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Deep Learning Approaches for COVID-19 and Pneumonia Detection Based On Chest X-Ray Images

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***Abstract*— In this paper, we utilized deep convolutional networks to classify X-ray pictures into Three groups: Normal, pneumonia, and COVID-19. Our dataset consisted of 575 pictures of COVID-19 patients, 4273 pictures of pneumonia cases, and 1583 Normal pictures. We employed various methods to optimize the network's performance, and we proposed a neural network that combined the VGG16 and ResNet50 networks. This hybrid network obtained the highest accuracy by leveraging the features extracted by the two robust networks. Our network was evaluated using 1288 pictures. and found that it had a Training Accuracy of 98.89% and an overall validation accuracy of 94.5% across all classes.**

Keywords— Chest X-ray images, COVID-19, Pneumonia, ResNet50 & VGG16 Networks.

I. INTRODUCTION

The outbreak of the COVID-19 pandemic has caused a global health crisis, necessitating the development of efficient and accurate diagnostic tools. The new coronavirus SARS-CoV-2 that causes COVID-19 mostly affects the respiratory system and exhibits many of the same symptoms as other respiratory illnesses like pneumonia. Rapid and reliable differentiation between COVID-19 and pneumonia is crucial for appropriate patient management, resource allocation, and containment of the virus.

Deep learning algorithms have been used recently by researchers to analyze and evaluate chest X-ray pictures in order to identify COVID-19. Using the CNN technique, the images are first pre-processed to extract better features that are then put into deep learning algorithms for image categorization. A deep neural network-based system with great accuracy (94.03%) was proposed by Ahammed et al. [1]. The algorithm was trained by the authors using chest X-rays from COVID-19 patients with pneumonia and normal conditions. The work was limited by the fact that only 285 photos were included in the dataset used to construct the system, and it was challenging to develop a deep learning-based system for COVID-19 prediction because of its size.

In order to create the unique framework known as PDCOVIDNet, which is based on parallel-dilated CNN, Chowdhury et al. [2] used chest X-ray pictures. The authors' solution incorporated a parallel stack with a dilated convolution that could stretch and capture the required characteristics to achieve a detection accuracy of 96.58%.

To identify COVID-19 patients from their chest X-ray images, Abbas et al. [3] devised and verified a deep convolutional neural network termed disassemble, transfer, and compose (DeTraC). In order to achieve high accuracy (93.1%) and sensitivity (100%), they suggested a decomposition mechanism to check abnormalities in the dataset.

A deep learning technique based on the ResNet-101 CNN model was utilized by Azemin et al. [4]. Thousands of photographs were used in their suggested method during the pre-trained phase to recognize significant objects and during the re-trained phase to recognize anomalies in the chest X-ray images. This method's accuracy rate was 71.9%.

Using pre-trained deep learning models like ResNet50, VGG16, VGG19, and DensNet121, Khan et al. [5] constructed a new architecture for the diagnosis of X-ray pictures as the COVID-19 or normal, with VGG16 and VGG19 demonstrating the best accuracies. Preprocessing and data augmentation, followed by transfer learning, made up the two phases of the suggested model, which ultimately demonstrated 95.3% accuracy.

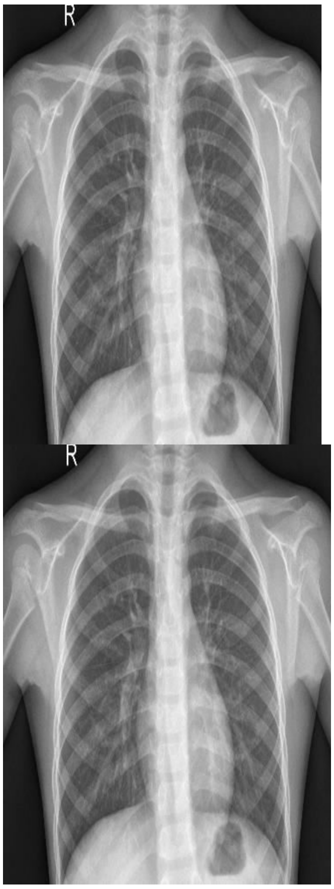
So, the utilization of CNNs in medical imaging analysis offers several advantages. CNNs can automatically learn discriminative features directly from the images, eliminating the need for explicit feature engineering. Moreover, their ability to capture spatial dependencies and hierarchies of features makes them well-suited for image classification tasks. By training CNNs on large-scale datasets of COVID-19 and pneumonia cases, it is possible to build accurate and efficient diagnostic models capable of assisting healthcare professionals in making informed decisions.

