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DETECTION AND CLASSIFICATION OF COVID-19 FROM X-RAY USING DEEP LEARNING

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Abstract: After its first reported occurrence on 31st December 2019 and getting its name on Feb 11, 2020, Covid-19 was declared a Pandemic on March 11, 2020, by the World Health Organization (WHO). The highly contagious nature of the disease along with its incompletely understood transmission process and the absence of a definitive cure made it extremely difficult for World Governments and their Health care providers to effectively contain the infection. In extreme cases, Covid-19 has been observed to result in severe respiratory discomfort, multiple organ failure, and eventually death. Covid-19 based Pneumonia was observed in a small percentage (2% to 8%) of the infected patients which was found to be more fatal compared to regular pneumonia. RT-PCR is the current recommended standard for the detection of Covid-19, but RT-PCR has been proven to be oblivious to early stages of Covid-19 Pneumonia and is associated with low sensitivity, reportedly as low as 30% to 70%. Chest CT and X-rays exhibit superior sensitivity over RT-PCR but cannot differentiate between Covid-19 and Non Covid-19 pneumonia. Therefore, this paper proposes the use of Artificial Intelligence (AI) to assist in the detection and classification of Covid-19 pneumonia from Non Covid-19 pneumonia and No Covid using X-Ray images. A 2D Deep Learning CNN architecture is proposed for solving Binary classification (Covid-19 vs Normal) and Multiclass Classification (Covid-19 pneumonia vs Non Covid-19 pneumonia vs Normal) problem of a custom created diverse X-ray dataset.

***Index Terms* – Deep learning, Binary Classification, Multiclass Classification, Convolutional Neural Network(CNN).**

I. INTRODUCTION

A. General Overview:

WHO (World Health Organization) declared COVID-19 as a Public Health Emergency of International Concern (PHEIC) on January 30, 2020 after the first reported infection on 31st December 2019. The lung infection caused by SARS-CoV-2 was given the name COVID-19 by the WHO on Feb 11, 2020. WHO declared COVID-19 as a pandemic on March 11, 2020 by which time there were already close to 5000 deaths and nearly 1,48,476[1] active cases. Inconsistencies in symptom features among infected subjects and an incompletely understood transmission process made it near impossible for world governments to contain the spread of the infection. The nature of the spread was heterogenic during the early stages of the pandemic but quickly started affecting entire communities. Healthcare systems of such sectors were put under a lot of stress due to constraints in the availability of key protective resources like diagnostic testing, hospital beds, ventilators and the lack of a definitive cure. Healthcare workers themselves fell victim to the infection due to lack of personal protective equipment. In extreme cases, Covid-19 has resulted in severe respiratory discomfort, multiple organ failure, and eventually death. About 2 to 8 percent of the infected subjects developed Covid-19 based Pneumonia which was more hazardous compared to regular viral pneumonia. We're currently in the middle of 2021, a whole year and a half after the virus was first detected, yet the virus still continues to mutate and affect world healthcare, economy, and normalcy. As of August 2021 there have been 4.3 million confirmed deaths, around 4.5 billion vaccinated worldwide. Anxiety and panic among general public still exists as we've gone in and out of multiple lockdowns and studies have suggested the existence of multiple variants of the virus as the virus continues to mutate.

Reverse transcription polymerase chain reaction (RT-PCR) is the current recommended standard for the detection of Covid-19. RT-PCR is performed by collecting samples from respiratory tracts (both upper and lower) of individuals suspected of harboring the virus [2]. However, RT-PCR is limited by its low sensitivity ranging from 37% to 71% according to early reports [3-5], which may lead to a lot of false negative cases resulting in infected people not receiving the required medical attention and further contributing to the spread of the virus to a larger population given the contagious nature of the virus. Factors like inadequate specimen collection, improper extraction of nucleic acid from the collected specimen, or collection at a too-early stage of infection, storage of the collected specimen also contribute to this problem. RT-PCR being an invasive testing method puts the medical professional collecting the sample at risk due to the said nature of the virus. A chest computed tomography (CT) scan can be used as an important diagnostic tool for COVID-19 in cases with false negative reports by RT-PCR [5-8]. CT scans and X-Rays are preferable screening tools due to their greater sensitivity at detecting early pneumonic changes. In addition, chest CT and X-rays are non-invasive and are easy to perform in equipped facilities. However, radiological diagnostic support is not available 24 hours per day in many institutions [9]. In addition, chest CT scans and X-rays may show similar imaging features between COVID-19 pneumonia and other types of viral pneumonia that are Non-Covid, thus hampering the correct diagnosis of the infected patients. The use of artificial intelligence (AI) may help overcome this shortcoming.

