Automatic detection for COVID-19 and Pneumonia from chest X-Ray and CT images

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Abstract**—**An automatic disease detection framework assists doctors in the diagnosis of disease, provides fast results, and reduces the death rate. X-Ray and CT machines are available in most hospitals. Therefore, an automated detect-ion system is the fastest diagnostic option. We introduce a deep learning technique to diagnose COVID-19 and Pneum-onia automatically from chest X-ray and CT images. Four deep learn-ing models are built, one based on the combination of a convolutional neural network (CNN) and long short-term memory (LSTM) and the other based on (CNN) only, the last one based on CNNs, the Squeeze Excitation Block (SE-block) and ResNet50. A collection of 4575 chest X-ray images, including 1525 images for each class, 17104 chest CT images, these images include 7593 COVID-19 cases. The results show that CNN model achieved better detection in X-ray and CNN with SE-block model achieved better detection in CT images. we showcase our research findings and provide a user-friendly platform for users to submit test samples for diagnosis called Pulmo AI which is a web an application

Keywords— *COVID-19, Pneumonia, Deep learning, Chest X-ray, Chest CT, Convolutional neural network, long short-term memory, squeeze and excitation block*

I. INTRODUCTION

A new coronavirus called COVID-19 was identified as a disease that can cause catastrophic heart infections, danger-ous respiratory issues, and even death. As a result, on January 30, 2020, The World Health Organization labeled this epidemic a Public Health Emergency of Worldwide Concern [1]. Despite a shortage of infrastructure, poor healthcare systems, and subpar diagnostic tools, all countries are involved in the fight against this tragic epidemic.

COVID-19 symptoms might vary from a cold and cough to a fever, shortness of breath, and acute respiratory syndrome [2]. One of the most often utilized assays for COVID-19 detection is real-time reverse transcription polymerase chain reaction (rRT-PCR), which extracts DNA via reverse transcription and then utilizes PCR to amplify DNA for analysis. While COVID-19 exclusively contains RNA, it can detect it [3]. Nevertheless, the RT-PCR tech-nique takes 4-6 hours to complete and the test kit is not commonly available and quite costly. It is also untrustworthy. CT scans and chest radiography image analysis may be useful in this scenario. [4] The sensitivity of CT scans for the COVID-19 infection rate was around 98%, compared to 71% for RT-PCR, [5] but chest X-ray and CT radiography is more often utilized in clinical practice owing to its benefits, including cheap cost, low radiation dosage, easy-to-operate, and broad accessibility in general or community hospitals [6].

This paper compares four deep learning-based system models: CNN and a fully connected layer neural network, combines CNN, LSTM, and fully connected layer neural networks, combines CNN, SE-block, and fully connected layer neural networks and ResNet50 transfer learning model to automatically identify COVID-19 from X-ray and CT pictures.

