Covid-19 and Pneumonia Chest Infection Detection and Classification using Convolutional Neural Networks

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Abstract**—**Various machine learning, deep learning and image processing techniques are used frequently in detecting the presence of diseases and infections from medical images. Detecting COVID-19 and pneumonic infections takes special skills and techniques because they are difficult to detect – especially in early stages. We have developed a web application which incorporates all the functionalities for uploading the chest radiograph input image, perform processing on the input image, perform classification and finally output the predicted disease category, its class probability, and provide an option to download the diagnosis report, generated automatically. The complete system incorporates a convolutional neural network model which performs classification on input mages after performing image processing operations. The convolutional neural network is trained on an extensive dataset of chest radiograph images, covering chest X-ray images of patients affected with pneumonia and COVID-19 as well as normal chest X-rays. This classification model was able to achieve a great accuracy and precision.

Keywords—CNN, Covid-19, Viral Pneumonia, Segmentation, Classification, Sequential Neural Network.

I. INTRODUCTION

Pneumonia is a deadly lung infection which impacts millions of people around the world. According to a report by the American Thoracic Society in 2015, it was the world's leading cause of death among children under 5 years of age. Even though there is increased awareness about pneumonia as well as advanced medical technology, we still face a high number of infections and a high fatality rate. More recently, the COVID-19 pandemic has put even more stress on medical professionals and systems. Similar to pneumonia, COVID-19 also affects the lungs of the patient. If not detected and diagnosed on time, both pneumonia and COVID-19 can have fatal consequences.

Medical imaging technique is used to create visual representation of interior of the human body for medical purposes and non-invasive possibilities can be diagnosed by this technology. More specifically, for the diagnosis of lung infections such as pneumonia and COVID-19, chest X-ray images are used. Confirming pneumonic as well as COVID-19 infection takes manual effort by medical experts by examining chest X-Rays of patients. Due to this, a lot of time and effort is wasted in grunt work. This paper attempts to automate the process of diagnosis and detection of pneumonia and COVID-19 in patients through chest radiograph images using a deep learning approach.

II. OBJECTIVES

The aim of this paper is to detect the presence of pneumonic or COVID-19 infections in chest X-ray images of patients. The detection is done using Image Processing algorithms and classification using Deep learning techniques.

The main objectives of this paper are:

- Identify major areas of image processing in medicine and in particular chest infection detection.
- Use the methods of Image Processing to study the chest radiograph images. This includes Chest X-ray pre-processing, feature extraction, and segmentation.
- To build and train convolutional neural network (CNN) architecture to categorize chest radiograph images.
- To provide better technical support for Covid-19 and Pneumonia detection so that correct precautionary measures can be taken in a timely manner.

III. RELATED WORK

For identification of background and recent trends in the domain of Brain Tumor Detection and Segmentation, we go through several recent research journals covering different aspects and implications of the new trends. The literature study provided some great insights about different advancements in the field of medical image processing. Each referenced journal is discussed below in brief as the part of literature review.

A. *Deep Learning for Automatic Pneumonia Detection*

This paper discusses the development of a computational approach to detect regions of pneumonic infection using deep convolutional neural networks, single-shot detectors, augmentations and multi-task learning. [1] This model managed to attain 2% higher accuracy than other deep learning approaches. The main drawback was the lack of pre—processing phase and no additional features were considered through Image Segmentation or common filters.

B. *Penumonia Detection using Deep Learning Approaches*

This paper focuses on surveying and comparing different computer-aided techniques to detect pneumonia. [3] It also suggests a model for the same. Some deep learning techniques reviewed in this research paper include RESNET and CheXNet.

C. *Pneumonia Detection in Chest Xray Images Using Deep Transfer Learning*

The paper introduces a novel approach based on a weighted classifier, that combines the weighted predictions from the state-of-the-art deep learning models such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3. The proposed approach is a supervised learning approach in which the network predicts the result based on the quality of the dataset used. Transfer learning [5] is also used to optimise the model. The model proposed obtains high accuracy of 98.43% and an AUC score of 0.9976.

D. *Pneumonia Detection Using CNN based Feature Extraction*

This paper examines the use of pre-trained CNN models for feature extraction from chest X-ray images. This is followed by examining the performance of different CNN models for classification. Based on the results, the most optimal method for detecting abnormal chest X-ray images is presented. Feature extraction from chest X-ray images is also done to obtain better accuracy in classification. To increase the model efficiency, comprehensive hyper-parameter tuning for the model and a better preprocessing technique can be conceived.