To accomplish this, the study will utilize a comprehensive dataset comprising chest X-rays of COVID-19-positive patients, pneumonia cases, and healthy individuals. The dataset will be appropriately labeled and pre-processed to ensure the quality and reliability of the training process. Multiple CNN architectures will be explored, considering factors such as network depth, filter sizes, activation functions, and pooling strategies, to identify the most effective model for COVID-19 and pneumonia detection.

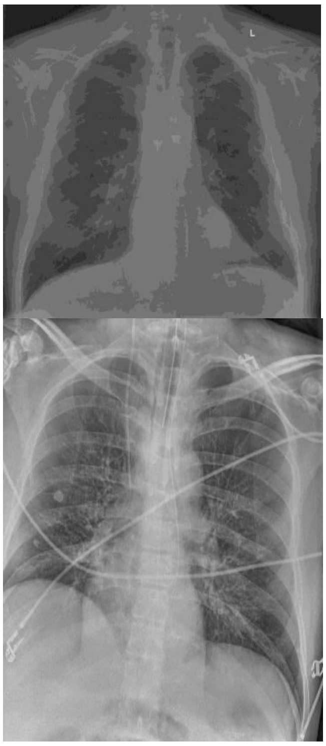
Various criteria, including accuracy, sensitivity, and specificity, will be used to assess the performance of the CNN models. Comparative analyses will be conducted to assess the proposed methodology's effectiveness in distinguishing COVID-19 and pneumonia cases from normal cases, as well as its performance in and existing approaches and benchmark models.

II. Dataset

For our study, we utilized an open-source dataset that includes COVID-19 patients' chest X-ray pictures, as well as individuals with pneumonia and normal X-rays. The dataset, which can be found at and is cited as [6], was obtained from Kaggle and contains a total of 4273 pneumonia cases, 1583 normal images, and 575 COVID-19 cases. The dataset was split into two sets: a training set, which had 459 COVID-19 images, 3418 pneumonia images, and 1266 normal images; a validation set, which contained 116 COVID-19 photos, 855 pneumonia images, and 317 normal images. Table 1 displays specifics on the distribution of the datasets.



(a) Chest X-ray of a regular person



(b)Covid Effected Chest X-Ray Pictures

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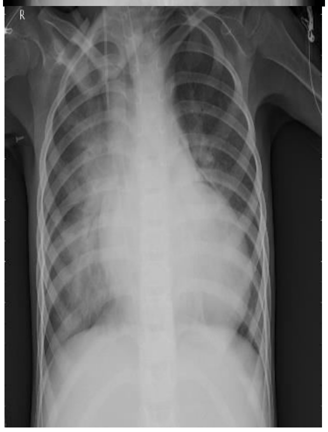

(c) Pneumonia Chest X-Ray Image

Table 1
The number of images included in the dataset's training and validation sets.

Image Dataset	COVID-19 Images	Pneumonia Images	Regular Images
Number of COVID, Normal, and Pneumonia X-Ray Images	575	4273	1583
Training Set	459	3418	1266
Validation Set	116	855	317

III. Proposed System

A. Convolutional Neural Networks (CNN)

In machine vision tasks, deep convolutional neural networks are helpful. These have led to advancements in a variety of fields, including industry [10], medical disease diagnosis [8,9], and agriculture [7]. The robust and important semantic properties that these networks create from the incoming data are what give them their excellence. In this case, categorizing the X-ray pictures as COVID-19, pneumonia, or normal is the major goal of deep networks in identifying infection in X-ray images. Deep convolutional networks like VGG [11], ResNet [12], DenseNet [13], Inception [14], and Xception [15] are among the most effective and widely used deep convolutional networks.