II. LITERATURE REVIEW

In recent years, the use of deep learning techniques, particularly convolutional neural networks (CNNs), has shown promising results in automated COVID-19 detection from chest X-ray and CT images. Several studies have been conducted to investigate the effectiveness of CNNs in detecting COVID-19 from chest X-ray images. In research [7], the authors proposed a neural network that is a concatenation of Xception and ResNet50V2 networks. This network achieved the overall average accuracy for all classes which is 91.4%. In a study [8], authors proposed a system where nine different pre-trained models extracted features from chest X-ray images. The system used SVM as classifier. Among all the models, ResNet50 was considered best for feature extraction. The system obtained an accuracy of 95.33%. In the study [9], the authors introduced a transfer learning strategy with CNN that diagnose COVID-19 from chest X-rays. The system used VGG19, Inception, MobileNet, Xception, and Inception-ResNetV2 to classify COVID-19 images. Among the pre-trained models, Mobile-NetV2 achieved 96.78% accuracy. In another study [10], the authors used fine-tuned deep-learning architectures which have been made to speed up the detection and classification of COVID-19 patients from other pneumonia ones. The models used are MobileNetV2, ResNet50, InceptionV3, DenseNet121, InceptionResNetV2, NASNetMobile, VGG16, Xception. DenseNet121 has obtained best accuracy of 97%. In research [11], the authors introduced an automated detection scheme named EMCNet was proposed to identify COVID-19 patients by evaluating chest X-ray images. They used an ensemble of machine learning classifiers, EMCNet has achieved 98.91% accuracy. In research [12], the authors used Simple CNN that makes an automatic diagnosis of COVID-19 cases by evaluating 2109 chest CT images and achieved accuracy of 85%. In a study [13], authors proposed a system where fifteen different pre-trained models extracted features from chest CT images to classify COVID-19 using 746 chest CT images, Xception model achieved best accuracy 85%. In the study [14], the authors introduced a transfer learning strategy to extract features from chest CT images, The system used VGG16 and ResNet50 , both VGG16 and ResNet50 achieved accuracy of 99% for two classes, VGG16 and ResNet50 achieved 86.74% and 88.52% for three classes respectively. In a study [15], authors proposed a system where seven different pre-trained models extracted features from chest CT images to classify COVID-19 using 17186chest CT images, InceptionV3, ResNet50V2, Xception, DenseNet121, MobileNetV2, EfficientNet-B0, and EfficientNetV2 (CNN +SE block), MobileNetV2 achieved an accuracy of 94.46% before fine-tuning, after fine-tuning is Xception, with an accuracy of 96.78% and LightEfficientNetV2 model achieved accuracy of 97.48%. In a study [16], authors used fine-tuned deep-learning architectures to classify COVID-19, NON COVID, pneumonia, and lung cancer from 33,676 chest CT images, the model used VGG19 +CNN, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional and GRU (Bi-GRU) and achieved accuracy of 98%. In a study [17], authors used VGG16, ResNet-50, Inception-v3 model to classify COVID-19, NON COVID, pneumonia from 3993 chest CT images, this network achieved average accuracy 99%.

III.DATASET DESCRIPTION

Deep learning models are data-driven. The training of a deep learning model requires a large amount of data. The datasets used in this analysis contains chest X-ray and chest CT images of patients with reported COVID-19 disease, Pneumonia, and Normal cases. X-ray dataset is taken from the dataset of a paper [19,20], CT dataset is taken from Kaggle website [21]. X-ray dataset contains 4575 chest X-ray images, these images are 1525 COVID-19 cases, 1525 Pneumonia cases, and 1525 Normal cases, according to the paper [15] covid samples were rare in which some of the images were obtained using data augmentation. CT dataset contains 17104 chest CT images, these images are 7593 COVID-19 cases, 2618 Pneumonia cases, and 6893 Normal cases. The Input shape of our models is the universally known ImageNet shape 224 x 224.

IV. METHODOLOGY

1. *CNN model*

The CNN Model depicted in Fig 1.a comprises a feature extractor consisting of 2 convolutional blocks and a Multi-layer Perceptron (MLP) as a classifier with 3 FC layers. Each block is made up of 4 2d convolutional layers, max-pooling, batch normalization, and a dropout layer with a drop ratio of 0.3.The CNN model convolutional layers were initialized with an L2 kernel regularization with a factor of 0.0001. LeakyRelu activation functions were used for all layers that required them, with SoftMax activation used for the output layer. The extracted features are flattened and passed to an MLP classifier with 3 hidden and an output layer with 3 neurons representing the classes.