B. Deep Learning for Medical Image Analysis:

Deep learning is a popular research field in artificial intelligence (AI), end-to-end models can be created to achieve promising results using input data, without the need for manual feature extraction. Deep Learning has a Multi-Layered Architecture which enables it to identify subtle abnormalities in medical imaging features, this can be called learning through observation. Deep Learning being used in medical image segmentation is not a new concept, it has been around for a long time but was limited by the hardware of its time. Since Deep Learning handles lots of data, it demands a fine piece of hardware equipment to be able to perform the required computations especially when images are involved. Typical CPUs will not be able to handle image processing tasks when the dataset is vast, a high-end GPU is required for this task. The hardware improvements over the years have made it easier to deploy Deep Learning models, both 2D and 3D for medical image segmentation Deep Learning is already being used for the detection of Skin Cancer, Tumors, Diabetic Retinopathy, Alzheimer's, Parkinson's Disease arrhythmia detection, breast cancer detection, brain disease classification, pneumonia detection from chest X-ray images and lung segmentation. In Deep Learning, CNNs are typically used for medical image analysis as they combine a number of techniques to solve detection and classification problems. CNNs can handle large amount of data efficiently and are well suited medical for image analysis, especially CT and X-rays. Due to this, a well-constructed and trained CNN can meet the standards or even surpass human accuracy in diagnosing radiological data.

C. Objective:

This paper proposes a 2D Deep Learning model for the detection and classification of Covid-19 pneumonia from viral pneumonia and no Covid-19 using X-ray data. Only X-rays are being considered in this proposal due to their more portable and accessible nature. Also, X-rays are cost effective and convenient as they can be set up easily in isolated environments and are available at most local hospitals as opposed to CT scans. A custom dataset containing 7200 X-ray images for binary classification (Covid vs normal) and 3900 X-ray images for multiclass classification (Covid pneumonia vs non Covid pneumonia vs normal) will be used to train and evaluate the proposed model. The model architecture, training optimization techniques are discussed in detail in the coming sections.

II. Proposed Methodology

A. Data preparation:

Deep learning is a data hungry process, so a fairly vast and diverse dataset is required to obtain acceptable level of model accuracy. A custom dataset created from X-ray data available on open-source platforms is considered for training and evaluation purpose. Covid, Normal and Non-Covid pneumonia X-rays were collected from multiple open-source platforms, Kaggle, Cohen JP [10] and wang et al [11]. The database set up by Cohen JP is updated regularly by various researchers from across many regions. For normal and pneumonia X-Rays, wang et al database was used. The kaggle dataset is also constantly updated and the platform invites researchers to use their model their dataset and publish results. Two datasets were created for training and testing purpose, one for Binary classification and the second one for Multiclass classification. The Binary classification dataset has a total of 7200 X-ray images, a 70-30 split is used to separate the train and test set. 70%, i.e., 6000 images were used for training (3000 in each class, Covid and Normal) and 1200 images in the test set (600 in each class). The multiclass dataset has 3900 images, 3000 in train set (1000 in each class, Covid, Normal and Non-Covid Pneumonia) and 900 in the test set (300 in each class). The figures below are a few dataset samples. As it can be observed below, to the naked eye all three class of X-ray images are similar and indistinguishable without label.

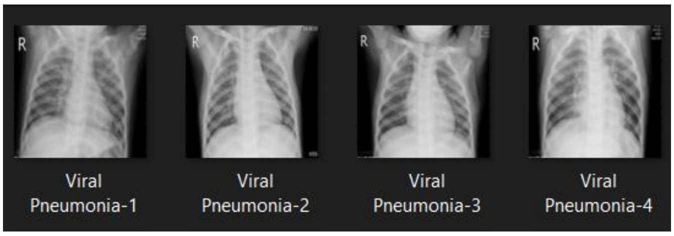

Fig.1a. Viral Pneumonia X-Ray sample

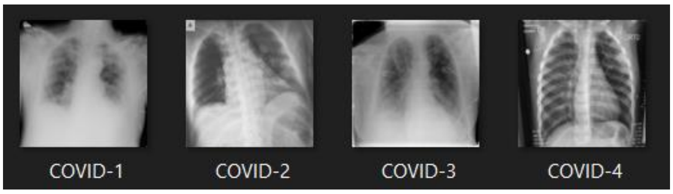

Fig.1b. Covid-19 X-Ray sample

Fig.1c. Normal X-Ray Samples

B. Data Preprocessing:

Deep Learning doesn't require a lot of pre-processing, but raw data cannot be fed directly to a model. Model performance can be greatly improved with simple zooming, shearing and image augmentation techniques. Raw data is not always aligned or in a balanced form, so the following basic pre-processing are necessary.