B. Block Diagram

One frequent way to find COVID-19 in labs is to utilize specialists to diagnose the illness. Using this technique, the specialist can identify COVID-19 in a healthy individual or an individual with different diseases by looking for

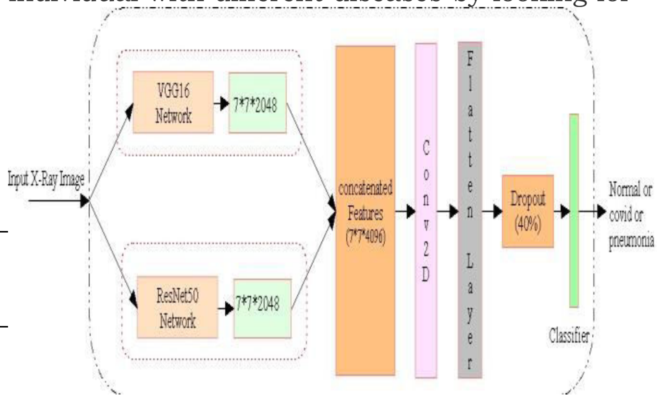

Fig: Block Diagram

symptoms and damage in the chest radiology imaging. The price of this operation is high.

Our dataset's pixels-based pre-processed input photos. On its final feature extractor layer, VGG16 produces a 10 * 7* 2048 feature map from the input image, while ResNet50 does the same action on its top layer. We integrated their features in order to employ both the inception-based layers and the residual-based layers, which would increase the quality of the generated semantic features because both networks produce feature maps of the same size.

The retrieved features from VGG16 and ResNet50 are combined to create a concatenated neural network, which is then

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constructed by connecting the concatenated features to a convolutional layer that is connected to the classifier. The convolutional layer that was added after the concatenated features had been combined had a kernel size of 1 * 1, 1024 filters, and no activation function. This layer was included to separate a more valuable semantic feature from a spatial point's features, where each channel is a feature map. With the use of this convolutional layer, the network is able to learn more effectively from the features combined from VGG16 and ResNet50.

IV. RESULTS

The developed CNN-based framework for the detection of COVID-19 and pneumonia demonstrates promising performance. The models were trained and evaluated on a comprehensive dataset comprising a significant number of COVID-19-positive cases, pneumonia cases, and healthy individuals. The dataset was appropriately split into training, and testing sets to ensure unbiased evaluation.

1. Confusion Matrix

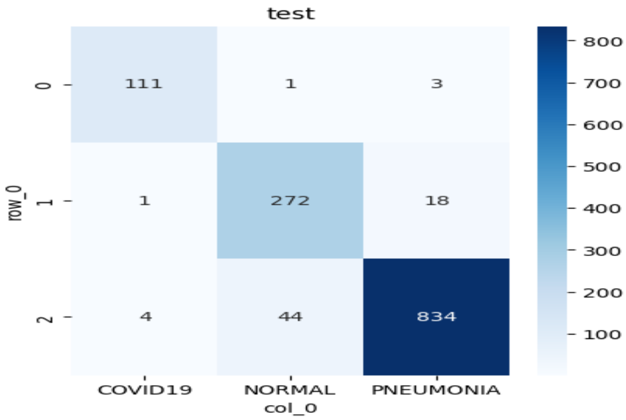
The performance of a classification model is summarised in a table called the confusion matrix. It shows the forecasts for true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The confusion matrix enables a detailed analysis of the model's performance, including insights into misclassifications and error types. Additional metrics such as specificity (TN rate) and the positive predictive value (precision) can be derived from the confusion matrix.

In the context of COVID-19 and pneumonia detection, the confusion matrix can provide valuable information on the models' abilities to differentiate between different respiratory conditions and normal cases.

The confusion matrix of the network and the evaluation results of the neural networks are displayed in Figure.

The model correctly identified 834 pneumonia photos as pneumonia and 111 covid instances as covid in the figure below. Our model correctly predicted 1217 out of the 1288 test photos.

The anticipated accuracy and loss curves, as well as classification reports, can provide us with a comprehensive understanding of our model.



2. ACCURACY CURVE

The accuracy curve illustrates the progression of the model's accuracy during the training and validation phases. It shows visually how the model's accuracy increases or stabilizes as training iterations or epochs are increased. The accuracy curve helps monitor the training progress, identify overfitting or underfitting issues, and determine the optimal stopping point for training. Accuracy is calculated using the formula

$$accuracy = (TP + TN)/ (TP + FP + TN + FN).$$

The CNN models achieved an overall accuracy of 98.89%.

3. LOSS CURVE

The loss curve depicts the variation in the model's loss function over the training process, indicating the convergence and generalization capabilities of the model. It shows how the loss decreases over time as the model learns to make more accurate predictions. Please enter the loss values and epochs. These curves help in monitoring the training progress, identifying overfitting or underfitting issues, and determining the optimal stopping point for training.