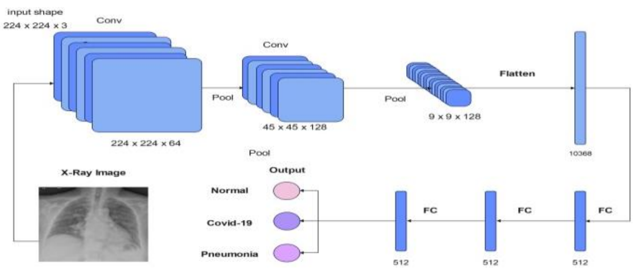

Fig 1. a CNN architecture

2. *Combined CNN with LSTM model*

CNN-LSTM is a hybrid deep learning architecture that combines convolutional neural networks (CNNs)[18] which are learning techniques for computer vision applications and long short-term memory (LSTM) which is a specialized RNN used for processing sequential data networks. our intended model is in Fig. 1.b consists of 5 convolutional blocks, representing the feature extractor, the output of the feature extractor is noticed to be 7 x 7 x 512, which needs to be reshaped to be an input for the LSTM layer. A reshape layer was used to convert these 7 x 7 into 1D vectors each with a length of 49, which is fed to the LSTM layer as sequences to return another sequence to be fed to a classifier layer with 3 neurons to predict a class from all the classes in the dataset. The architecture used Relu as the activation function in all layers that required activation except for the output layer, using the Sigmoid function. A dropout layer was included after the FC layer with a drop ratio of 0.15, and batch normalization layers were inserted after each Max-pooling layer to improve the model's generalization. Additionally, the Convolutional layers were initialized with the L2 kernel regularization for improved performance.

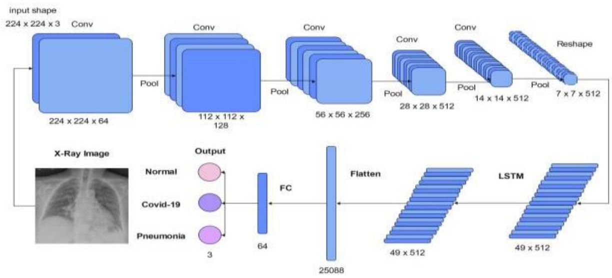

Fig 1. b CNN-LSTM architecture

3. *Combined CNN with SE-block model*

CNN- SE-block is a deep learning architecture that combines convolutional neural networks (CNNs), pooling and the Squeeze Excitation Block (SE-block). The SE-block is an architectural unit improve the representational power of a network by enabling it to perform dynamic channel-wise feature recalibration. In Fig. 1.c The feature extraction process is performed in 4 blocks, each block consists of convolutional layer with Relu activation function, Mish activation layer to improve the classification capacity in nonlinear cases, batch normalization, dropout layer with ratio 0.5 and SE-block. the features are flattened and passed to classifier layer with 3 neurons representing the classes.

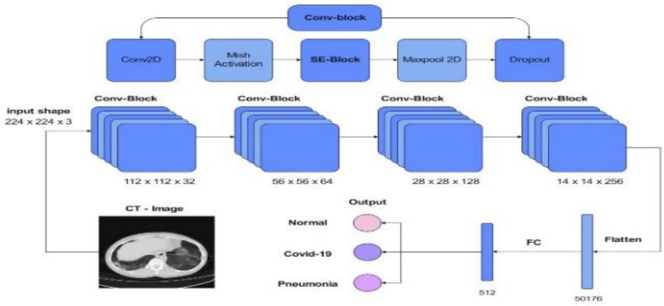

Fig 1. C CNN with SE-block model

4. *ResNet50-Transfer learning model*

In this model, transfer learning is used with ResNet50 as the base architecture for COVID-19 detection. The model's base architecture is ResNet50, which is further optimized and fine-tuned. The pre-trained weights from ResNet50, trained on millions of images, are utilized. Modifications to ResNet50 include retraining the convolutional blocks, incorporating a GlobalAveragePooling2D layer to reduce spatial dimensions, flattening the output, adding two dense layers with ReLU activation, using batch normalization and dropout for regularization, and a final dense layer with SoftMax activation for classification

V. RESULTS

A. Metrics

To evaluate the performance of our models, we utilized several metrics, including precision, recall, and F1 score to provide a more comprehensive view of model performance than just loss and accuracy metrics. By using a combination of metrics, we were able to better assess the accuracy of our models over the long term.

$$precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}, F1\ score = \frac{2 * TP}{2 * TP + FP + FN}$$

B. Experiment Setup

The dataset was divided into 80% for training and 20% for testing. For X-ray images SGD optimizer was used with a learning rate of 0.0001 and a decay rate of 1e-6, but for CT images rectified Adam optimizers was used. The number of epochs for X-ray was set to 125 with a batch size of 24 images, but an early stopping criterion was employed in the experiments, but for CT The number of epochs was 70 with a batch size of 64 images. The experiments were conducted using Kaggle's Free GPU P100 with 16 GPU RAM.