E. *An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare*

A convolutional neural network to extract features and detect pneumonia from chest X-ray images is developed from scratch and explained in this paper. The paper also describes several data augmentation algorithms to improve the performance of the CNN model even on a small dataset. The proposed method utilises a relatively small dataset for model training and testing. However, several data and image augmentation methods are employed to improve the validation and classification accuracy of the CNN model and achieved remarkable validation accuracy.

F. *Diagnosis of Pneumonia from Chest X-Ray Images Using Deep Learning*

This paper compares two popular convolutional neural network models, Xception and Vgg16, for the detection of pneumonia through chest X-ray images [7]. Transfer learning and fine-tuning was used during the model training process. It was noted that the Vgg16 model obtains an accuracy of 87% while the Xception model obtains an accuracy of 82%.

G. *Identifying pneumonia in chest X-rays: A deep learning approach*

This paper describes a deep learning technique based on Mask-RCNN to identify and localise pneumonia in chest X-ray images. The method proposed performs pixel-wise segmentation for images and combines the results from multiple models to achieve high robustness and performance.

IV. PROPOSED METHODOLOGY

A. *Dataset Description*

The dataset for Covid-19 is very limited at the moment. To overcome the limitation and have a diverse dataset, we merged two datasets from Kaggle. The 2 datasets considered for training the classification model are: Covid CXR Image Dataset and Covid-19 Image Dataset.

In the combined dataset, we have 1955 training images and 185 test images. The first dataset comprised of 251 Chest MRI Training Images (111-COVID, 70-Viral Pneumonia, 70-Normal) and 66 Test Images (26-COVID, 20-Viral Pneumonia, 20-Normal), while the second dataset had 1704 new Training Images (504-COVID, 576-Viral Pneumonia, 624-Normal) and 119 Test Images (32-COVID, 43-Viral Pneumonia, 44-Normal). Both the datasets are divided with 3 class labels: Covid, Viral Pneumonia, and Normal. We performed image augmentation on the dataset by horizontally flipping the images and obtained 3910 total samples out of which 15% (587 samples) formed the Validation Set and rest (3323 samples) formed the Training Set.

For Image Segmentation, we took a public dataset of Covid-19 CT scans (https://zenodo.org/record/3757476). This dataset consists of 20 annotated Covid-19 chest CT volumes. All cases were confirmed Covid-19 infections with a lung infection proportion ranging from 0.01% to 59%. This dataset was one of the first publicly available 3D volume sets with annotated Covid-19 infection segmentation.

B. *Functional Requirements*

- **Noise Removal and Sharpening**: Users enter from MRI images. MRI pictures need to be converted into grayscale photographs earlier than image processing. Some filtration techniques may be used to put off noise of the photograph. Image segmentation strategies are implemented to stumble on lungs edges. The system processes images in acceptable image formats (JPG, PNG, TIFF etc.) The system shall detect chest infection present in the image and display it with different colors.

- **Negation**: Selecting the CT scan images of the chest and Extracting only the infected region from the scan images.
- **Contrast Adjustment**: Creating a GUI for easy access to the model.
- **Subtraction**: Plotting the contour of the lung infections and the boundary of the lungs.
- **Boundary detection**: Finding the boundary of the infectious regions.

C. *Architecture Strategies*

- **Dataset Preparation:** Dataset is split into 3 parts for training, validation, and testing respectively. Available features are identified from the dataset and non-relevant features are dropped.
- **Image pre-processing**: The MRI images from the dataset contain noise, which are fixed by the use of median and bilateral filters in the image pre-processing system
- **Feature Extraction**: Image Segmentation and Clustering algorithms are used for Edge Detection and Feature extraction respectively. The system processes the data to be fed into a Classification model.
- **CNN Classification Model**: Sequential Convolutional Neural Network is designed for classification of testing dataset and input images into 3 categories: Covid-19, Viral Pneumonia, or Normal.

D. *Neural Network Architecture*

We have used a sequential Convolutional Neural Network for building the Chest Infection Classification Model. The architecture of implemented classifier is comprised of 5 Convolutional Layers and 4 Dense Layers.

The first layer started with 32 filters and kernel of 2x2 and the number of filters is doubled at every next layer and kernel is incremented by 1. To avoid over-fitting and reduce computational costs, several max-pooling layers were introduced after Convolutional layers. The output of convolutional layer is flattened and passed to Dense layers, which has initially 512 neurons and they are reduced to half over next two dense layer.

To further avoid the over-fitting issue, we used Dropout layers along with ReLU activation in all layers except output layer. The Output Layer was constructed containing 3 neurons (1 for each class) and SoftMax activation.

