography Images.

(a) (b) (c) (d)

Fig. 2. Chest X ray Images (a) Covid 19, (b) Bacterial Pneumonia (c) Viral Pneumonia (d) Normal.

III. Proposed Model

Presently, the most popular machine learning method is the convolution neural network (CNN), a kind of deep artificial neural network with superior feature extraction and identification capabilities [14, 15]. One of its most distinguishing characteristics is weight sharing, which drastically decreases the network complexity and total weights [16]. With numerous convolution layer, followed by pooling layer, activation functions like softmax. ReLu, and fully connected layers reduce the loss function to a minimum.

The ultimate result of a typical CNN network structure is often one or more fully-connected layers [17, 18, 19], however the network itself is typically composed of convolutional and pooling layers. The final output of the layer is obtained by applying a bias to fully connected layer and activation function.

$$D_j^l = f\left(\sum_{D \in M_j} D_j^{l-1} . h_{ij}^l + v_i^l\right) \quad (1)$$

The Eq. 1 illustrates this process. feature map is represented as D_j^l , excitation function is shown as f, input feature maps is shown as M, convolution operation is mentioned as . , and bias term is represented as h.

IV. Deep Residual Networks

ResNet is built on top of deeper networks, the theoretical foundation of which is described in [20, 21]. There are 50, 101, and 152 nodes in a traditional ResNet network. The 2015-ILSVRC competition was won by a CNN with 152 layers. In addition, ResNet improves by 28% on the well-known cOco132 example dataset for image recognition [22, 23]. For the most part, ResNet takes use of the concept of bypass channels in the "road network," as seen in the mathematical Eq. 2 and Eq. 3.

$$g(y_i) = f(y_i) + y_i \quad (2)$$

$$f(y_i) = g(y_i) - y_i \quad (3)$$

The transformed signal, denoted by f in Eq. 2 and Eq. 3, is defined in relation to the input signal, y_i. A side-channel adds the first input to $f(y_i)$. When computing the residual in Eq. 4, $g(y_i)$ is employed. In order to facilitate communication across layers, ResNet deploys "shortcut channels" inside those levels; in contrast to the gates used in traditional highway networks, however, these gates are both data-agnostic and parameter-free. They stand for the non-residual functions of a highway system after the bypass route has been closed. A linear direct mapping

$y \rightarrow y_i$ and a nonlinear mapping F are both possible components of the submodule $f(y_i)$. Once the learning algorithm determines that the direct mapping, $y \rightarrow y_i$, is best, it may simply zero out the weight parameters of the nonlinear mapping $f(y_i)$. When there is no one-to-one mapping, it might be challenging to learn a linear mapping from a nonlinear function $f(y_i)$ [24, 25]. On the other hand, with ResNet, residual information is continuously sent and the shortcut channel is never closed. In order for ResNet to circumvent the gradient reduction issue, it makes use of residual links, which are rapid channel connections that speed up the fusing of deep networks. The architecture of ResNet50 is shown in Fig. 3.

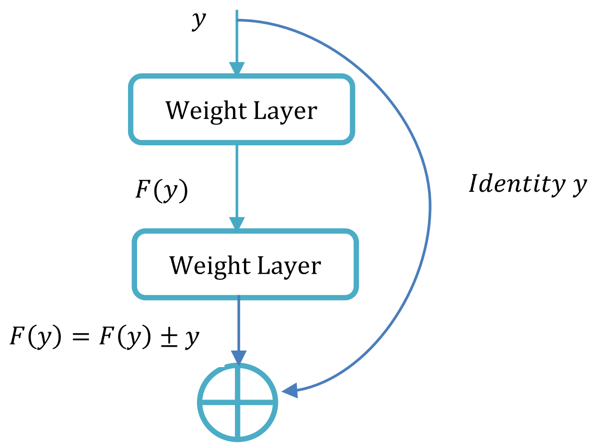


Fig. 3. ResNet Network Architecture.

Algorithm:

Input: Feature vector from CNN model(F), Size of F(S), F average (Avg), F Standard Deviation (SD), Threshold (T), Parameter Tuning ($F(X)$)

Output: Reduced Feature (OF)

Step 1: $Feature\ Reduction\ (F, SD, Avg, T)$

Step 2: Begin

Step 3: $OF = F$

Step 4: $For\ i = 1\ to\ S\ do$

Step 5: $X = SD/OF[i]$

Step 6 $Y = Avg/OF[i]$

Step 7: $if\ X > T\ and\ Y > T$

Step 8: Parameter Tuning

$F(X) = F(X) \pm X\ and\ F(Y) = F(Y) \pm Y$

Step 9: $OF[i] =[]$

Step 10: end if

Step 11: end for

Step 12: end

V. Results and Discussions

We started by analysing X-ray and CT scans of the lungs taken from a wide range of patients and healthy individuals (https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database). We gathered X-ray and CT scans of the lungs from 2045 healthy controls, 785 mild cases, and 130 severe cases of COVID-19. Data sets were obtained and manually annotated by expert imaging specialists, and pictures were utilised with patient and hospital permission. Ethical clearance is given by the institution's review board. A total of 2960 samples were obtained. All pictures were exactly 299 pixels in width and height. Table II displays the experimental data distribution. We combine COVID-19 features with clinical knowledge to segment the lesion area, to train a neural network to predict COVID-19 diagnoses, ultimately narrowing down the features to 20 that have the highest diagnostic value. This offers a non-invasive technique for detecting COVID-19 in advance.