C. analysis and comparison

The chosen loss metric for models was the Categorical Cross Entropy (CE) loss. The CNN showed better performance in X-ray images in terms of CE loss with 0.14 on training and 0.3 on validation, while the CNN-LSTM had a higher loss of 0.41 on training and 0.56 on validation, CNN-SE-block had a loss of 0.02 on training and 0.73 on validation and ResNet50 model had a loss of 0.04 on training and 0.11 on validation, Also performing much better the CNN model had a training accuracy of 97.6% and validation accuracy of 95.41% while the CNN-LSTM had a training accuracy of 98.88% and validation accuracy of 94.31%, the CNN-SE-block had a training accuracy of 99.28% and validation accuracy of 90.48% and ResNet50 model had a training accuracy of 95.21% and validation accuracy of 97.66% which indicated the effect of larger convolutional kernels in the CNN model. For the CT images the CNN-SE-block showed better performance than the other three models with loss 0.00007 on training and 0.07on validation, while the CNN-LSTM had a higher loss of 0.75 on training and 0.86 on validation , The CNN had a loss of 0.29 on training and 0.27 on validation and ResNet50 model had a loss of 0.01 on training and 0.10 on validation, Also performing much better the CNN-SE-block model had a training accuracy of 99.98% and validation accuracy of 98.46% while the CNN-LSTM had a training accuracy of 85.06 % and validation accuracy of 86.07% , the CNN had a training accuracy of 97.73% and validation accuracy of 97.51% and ResNet50 model had a training accuracy of 99.73% and validation accuracy of 97.40%.

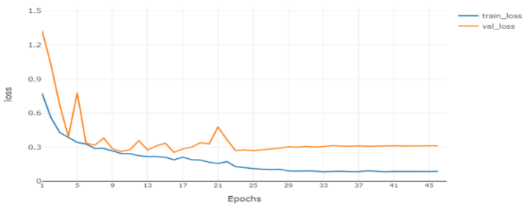

Fig 2. a – X-ray model loss

As we previously mentioned the duo to limitations of using only loss and accuracy as metrics for evaluating models. In Fig 4. a and Fig 4. b, we presented other metrics to evaluate the performance of the best models, the CNN model for X-ray and the CNN-SE-block model for CT, respectively.

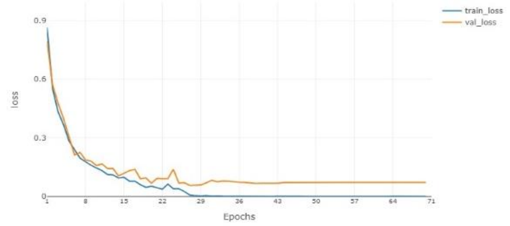

Fig 2. b – CT model loss

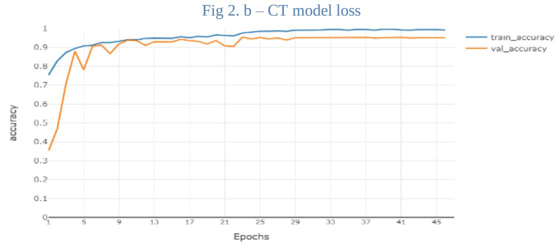

Fig 3. a – X-ray model accuracy

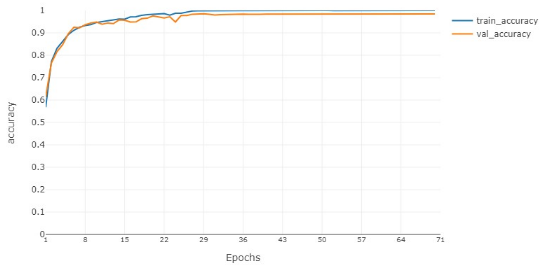

Fig 3. b – CT model accuracy

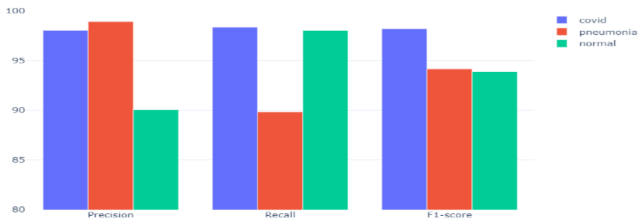

Fig 4. a – X-ray model precision, recall, and F1 score

Fig 4. b – CT model precision, recall, and F1 score

Table 1: Performance of models on the X-ray images.