I. Random Rotations, Zoom, Flips and Shifts
II. Shearing
III. Rescaling

Image Data Augmentation is a technique to artificially create a new custom dataset from the existing training data. This technique involves creating transformed versions of the images in the training dataset. Image transformation includes operations like shifts, zooms, flips, and more. These image augmentation techniques make the model more generic allowing it to handle unseen data better by creating small variations in the dataset.

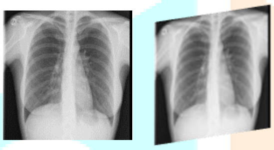

Fig.2a.Random rotations

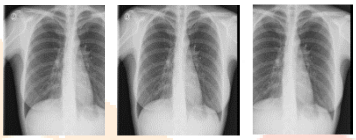

Fig.2b.Random shifts

Fig.2c.Random Zoom

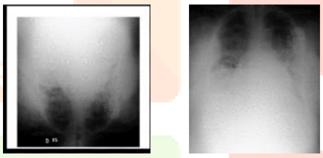

Fig.2d.Random flips

C. Model Architecture:

The proposed model has 5 convolution layers, each convolution layer is followed by a batch normalization, maxpooling and dropout layer. Batch normalization gives each layer in the network independence to learn which makes the training process more stable. Each convolution layer has different number of filters in each layer so the feature map produced after the filter strides across each layer is of a different size. The traditional approach of increasing the number of filters in each layer is followed, starting from 64 and going up to 256 filters per layer. Sigmoid function is used in the case of binary classification and softmax is used for multiclass classification. The letter C denotes a convolution layer; letter M denotes a Maxpooling layer in the layer layout representation of the model.

$$C_1\text{-}M_1\text{- }C_2\text{-}M_2\ C_3\text{-}M_3\text{- }C_4\text{-}M_4\text{- }C_5\text{-}M_5$$

In the model layout representation above, C_1 represents input layer. This architecture a ReLU as an activation function. A ReLU function is defined as:

$$f(x)=\begin{cases}0.01x & \text{for } x<0\\ x & \text{for } x\geq 0\end{cases} \qquad (1)$$

Each convolution layer has increasing number of learnable filters. Each convolution layer is followed by a maxpooling layer. Towards the end, there is a Dense layer with 512 filters which is a fully connected layer, the features are flattened and Softmax provides the probability distribution input belonging to a particular class. The number of outputs the model will have depends on the classification problem we are attempting to solve which in this case is two and three. The proposed model has a total of 1,721,859 parameters, out of which 1,719,747are trainable and the remaining 2112 are non-trainable parameters that have been extricated by the dropout layer. The proposed model architecture is shown in the figure below.

