Deep Learning Model for Edge Devices for COVID-19 Detection from CXR Images

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***Abstract*—The novel coronavirus 2019 (COVID-19) emerged in December 2019, and subsequently underwent rapid global spread, culminating in a pandemic declaration. The emergence of COVID-19 has affected public health significantly and sparked major socio-economic crises. Worldwide, more than 6 million deaths linked to COVID-19 and more than 758 million cases have been reported. Prompt and precise identification of individuals as either healthy or infected is a crucial strategy in managing and preventing the spread of coronavirus outbreaks. Recent findings suggest that patients with COVID-19 infection can be identified by chest radiography anomalies. Chest X-ray (CXR) pictures are more easily obtainable when compared to chest computed tomography (CT) images, especially in less economically developed regions where CT machines are prohibitively costly. In this research, we introduce an exceptionally lightweight convolutional neural network (CNN) tailored for the automated assessment of chest X-ray images, aiming to differentiate between COVID-19, non-COVID-19, and normal conditions. Our model has total of 59,467(0.059 million) parameters, our model's total size is 19.67 MB. Our model surpasses other COVID-19 detection models due to its substantially reduced parameter count and comparable accuracy, making it well-suited for use on machines with limited computational capabilities.**

***Index Terms*—COVID-19, Chest X-Ray, Edge Devices, Convolutional Neural Network**

I. Introduction

The COVID-19 pandemic, caused by the novel coronavirus 2019 (SARS-CoV-2), is an acute respiratory disease that has resulted in more than 6.8 million fatalities and over 758 million confirmed cases worldwide. The World Health Organization (WHO) has officially declared COVID-19 a contagious illness. It was first detected in December 2019 in Wuhan City, situated in China's Hubei province. [1]. The virus can be transmitted when people breathe in droplets that are expelled from the mouth or nose of an infected person while they cough, sneeze, talk, or simply breathe. It takes between 1 to 14 days for symptoms to appear after exposure. Typical signs of infection encompass a cough, fever, headache, tiredness, breathing challenges, and a diminished sense of smell and taste, though these manifestations can diverge among individuals [2]. In more critical instances, symptoms can escalate to encompass difficulty breathing, decreased oxygen levels, respiratory failure, and a state of shock. On January 30, 2020, and March 11, 2020, the World Health Organization (WHO) officially designated the COVID-19 outbreak as a pandemic and a global public health crisis, respectively. Since then, rapid detection of the virus has become a highly significant area of real-time research interest. Individuals characterized by compromised immune function or advanced age exhibit heightened susceptibility to developing severe complications, including cardiac and renal failure, along with septic shock. This epidemic is still having a devastating effect on global health and wellbeing. The formulation of an effective classification system is a vital phase in the COVID-19 battle cycle since it allows patients to begin receiving immediate medical care, treatment, and control transmission.

The reverse transcriptase-polymerase chain reaction (RT-PCR) plays a vital role as a screening technique to identify the presence of SARS-CoV-2 and COVID-19. While the RT-PCR test is the most often used approach for detecting COVID-19, it has some drawbacks. The RT-PCR technique is difficult and time-consuming, it suffers from three major issues: 1. A scarcity of RT-PCR kits. 2. Community hospitals located in rural areas do not have the necessary PCR infrastructure to handle a high volume of samples. 3.To conduct RT-PCR, it is necessary for the samples obtained to contain detectable amounts of SARS-CoV-2. [3].

Consequently, efforts to detect COVID-19 have been undertaken through the utilization of chest imaging techniques, such as computed tomography (CT) scans or radiographic pictures of the chest X-ray. However, The use of CT images as a diagnostic method for COVID-19 does come with a set of drawbacks. Firstly, CT imaging equipment comes with a substantial cost and demands a significant level of expertise for efficient operation. This poses challenges for healthcare facilities that may not have the financial resources or specialized personnel to utilize CT scans for COVID-19 diagnosis. Moreover, non-portable CT imaging equipment can heighten the chances of human-to-human transmission when patients need to be transported. The situation is compounded by the shortage of personal protective equipment (PPE) kits for healthcare workers, which further increases this risk. Furthermore, CT imaging typically takes longer to process compared to X-ray imaging, potentially causing delays in diagnosis and treatment. Lastly, access to high-quality CT imaging systems may be limited in rural regions, making it difficult to promptly screen for COVID-19 infections in these areas. These limitations highlight the need for alternative diagnostic methods that are

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more accessible, cost-effective, and efficient for COVID-19 detection.