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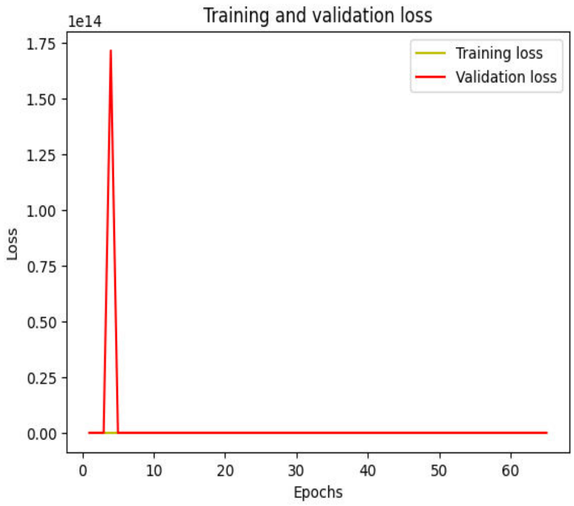

The CNN models achieved an overall loss of 0.012.

4. Classification Report

The key criteria for assessing the classification performance of the CNN models are precision, recall, and F1 score. These metrics provide insights into the models' ability to correctly identify positive (COVID-19 or pneumonia) and negative (normal) cases.

The precision measures the proportion of accurate positive forecasts to all positive predictions. It assesses the precision of optimistic forecasts and shows how well the model can reduce false positives.

The mathematical formula for precision is given by

Precision = TP/(TP+FP)

The proportion of correctly predicted positive instances to all of the actual positive cases is known as recall, also known as sensitivity or true positive rate. It represents the model's ability to identify all positive cases correctly and avoid false negatives.

The mathematical formula for the recall is given by:

recall = (TP)/(TP+FN)

The F1 score is calculated using the harmonic mean of recall and precision. It provides an honest evaluation of the model's overall accuracy by accounting for both precision and recall. The F1 score is especially useful when the dataset contains an unequal distribution of classes.

f1 = 2*(precision * recall)/ (precision + recall)

In this paper, we are sharing the classification reports for the training and testing data in this study. The training and testing data classification report is displayed in the image below.

```
Training set:
        Accuracy:0.987
        Classification Report
              precision    recall  f1-score   support

           0       0.97      1.00      0.98       459
           1       1.00      0.95      0.98      1266
           2       0.99      1.00      0.99      3418

   micro avg       0.99      0.99      0.99      5143
   macro avg       0.99      0.98      0.98      5143
weighted avg       0.99      0.99      0.99      5143
 samples avg       0.99      0.99      0.99      5143

41/41 [==============================] - 3s 71ms/step
Test set:
        Accuracy:0.945
        Classification Report
              precision    recall  f1-score   support

           0       0.97      0.96      0.96       116
           1       0.93      0.86      0.89       317
           2       0.95      0.98      0.96       855

   micro avg       0.94      0.94      0.94      1288
   macro avg       0.95      0.93      0.94      1288
weighted avg       0.94      0.94      0.94      1288
 samples avg       0.94      0.94      0.94      1288
```

V. CONCLUSION

In conclusion, this study focused on developing and evaluating a CNN-based framework for detecting COVID-19 and pneumonia using medical imaging data. The CNN models were trained and evaluated on a carefully curated dataset comprising chest X-rays of COVID-19 patients, pneumonia cases, and healthy individuals. The results obtained demonstrate the effectiveness of the proposed CNN framework in accurately distinguishing between COVID-19 and pneumonia cases, as well as normal cases.

The accuracy of the CNN models was measured to be 98.89. This indicates the models' ability to correctly classify images across different respiratory conditions. The loss curve showcased a decreasing trend over the training iterations, indicating that the models successfully learned to make more accurate predictions.

The classification report also provides additional information on the models' performance for each class, including COVID-19, pneumonia, and normal cases. It offers a comprehensive assessment of the models' precision, recall, and F1-score for each class, providing a deeper understanding of their capabilities and potential biases.

Overall, the CNN-based framework showcased promising results in the detection of COVID-19 and pneumonia. The accuracy, loss curves, and classification report metrics indicate the models' ability to accurately classify different respiratory conditions.

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