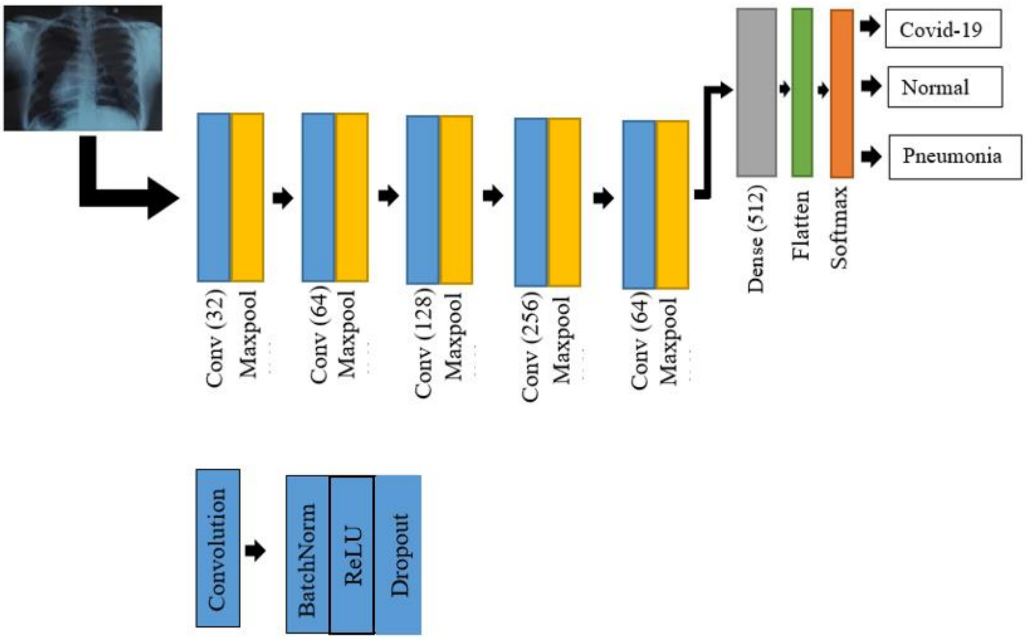

Fig.3.Proposed Model Architecture

ReLU stands for rectified linear unit. It is a piecewise linear function that sets all the negative pixels to 0 and outputs all the positive inputs directly, thus introducing non-linearity to the network. A pooling layer is used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters the model has to learn and the amount of computation the network has to perform. Flattening is used to convert all the 2D array output from pooled feature maps into a single long continuous linear vector as input to the next layer for classification. Softmax layer converts the output of the fully connected layer to a probability distribution of the input vectors that determines to which class a particular input belongs to in a multi-class problem.

D. Training and Validation:

The training process is reinforced with feedbacks from early stop and learning rate reduction methods. By reinforcing the training process, the model can make parametric changes dynamically during the training process according to the feedback from the output. Overfitting a model makes it less generic and incapable of learning new features if introduced during the training process, so to prevent model overfitting, early stop method is used. If the parameter val_loss is observed to be the same instead of decreasing with each epoch, the training process is interrupted or stopped prematurely before the set number of epochs prompting a change to be made in the architecture and parameters. Early stop is used to achieve this and the patience is set to 10. Learning rate reduction technique is also employed to allow the learning rate to be altered dynamically during the training process to optimise it so that the model is not overwhelmed. When the parameter val_accuracy is observed to be constant and not increasing with each iteration, the learning rate is reduced. This is achieved using the EarlyStopping() and ReduceLROnPlateau methods of Keras library.
The parameters set for the training of this model are as shown below.

Table.1. Training Parameters

Parameter	Binary	Multiclass
Epochs	50	50
Batch Size	32	32
Steps per epoch	188	94
Validation Steps	38	28

A models performance is measured by its ability to detect and classify images used outside of training, this dataset is called the test or validation dataset. 1200 images were used for validation in binary classification problem and 900 images were used for multiclass classification problem. Also, a Gradcam filter can be used to visualize the output to make predictive analysis. Gradcam library is used to visualize the classification output of a CNN. It is class-specific, meaning the gradcam results will vary according to the class of data that is being identified. Gradcam works by first looking at the final CNN layer and then taking in the gradient information of that layer. The output is typically a heat map visualization of a feature the CNN is looking for in an image of a given class. The accuracy of a gradcam is largely reliant on the CNN model accuracy.

III. Results and Discussion

The model achieved an accuracy of 96% when solving the binary classification problem and 94% accuracy when solving the multiclass classification problem. When solving the 2-class problem, the model showed better performance than when solving the 3-class problem as the dataset gets more diverse in the 3-class problem. The model performance is often represented by a confusion matrix. Confusion Matrix is a table that charts the classifiers performance on the validation dataset for which the actual values are known. This table basically compares the actual values and the predicted values.

	precision	recall	f1-score	support
Covid-19	1.00	0.97	0.99	600
No_findings	0.98	1.00	0.99	600
accuracy			0.99	1200
macro avg	0.99	0.99	0.99	1200
weighted avg	0.99	0.99	0.99	1200

Fig.4a. Binary classification training summary

	precision	recall	f1-score	support
Covid-19	1.00	0.99	0.99	300
No_findings	0.89	0.99	0.94	300
Pneumonia	0.97	0.88	0.93	300
accuracy			0.95	900
macro avg	0.96	0.95	0.95	900
weighted avg	0.96	0.95	0.95	900

