Beyond the Human Eye: Using CNNs to Decipher COVID-19 in Chest X-rays

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ABSTRACT

The COVID-19 pandemic has posed challenges, for healthcare systems worldwide requiring effective diagnostic methods and patient management strategies. As a result, the analysis of large-scale data statistics and the precise identification of COVID-19 patients using chest X-rays have become crucial in the fight against the virus. Radiologists, who are at the forefront of this battle face the task of sifting through several X-ray images to accurately identify cases of COVID-19. While traditional diagnostic procedures like Polymerase Chain Reaction (PCR) tests are accurate they suffer from time delays and resource limitations. Chest X-rays offer a cost-effective alternative; however, radiologists may encounter difficulties in interpreting them due to the features that indicate COVID-19-related pneumonia. To address these challenges, we propose a Conventional Convolutional Neural Networks (CNNs) model in deep learning using Adam optimizer. We aim to improve management efficiency enable early detection and ultimately enhance patient outcomes in detecting the disease.

Keywords: - *COVID-19, CNN, Chest X-Rays, Adam Optimizer and PCR*

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1. INTRODUCTION

The global health emergency brought about by the COVID-19 pandemic originating from the coronavirus_SARS_CoV_2 has caused unprecedented challenges worldwide. Starting in Wuhan, China the virus rapidly spread across borders impacting millions of individuals and resulting in loss of life. COVID-19 primarily affects the system manifesting through symptoms like coughing, breathing difficulties, and pneumonia. The exposed vulnerabilities in healthcare systems reveal disparities in access to medical care and funding. In response to this crisis, technology has played a role in healthcare advancements with deep learning algorithms emerging as valuable tools. These algorithms enable precise analysis of medical images a promising development for enhanced diagnostic capabilities. While conventional methods like PCR testing have proven effective, they are hindered by processing times and occasional false positive results. Utilizing chest X-ray imaging presents an invasive approach to detecting respiratory infections like COVID 19 making it a focus, for technological innovation. The goal of initiatives, like developing CNN models is to enhance the effectiveness of diagnosing COVID-19 by automating the analysis of chest X-ray images. Through utilizing CNN architectures and optimization methods these models strive to surpass current standards ultimately aiding in early detection initiatives and improving patient care. The intersection of deep learning and medical imaging holds potential not only for solving the current challenges brought by COVID-19 but also for shaping the future of diagnostic medicine.

2. LITERATURE SURVEY

Pavipra Singh and Shashank Sahu[1] in their research “Detection of COVID-19 using CNN from Chest X-ray Images,” used pooling layers and CNNs with ReLU activation functions. The model achieved 88% accuracy by processing over 40,000 photos in four categories: COVID-19, Viral Pneumonia, Normal, and Lung Opacity. There were 20 epochs in the training phase, and the dataset was split 70:30 for training and testing.

Sanhitha Basu, Sushmitha Mitra, and Nilanjan Saha[2] in their influential work, "Deep Learning for Screening COVID-19 using Chest X-ray images," used domain extension transfer learning with Grad-CAM for visualization to obtain a 90.13% accuracy. Using the TensorFlow Python framework, they efficiently trained on 108,948 pictures from the NIH Chest X-ray dataset over 100 epochs by employing stochastic gradient descent and Adam optimizers.

Arpan Mangal, Suriya Kalia[3] with their model in "CovidAID: COVID-19 Detection Using Chest X-Ray,"obtained a ground-breaking 90.5% accuracy in COVID-19 detection from chest X-ray pictures. In response to lack of radiologists, the authors provide CovidAID, an advanced AI model that outperforms earlier benchmarks like Covid-Net, recognizing COVID-19 on the COVID Chest X-Ray dataset with 90.5% accuracy and 100% sensitivity.

Matteo Polsinelli, Luigi Cinque, and Giuseppe Placidi[4] in "A light CNN for detecting COVID-19 from CT scans of the chest," presented a unique method based on data from Zhao et al. and an Italian dataset. They creatively swapped out ReLU layers with ELU layers using a 200-epoch training that was optimized using Bayesian techniques, and they achieved an astounding 85.03% accuracy. Their lightweight CNN, which was modeled after SqueezeNet, outperformed more intricate architectures with a 10% increase in efficiency.