Metrics / Model	precision	recall	f1-score
CNN	98.03%	98.36%	98.19%
Combined CNN with LSTM	98.55%	89.18%	93.63%
Combined CNN with SE-block	88.47%	88.30%	88.32%
ResNet50	96.02%	96.04%	96.01%

Table 2: Performance of models on the CT images.

Metrics / Model	precision	recall	f1-score
CNN	97.42%	97.39%	97.40%
Combined CNN with LSTM	87.49%	87.37%	87.35%
Combined CNN with SE-block	98.24%	98.24%	98.24%
ResNet50	97.04%	97.04%	97.04%

In **table:1** the CNN model outperformed with a high precision of 98.03% with a higher recall of 98.36% and an F1 score of 98.19%, while the CNN-LSTM model had a slightly higher precision of 98.55%, but a much lower recall of 89.18% and an F1 score of 93.63%. In **table:2** the CNN-SE-block achieved the highest precision, recall and F1 score with 98.24% while the CNN model had a slightly lower values in precision, recall and F1 score with 97.42%,97.39% and 97.40%, respectively. To support our results, we also plotted a confusion matrix for each model performance, shown in fig 5. a for CNN and fig 5. b for CNN-SE-block, both models showed great performance in diagnosis covid cases which is the main of the experiment, on the hand the CNN failed to differentiate well between pneumonia cases and normal cases and the CNN-SE-block has some conflict between covid and normal which demonstrates the major common features between both classes.

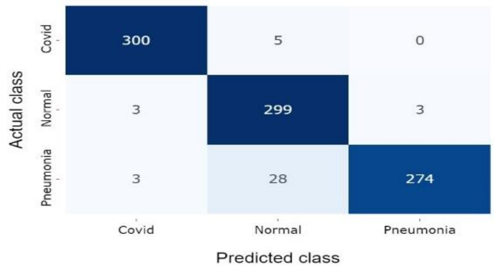

Fig 5. a –X-ray model Confusion matrix

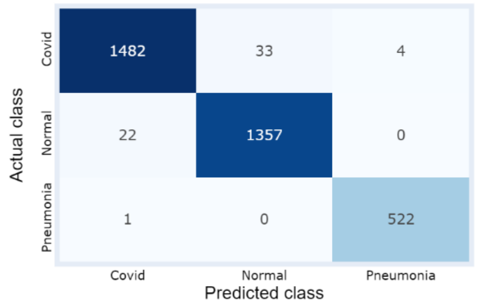

Fig b- CT model Confusion matrix

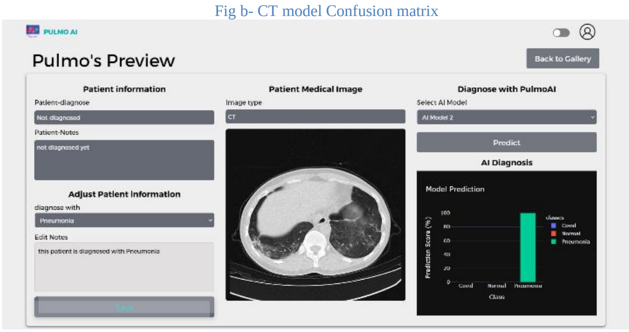

Fig 6- Pulmo AI : Web Application

VI. CONCLUSION AND FUTURE WORK

From the previously shown results, it's safe to assume that the CNN model performed better in X-ray images, having larger convolutional kernels, it was able to distinguish between covid and non-covid effectively, but it was hard for not to misclassify when it came to pneumonia vs normal cases. The CNN-SE-block performed better in CT images than the three models specially between covid and pneumonia, but it has a little conflict between covid and normal.

our web application (Pulmo AI) [22] fig 6 demonstrates remarkable efficiency, with the largest model loading in just 5 - 8 seconds, presenting results through interactive graphs. This integration of complex AI models and user accessibility transforms the diagnosis and understanding of respiratory conditions, revolutionizing healthcare outcomes.

The future work of this project involves expanding the models to diagnose various lung diseases, improving the accuracy and reliability of the diagnoses, leading to better health outcomes for patients.

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