Fig.4b. Multiclass classification training summary

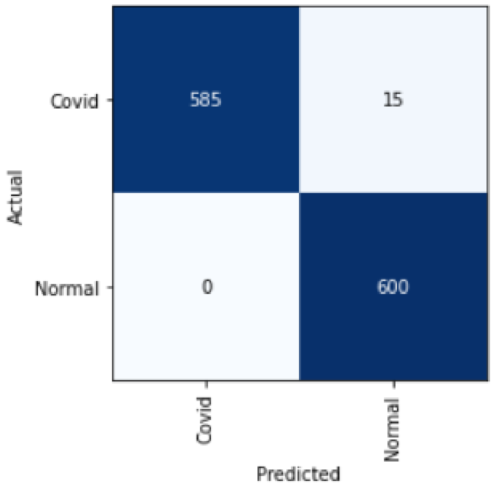

Fig.5a. Confusion Matrix: Binary

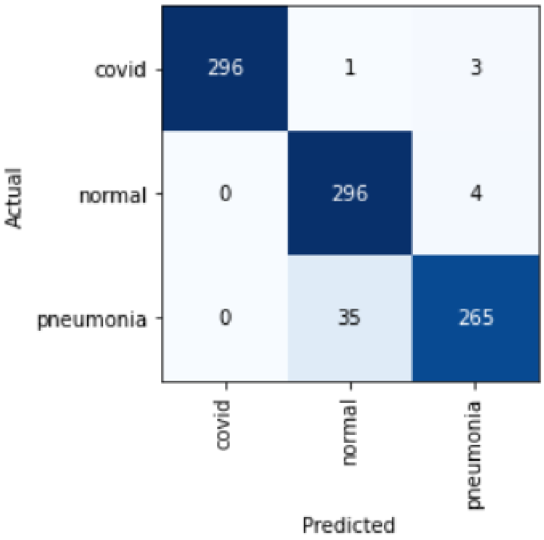

Fig.5b. Confusion Matrix: Multiclass

Discussion

The results of this proposed model are only to be treated as an auxiliary solution and not as a Primary Medical Diagnosis. This proposal is a research centric intended to demonstrate how Deep Learning applications can be extended in the field of medical image classification. This work includes more medical data than most previously existing attempts but the amount of images used is still not enough to claim that are results are absolutely accurate. Though the number of false negatives were low, it was not zero therefore, a second opinion is mandatory. To further optimize the work, the Deep learning architecture used has to be made denser and optimized with careful consideration given to more parameters and hyper parameters.

Conclusion

A simple 2D Deep Learning CNN model was proposed for the detection and classification Covid-19 from Normal and Pneumonia findings. The model is built on keras and is able to handle both binary classification (covid-19 vs normal) and multiclass classification (covid vs normal vs pneumonia). Binary and multiclass problems were solved with an acceptable accuracy of 96% and 94% respectively on fairly vast datasets consisting of 7200 images and 3900 images respectively.

REFERENCES

[1] https://covid19.who.int/

[2] Udugama, Buddhisha et al. "Diagnosing COVID-19: The Disease and Tools for Detection." *ACS nano* vol. 14,4 (2020): 3822-3835. doi:10.1021/acsnano.0c02624.

[3] Li Y, Yao L, Li J, Chen L, Song Y, Cai Z, et al. Stability issues of RT-PCR testing of SARS-CoV-2 for hospitalized patients clinically diagnosed with COVID-19. J Med Virol 2020 Jul;92(7):903-908.

[4] Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, et al. Correlation of Chest CT and RT-PCR Testing in Coronavirus Disease 2019 (COVID-19) in China: A Report of 1014 Cases. Radiology 2020 Feb 26:200642.

[5] Rubin GD, Ryerson CJ, Haramati LB, Sverzellati N, Kanne JP, Raoof S, et al. The Role of Chest Imaging in Patient Management during the COVID-19 Pandemic: A Multinational Consensus Statement from the Fleischner Society. Radiology 2020 Jul;296(1):172-180.

[6] Vashist SK. In Vitro Diagnostic Assays for COVID-19: Recent Advances and Emerging Trends. Diagnostics (Basel) 2020 Apr 05;10(4):202.

[7] Li D, Wang D, Dong J, Wang N, Huang H, Xu H, et al. False-Negative Results of Real-Time Reverse-Transcriptase Polymerase Chain Reaction for Severe Acute Respiratory Syndrome Coronavirus 2: Role of Deep-Learning-Based CT Diagnosis and Insights from Two Cases. Korean J Radiol 2020 Apr;21(4):505-508.

[8] Long C, Xu H, Shen Q, Zhang X, Fan B, Wang C, et al. Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT? Eur J Radiol 2020 May;126:108961.

[9] Mossa-Basha M, Medverd J, Linnau K, Lynch JB, Wener MH, Kicska G, et al. Policies and Guidelines for COVID-19 Preparedness: Experiences from the University of Washington. Radiology 2020 Apr 08:201326.

[10] COVID-19 Image Data Collection, Joseph Paul Cohen, Paul Morrison, Lan Dao. arXiv:2003.11597 [eess.IV]

[11] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. (2017). Chestx-ray8: Hospitalscale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2097-2106).