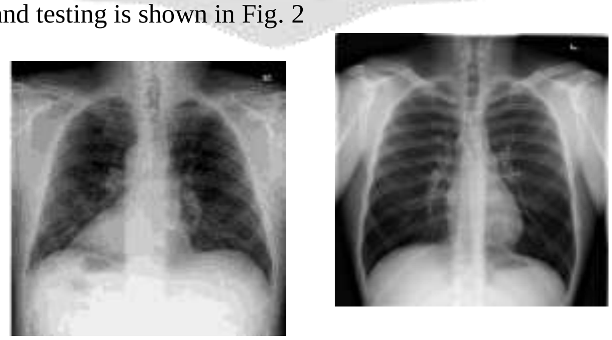
Singh, Shrinjal, Piyush Sapra, Aman Garg, and Dinesh Kumar Vishwakarma[5] "CNN based Covid-aid: Covid 19 Detection using Chest X-ray." This study endeavors to develop a deep learning model leveraging CNNs to detect COVID-19 from chest radiography images. Employing a publicly available dataset, our model achieved a classification accuracy of 87%, demonstrating promising potential for aiding in the timely diagnosis of the disease.

Maghari, Ashraf Yunis[6] "COVID-19 Detection in X-ray Images using CNN Algorithm." In this study, they applied a CNN algorithm similar to the CheXNet approach. Using a dataset of 550 chest X-ray images, sourced from Kaggle and including some infected with the COVID-19 virus, we achieved an acceptable prediction accuracy of 89.7%, closely matching the performance of the CheXNet algorithm.

Sahinbas, Kevser, and Ferhat Ozgur Catak[7] "Transfer learning-based convolutional neural network for COVID-19 detection with X-ray images". This study proposed a deep CNN model using pretrained architectures (VGG16, VGG19, ResNet, DenseNet, InceptionV3) for COVID-19 detection from chest X-ray images. The pretrained VGG16 model achieved the highest accuracy of 80%, demonstrating its efficacy in radiology departments.

3. DATASET

The researchers worked with medical professionals to generate the Chest X-ray picture dataset, which was obtained from the Kaggle Repository [8] using a variety of internet resources such as GitHub, SIRM, and other sites. published works, the Pad chest dataset, the Pneumonia dataset, and the Radiology Society of North America (RSNA). 42330 photos overall from 4 categories—COVID-19, non-COVID-19 (lung opacity & viral pneumonia), Normal—are included in the experiment dataset. Given the intricacy of the system, we have selected 4,000 images from the COVID-19 and Normal categories. The training and testing dataset is split 70:30, with 2800 training images and 1200 testing images. Fig. 1 represents the various classes of X-ray images of Chest and the splitting of chest X-ray images for training and testing is shown in Fig. 2



(a) (b)

Fig. 1: Categories of Chest X-ray images (a) COVID-19 (b)Normal [9]

The dataset is divided as follows

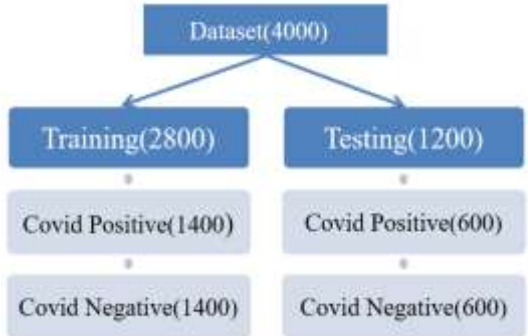


Fig. 2: Dataset flow chart

4. PREPROCESSING AND AUGMENTATION

Preprocessing of image data is made easier by utilizing the Keras Image Data Generator. Each pixel value in the training set is normalized because the generator is configured with the rescale parameter set to 1/255, which results in the range [0, 1]. To provide consistent input data for both the training and assessment phases, the testing set also goes through the same rescaling process. The generated normalized images are used as the basis for X-ray dataset analysis and efficient model training.

Keras Image Data Generator facilitates augmentation in the training set at improve dataset variety, it adds shear and zoom transformations, with training parameters set at 0.2. We lower the possibility that the model may focus too much on particular details by improving its adaptability to various types of input data. As the model's flexibility increases through modifications, so does its capacity to analyze images

5. PROPOSED WORK

The proposed model has 15 layers, which have varied contributions toward its efficacy which includes five convolutional layers followed by five max pooling layers, two dense layers, one output layer, one flatten layer and one dropout layer. First, five layers analyze photos to identify significant patterns, and then another five layers downscale and extract features of images for easy processing. Then the image is flattened ready for the final decision-making stage whereby the output layer checks the presence of COVID-19 indicators. A dropout layer helps to prevent over-emphasis on certain areas, whereas two more layers are there to study complex features. To make progress, a model is trained on different pictures to improve accuracy without becoming too obsessed with minor details. Overall, our model combines adaptable nature and experience-based learning enabling reliable COVID-19 detection. Fig.3 illustrates our model's flowchart, whereas Fig. 4 depicts our model's architecture.