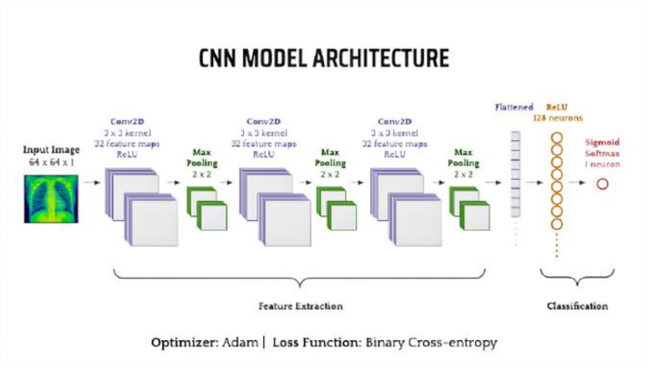

Fig. 1. Sequential CNN Architecture for classification model

E. *Graphical User Interface*

A user-friendly GUI is designed for this system, where users can detect the presence and type of chest infection or not from raw MRI images of lungs, extract and calculate infected area with probabilistic classification. Even an untrained user can input an MRI image using the "Load MRI Image" option. Following the proposed algorithm, the system will provide the step-by-step processed classification for that with confidence probability.

F. *Image pre-processing*

Input to improve on the pattern finding and fitting process for the model, we applied a few preprocessing techniques on the dataset.

We took advantage of the Hounsfield units (HU) scale by cutting the pixel intensity values of the pictures to -1250 as least and +250 as maximum, in light of the fact that we were interested only on infected regions (+50 to +100 HU) and lung areas (-1000 to -700 HU). [16-18] It was possible to apply this approach as the images in dataset were in range of 0 to 255 after gray-scale normalization.

Fluctuating signal intensity ranges of pictures can radically impact the fitting system and the subsequent performance of segmentation models. For accomplishing dynamic sign power range consistency, it is recommended to scale and normalize imaging information. In this way, we normalize the excess CT volumes in like manner to grayscale range. Thereafter, all samples were normalized by means of z-score.

G. *Tumor Segmentation from MRI*

Image The neural network architecture along with its hyper parameters are one of the vital parts in a medial picture segmentation pipeline. The current scene of profound learning structures for semantic segmentation obliges an assortment of variations which recognize by proficiency, power or execution. By and by, the U-Net [16] is at present the most well-known and promising design as far as the collaboration between performance and variability [18]. In this work, we carried out the standard 3D U-Net as design with next to no custom change in request to keep away from superfluous boundary increment by more mind-boggling models like the remaining variation of the 3D U-Net.

The contribution of our design was a 160x160x80 patch with a solitary channel comprising of standardized HUs. The result layer of our design normalized the class probabilities through a SoftMax function and returned the 160x160x80 mask with 4 channels addressing the likelihood for each class (foundation, lung left, lung right and COVID-19 contamination). Up sampling was accomplished through rendered convolution and down sampling through most extreme pooling.

The design utilized 32 element maps at its most elevated goal and 512 at its most minimal. All convolutions were applied with a bit size of $3 \times 3 \times 3$ in a step of $1 \times 1 \times 1$, with the exception of up-and down sampling convolutions which were applied with a piece size of $2 \times 2 \times 2$ in a step of $2 \times 2 \times 2$. After each convolutional block, batch normalization was applied. The architecture can be found in Fig. 2.

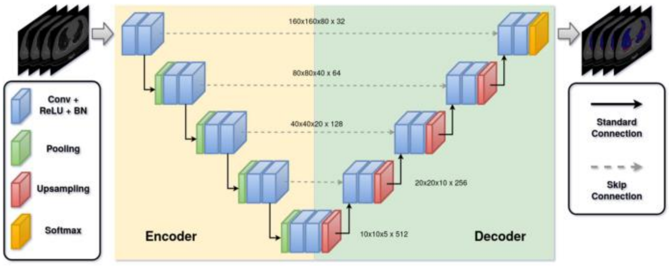

Fig. 2. Standard 3D U-Net Architecture for Chest MRI Segmentation

H. *CNN Model Evaluation*

Accurate chest infection classification is a critical task in the case of Covid-19 and Viral Pneumonia due to the nature of these diseases and threat they possess against the well-being of patients. In this matter, a small difference between wrong and right prediction is very vital. So, we performed appropriate testing and validation of the trained sequential model. Before validation, the designed model was trained for 100 epochs (early stopped after 79 epochs). The model loss and accuracy graphs while training is given in Fig. 3.