Chest X-Ray images from Kaggle: 6110 pre-processed images are used for training and testing. If model can train in a shorter time, this means that model will be more efficient at more training iterations. As it can be seen on the Table I below DenseNet-121model is more in the aspect of time. It is common knowledge that classification algorithms are evaluated based on parameters like specificity, sensitivity, and accuracy as shown in Eq. (4), Eq. (5), and Eq. (6). And proposed model attain values are mentioned in Table II. Accuracy is defined as the ratio of correctly categorized instances to the total number of examples. The output images are represented in Table III. Proposed method compared with the existing method are shown in Table IV.

Accuracy is compared with number epoch as shown in Fig. 3.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (5)$$

$$Specificity = \frac{TN}{TN+FP} \quad (6)$$

TABLE I. DEEP LEARNING BASED CLASSIFICATION

Year	Author	Model	Dataset	Application	Remarks
Supervised classification					
2019	Schlemper et al.	AG-Sononet: attention-gated model	ChestX-ray14	image plane classification using 2D fetal ultrasound	To better leverage local information and aggregate attention vectors at various sizes for final prediction, Baumgartner et al. (2017) integrated grid attention.
2018	Guan et al.	AG-CNN: an attention guided CNN	Private dataset	chest X-rays Thorax disease classification	The global picture was parsed for discriminative areas using an attention mechanism, and those regions were utilized to train a local CNN node
Unsupervised image synthesis					
2018	Wu et al.	cGAN	DDSM dataset	Mammogram classification	Using labels of malignant and non-malignant to exercise control over the development of a certain kind of lesion.
2018	Frid-Adar et al.	ACGAN	Private dataset	CT liver lesion classification	Analyzing the differences in performance of GAN's
Self-supervised learning based classification					
2019	Chen et al.,	Common CNN Structure	Private dataset	Fetal ultrasound image plane classification	Developing a novel context-restored self-supervised method
2021	Azizi et al.	MICLe: based on SimCLR	CheXpert, and private dataset	Chest X-Ray Image classification	Proposing a novel contrastive learning strategy based on SimCLR that uses several pictures for self-supervised pre-training.
2021	Vu et al.	MedAug: Based on MoCo	CheXpert	Pleural effusion based chest X-ray classification	Self-supervised pre-training outperforms ImageNet pre-training.
2021	Zhou et al	Models Genesis	LUNA 2016	CT lung nodule for false positive reduction.	Combining four self-supervised techniques to learn from diverse viewpoints (appearance, texture, and context)

TABLE II. PROPOSED MODEL TRAINING TIME AND ACCURACY RATE

Model	Training Time	Accuracy Rate	Accuracy on Testing Data
ResNet	512 secs	88.7	4/100
DenseNet	248 secs	84.9	6/100
Featured ResNet	214 secs	88.2	6/100

TABLE III. OUTPUT IMAGES CLASSIFICATION

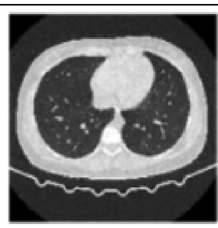
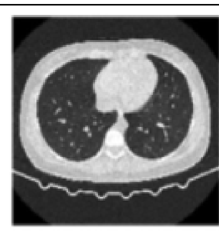
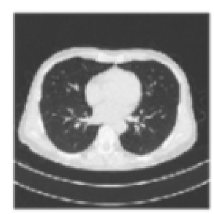
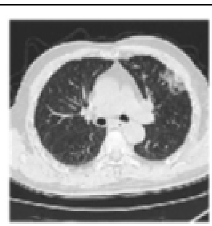
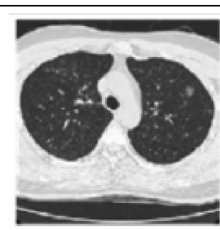
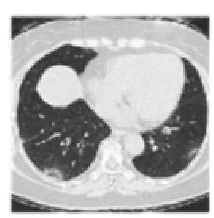
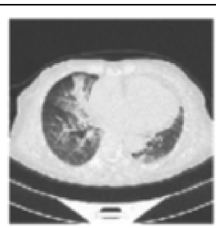
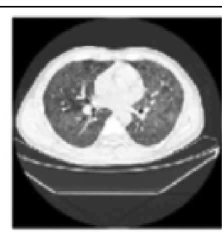
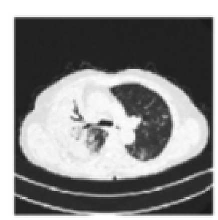
Normal				
Mild				
Severe				

TABLE IV. PROPOSED CNN VS. EXISTING CNNS

Deep Models	Accuracy	Sensitivity	Specificity	TP	FP	FN	TN	MCC	F Score
Squeeze Net	97.874	0.9	0.9	609	19	20	618	0.92	0.95
DenseNet201	97.564	0.9	0.89	610	25	18	612	0.92	0.96
Xception	96.644	0.89	0.89	624	29	28	634	0.92	0.94
Inceptionv3	98.044	0.91	0.91	610	24	26	612	0.92	0.94
Google Net	97.344	0.9	0.89	609	26	20	614	0.92	0.95
Resnet50	97.574	0.89	0.89	613	22	21	614	0.93	0.94

VI. CONCLUSION

The approach described in this work has been developed primarily for the purpose of making early and definitive diagnoses for patients, although it has broad use in pathological categorization and prognosis prediction. When compared to the riskier and slower nasal swab, CNN is a preferable approach for identifying people infected with COVID-19. Importantly, the proposed approach allows for a multiclass diagnosis with other pulmonary disorders, which is important since many of these diseases may have startling similarities in their symptoms and consequences on the lungs. The superiority of CNN models like COVDC-Net in real-world applications may soon become apparent, rendering other testing obsolete. Another advantage of AI-assisted diagnosis is that it may be quickly scaled to existing hospitals and clinics using X-ray machines, without the need for specialised infrastructure and testing equipment. We want to improve the suggested model's robustness in the future by testing it on a more comprehensive range of pulmonary disorders.

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