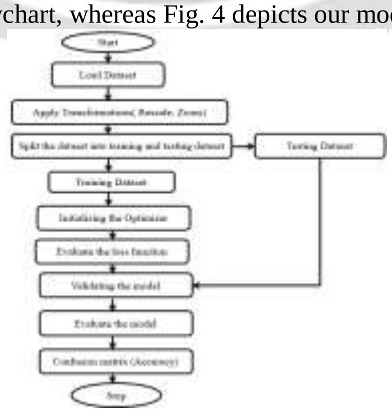


Fig. 3: Flowchart of the model

5.1 CNN

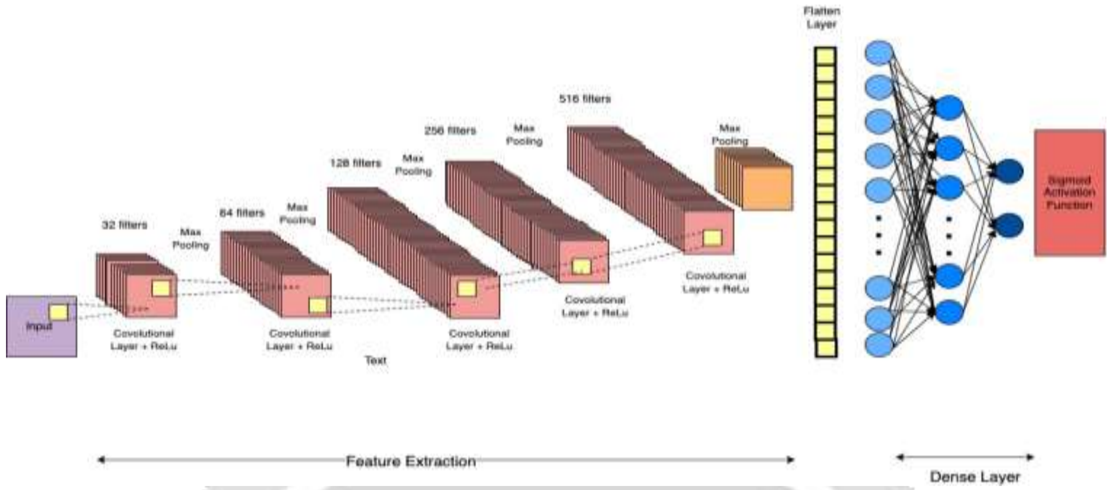


Fig 4: Convolutional Neural Network Architecture

5.1.1 CONVOLUTIONAL LAYER:

This model consists of five convolutional layers, employing filter sizes ranging from 32 to 512 and utilizing a 3x3 filter size alongside ReLU activation functions. These layers play a vital role in identifying spatial patterns such as edges and textures within the input images. As the network deepens, these layers progressively capture increasingly complex features, which are essential for accurate classification.

5.1.2 MAXPOOLING LAYER:

In this model, we use five max-pooling layers to reduce feature map size by selecting the maximum value in 2x2 windows. This enhances computational efficiency while preserving important features. Max-pooling promotes generalization, and robust feature extraction, and prevents overfitting, maximizing CNN effectiveness in image categorization.

5.1.3 DENSE LAYER:

In this model, we use two dense layers: the first layer uses 512 neurons that are activated with ReLU to help with feature extraction, and the second layer uses one neuron that is activated with sigmoid to help with the final prediction of COVID-19 presence. The model's learning ability and classification accuracy are greatly improved by these layers.

5.1.4 DROPOUT LAYER:

The dropout layer is a regularization technique employed to mitigate overfitting in neural networks. By randomly deactivating a portion of input neurons during training, the model avoids relying excessively on specific features, thus enhancing its ability to generalize to new data. In our model, Dropout (0.3) signifies that 30% of input units will be randomly dropped during training, striking a balance between reducing overfitting and preserving valuable information.

5.1.5 FLATTEN LAYER:

The final convolutional layer's output is converted into a 1D vector in our model's `Flatten` layer so that it may be fed into the dense layers. Dense layers require this reshaping to process the data efficiently for prediction, as they anticipate one-dimensional data.

Libraries used in the above discussed model:

- Keras
- TensorFlow
- Numpy
- Scikit-Learn
- Matplotlib

Table I shows a brief introduction to libraries used in this model.