In contrast, X-rays are the most widely used and readily accessible radiographic diagnostic methods in clinical settings [4]. They prove highly valuable for cost-effective and swift COVID-19 infection screening.

The healthcare sector has benefited from recent progress in computer vision, which has led to affordable and dependable solutions by integrating deep learning techniques. Especially, the Convolutional Neural Network (CNN) regained attention in 2012 due to its remarkable ability to classify images with high accuracy. Subsequent studies have demonstrated the groundbreaking potential of CNNs in the realm of deep learning. Particularly, the focus of this paper lies in the convergence of computer vision methods with the healthcare industry. Automation has become increasingly prevalent in diagnosis and disease detection, thanks to the incorporation of deep learning techniques.

A robust AI-based COVID-19 diagnostic system that can attain excellent sensitivity and specificity, or precision and recall, on edge/mobile devices is highly demanded. Such AI-based tools for COVID-19 diagnosis have the potential to make screening tests more cost-effective and efficient for widespread, real-time testing. Additionally, they can reduce the risk of transmission to healthcare workers and alleviate the burden on the already limited healthcare professionals and radiologists. In this study, we introduce an exceptionally lightweight CNN model that can effectively detect COVID-19 from chest X-ray (CXR) images, which are commonly accessible in most clinical settings and imaging facilities. While numerous Deep Learning (DL) models have been created, the majority of them are characterized by a large number of parameters, rendering them unsuitable for deployment on devices with limited computational resources, such as mobile devices. Our model achieves similar accuracy compared to the existing deep learning-based models, all while maintaining a significantly reduced number of parameters.

The following sections comprise the paper: The extensive literature analysis in Part II provides an understandable appraisal of past techniques. Part III describes the specifics of the suggested model's implementation. The experimental findings collected are presented in Section IV. Part V reviews the project and concludes.

II. Related Work

In the field of medical image recognition, classifying medical photographs into groups is important for disease diagnosis and research. This involves extracting valuable features from the image and developing classification models to identify diseases [5]. [6] corroborated the efficiency of Convolutional Neural Networks (CNNs) in diagnosing COVID-19 through the analysis of digital images and CT scans for detecting the disease. Furthermore, further investigations into deep learning models were assessed for their accuracy in detecting COVID-19. L. Wang et al. [7] conducted a comparison among three models: VGG-19 (a deep CNN architecture with 19 layers), ResNet-50 (a deep CNN architecture with 50 layers), and COVID-Net (a deep CNN designed for COVID-19 detection using publicly available CXR images). The findings revealed that COVID-Net exhibited lower architectural and computational complexity in comparison to VGG-19 and ResNet-50., with COVID-19 sensitivity (91%). Their model COVID-Net has 11.75 million parameters and achieved accuracy of 92.4%. They conclude future research to be focused on risk stratification for survival analysis, and the prediction of risk status and prediction of hospitalization duration, which would be key factors in managing patients, and providing better treatments in the control of COVID-19 cases. N. Awasthi et al. [8] went a step further and introduced Mini-COVIDNet, a streamlined variant of the COVID-Net model. This version has significantly fewer trainable parameters, approximately 4.39 times fewer than its counterparts. Notably, the suggested model boasts a swift training period of under 30 minutes and demonstrates an 83.2% accuracy in detecting COVID-19. It's important to mention that their model comprises 3.36 million parameters. T. Ozturk et al. [9] used the DarkNet model, which is a state-of-the-art architecture for object detection, to propose DarkCovid-Net by changing the number of convolutional layers to 17. DarkCovid-Net obtained an accuracy of 98.08% and 87.02% on binary and multiclass classification tasks respectively. There multiclass classification model had 1.16 million parameters, and as with other works, this model was trained on only 1125 chest X-ray images which can be problematic as a more accurate model needs a significantly more robust dataset.