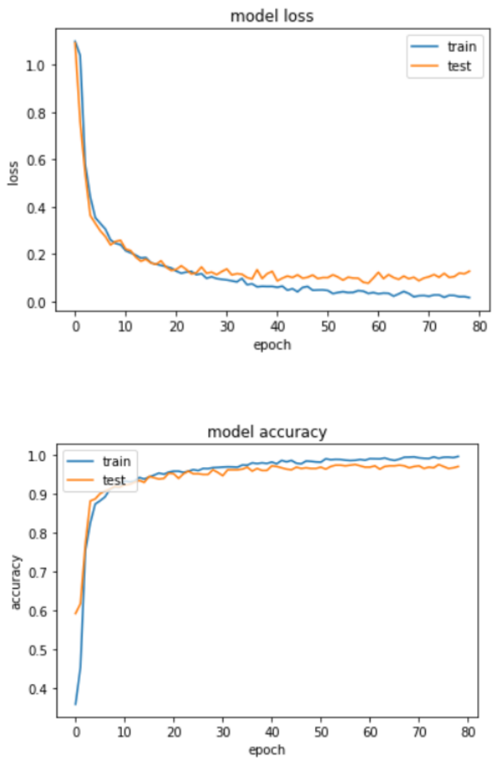

Fig. 3. Model Loss and Accuracy Plot agains epochs while training

The model with least Validation Loss was saved during the training and reloaded before obtaining the final results. The model was able to classify 99.45% of the samples correctly while also maintaing good Precision and Recall values for all classes.

To further improve the real-time use of our model, we used Quantization Aware Training to reduce the Trained Model size from 30.1 MB to 2.41 MB (92% reduction in Size) and this also reduced the request serving time from 1.54 seconds earlier to less than 1 second now (50% reduction in serving time).

V. RESULTS

After training the Convolutional Neural Network over 100 epochs, the performance of the trained model is determined based of training and validation accuracy score as well as loss. The trained CNN model obtains a training accuracy of 99.52% and a validation accuracy of 96.93%. Training and validation accuracy score and loss are plotted.

Conventional performance parameters were considered while performing the evaluation of Neural Network classification model. Performance of any ML model or algorithm can be evaluated or put into scale with the predefined metrics such as Precision, Accuracy, F-measure and all these are calculated with the help of confusion matrix. Also, these help us identify the limitations and efficiency of the models.

- *PRECISION*: This entity tells us about the positive identification percentage or ratio was correct.

$$Precision = \frac{TP}{TP + FP}$$

- *RECALL*: It tells us about how much a correct value is positively chosen correct.

$$Recall = \frac{TP}{TP + FN}$$

- *F – MEASURE*: It is a weighted harmonic mean of the parameters calculated such as precision and recall of the approach.
- *CONFUSION MATRIX*: A confusion matrix is 3X3 matrix consisting of 9 quantities namely True and False values of all 3 types of Brain Tumors. These are used to calculate the parameters that are discussed above, it is the foundation for any of the above parameter's calculation.
- *ACCURACY*: It helps evaluating classification models, it is percent or fraction of value of predications that are absolutely correct to the total predictions made.

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ predictions}$$

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

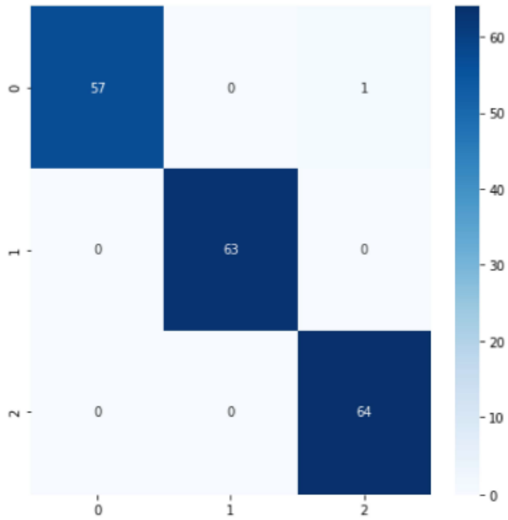

Fig. 4. Confusion Matrix of trained CNN Model

TABLE I. RESNET50 MODEL PERFORMANCE

Tumor Label	**CLASSIFICATION REPORT**		
	Precision	***Recall***	***F1-Score***
1	1.00	0.98	0.99
2	0.97	1.00	0.99
3	0.98	0.98	0.98

Fig. 5. Classification Report of RESNET50 Model

The performance of the trained model is then evaluated using the testing dataset. The model obtains a testing accuracy score of 99.45% i.e., the CNN model correctly classifies 99.45% of unseen images.