Table -1 : List of Libraries

Software Package	Purpose
Python	Base programming language.
Keras	High-level deep learning API for building and training models.
TensorFlow	Backend used by Keras (may not be needed if your Keras installation includes it automatically).
NumPy	Fundamental library for numerical computations.
scikit-learn	Used for data manipulation, specific metrics, etc.
matplotlib	Main plotting library for creating graphs.

System requirements for implementation

- Processor: Multi-core CPU
- RAM: Minimum 8GB
- Storage: Adequate disk space
- Internet Connection: Stable and high-speed
- Coding Language: Python
- IDE: VS Code /Google Colab

6. EXPERIMENT AND RESULT

The model was trained and validated for 100 consecutive epochs as part of the experimental work. According to the findings, the proposed approach has a training accuracy of 97.88% and a validation accuracy of 93.58%. For training and validation, the corresponding loss values were 0.0062 and 0.2872, respectively. Table II summarises the accuracy and loss for both training and testing and Table III represents the evaluation metrics of each class. Fig. 5 illustrates the confusion matrix. The link between epochs and accuracy and epochs and loss for the training and validation sets is depicted in the graph in Fig. 6 and Fig. 7 below.

Table -2 : Accuracy and Loss

Values	**Training**	**Testing**
Accuracy	97.88	93.58
Loss	0.006	0.2872

Table -3: Evaluation Metrics Of Each Class

	Precision	Recall	F1-score	Support
Class 0	0.95	0.91	0.93	600
Class 1	0.91	0.95	0.93	600
Accuracy			0.93	1200
Macro avg	0.93	0.93	0.93	1200
Weighted avg	0.93	0.93	0.93	1200

Fig -5: Confusion Matrix

Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$ = 93

Precision: $\frac{TP}{TP+FP}$ = 91

Recall: $\frac{TP}{TP+FN}$ = 95

F1-score: $2*\frac{(Precision*Recall)}{(Precision+Recall)}$ = 93

Support: Number of actual occurrences of a particular class in the dataset

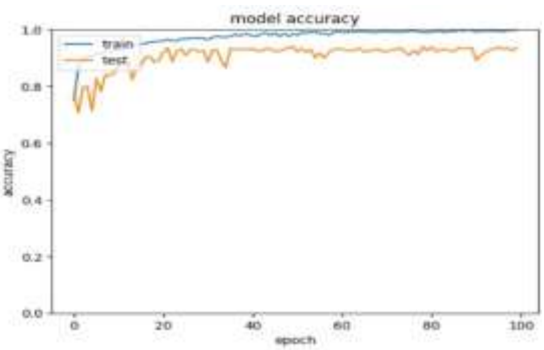


Fig -6: Epoch vs Accuracy Graph

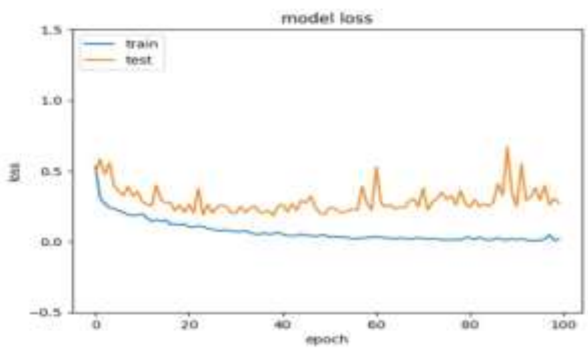


Fig -7: Epoch vs Loss Graphs

7. RESULT

The following images showcase the outcomes of applying the provided code, depicting predictions made for both COVID-19 positive and normal cases. Fig. 8 represents both COVID positive and normal chest X-Rays.

(a) (b)

Fig -8: Result (a) COVID (b) Normal

8. CONCLUSION

Our strategy combines feasible techniques like data augmentation, optimization functions, and loss functions to achieve 93% accuracy in COVID-19 detection. By diversifying the dataset and optimizing functions, we aim to improve the model's ability to identify subtle COVID-19 indicators in chest X-ray images. Our approach emphasizes the development of precise diagnostic tools crucial for combating the pandemic. In this paper, we enhanced the precision of the Convolutional Neural Network by incorporating layers and integrating dropout layers to combat overfitting. Adam optimization accelerated training, enhancing the CNN's ability to identify COVID-19 patterns across the dataset. These efforts promise effective diagnostic solutions for addressing the COVID-19 crisis.

9. REFERENCES

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