The Image segmentation was done for Covid-19 infected CT scans to identify the infected areas of lungs.

Fig. 6. Chest CT scans of people having Covid

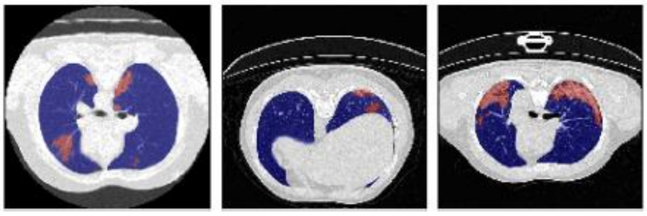

Fig. 7. Segmentation of Chest MRI images using our Model

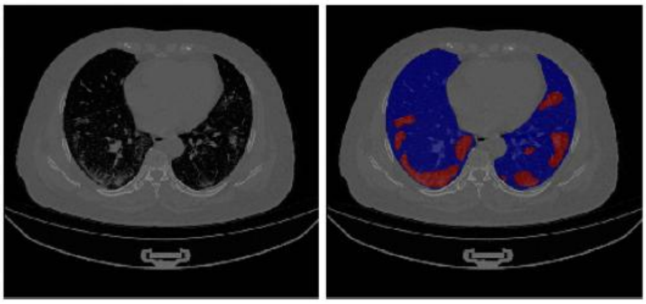

Fig. 8. Segmented Covid-19 Lungs where Red Areas show the infection

For the web application we used the result from hybrid K-means algorithm to show the segmented tumor. The screenshots of final website are attached hereby.

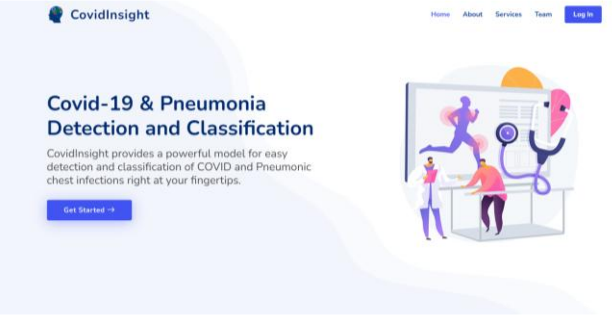

Fig. 9. Landing (Home) page of CovidInsight

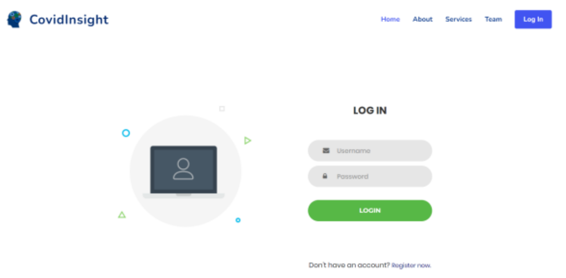

Fig. 10. Login page for user to sign in to CovidInsight

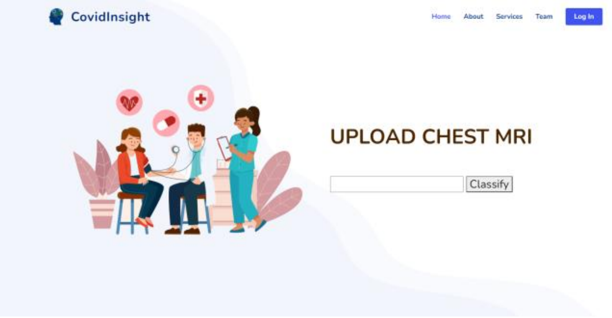

Fig. 11. File Upload page to upload the Chest MRI

Fig. 12. Final Result Page

The Web Application was then deployed on heroku and can be used by anyone to detect the position and type of Chest Infection (Viral Pneumonia or Covid-19) by simply uploading the chest MRI image.

VI. Conclusion

In this project, we have implemented a deep learning model for the detection and classification of pneumonic and COVID-19 infections in patients through chest X-ray images. We have used a convolutional neural network model to develop a classifier to classify chest x-ray images as "normal" (indicating no presence of pneumonic or COVID-19 infection), “pneumonia” (indicating presence of pneumonic infection), or “COVID” (indicating presence of COVID-19). The model is trained using a dataset of 5823 images and achieves considerably high accuracy in classification of chest X-ray images.

Finally, we have also developed a web application that can be used by medical staff for quick and accurate detection of pneumonia and COVID-19 in patients. This will help them to perform quick diagnosis of these deadly diseases.

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