Hemdan et al. [10] introduced COVIDX-Net, a deep-learning framework, built on VGG19, DenseNet121, InceptionV3, ResNetV2, Xception, and MobileNetV2. Since it was one of the earliest attempted works in automated COVID detection, it faced the trouble of getting adequate training images and thus was trained on only a total of 50 chest x-ray images, and they achieved 90% accuracy. Abdani et al. [11] proposed SPP-COVID-Net model, and conducted a comparison between the SPP-COVID-Net model and six other lightweight deep learning models for X-ray image detection. The SPP-COVID-Net model achieved the highest average accuracy of 94.6% while utilizing fewer than one million parameters, specifically 0.86 million parameters.

Combining transfer learning methods with convolutional neural networks (CNNs) can significantly enhance the automated recognition and extraction of important features from X-ray images. In the context of COVID-19 detection, with this approach they achieved a multi-class classification accuracy of 93.48%., their model has 20.55 million parameters. [12]. Khan et al.[25] proposed coronet, they achieved 89% accuracy and their model has 33 million parameters.

Chakraborty et al. suggested Corona-Nidaan as a compact model [13]. They compared their model's performance to others with a higher number of parameters and discovered that their model surpassed them, achieving a 95% accuracy rate. Despite being labeled as lightweight, their model still incorporates 4.02 million params.

III. Proposed Method

The suggested method is executed through a sequence of steps: initially obtaining the chest X-ray (CXR) images, followed by preprocessing, then building and training the classification model and, at the end, utilising test data to evaluate its effectiveness.

A. The Dataset

We employed a dataset proposed in [14], which included a collection of 33,920 chest X-ray (CXR) images, to both train and assess our deep learning model. This dataset encompasses three distinct categories: COVID-19, Non-COVID, and Normal. Figure 1, Figure 2 and Figure 3 displays a selection of sample images for COVID-19, Non-COVID and Normal class respectively from this dataset. During our model development, we utilized 21,715 images for training, allocated 5,417 images for validation, and earmarked 6,788 images for testing purposes. The distribution of these classes among the training, validation, and test datasets can be found in Table 1. All images were resized to dimensions of 256 by 256 pixels in RGB format for model training. We also used augmentations while training(on the fly), image augmentation is a method employed in image classification to artificially enhance the variety of training data by implementing various alterations to the initial images, this helps improve the model's ability to generalize and recognize patterns in different variations of the same image, ultimately enhancing its performance and reducing the risk of overfitting.

TABLE I
Classwise count of train, validation and test set images

Class	Train	*Validation*	*Test*
COVID-19	7658	1903	2395
Non-COVID	7208	1802	2253
Normal	6849	1712	2140

Fig. 1. Example CXR images from our dataset for COVID-19 class

Fig. 2. Example CXR images from our dataset for Non-COVID class

Fig. 3. Example CXR images from our dataset for Normal class

B. Model Architecture

The literature survey reveals that most of the methods examined in terms of parameters have a significant number of parameters. Although a few attempts have been made to propose lightweight models, they still have more parameters compared to our method. Additionally, some of the evaluated methods were tested on a limited number of images, which reduces their reliability. In contrast, our method achieves comparable performance to these methods while maintaining a lightweight design. Our approach uses a classification network to label an input X-ray picture as one of three classes mentioned above. In order to use our recommended technique on computers with minimal processing capacity, we sought to reduce the number of parameters as low as possible without sacrificing accuracy. Many earlier deep learning approaches for COVID-19 detection used models with a significant number of parameters or depended on well-tailored pre-trained convolutional neural networks (CNNs) like VGG16, MobileNetV2, MobileNetV3, ResNet, and similar architectures. Even though transfer learning can help reduce the number of trainable parameters, it doesn't solve the problem of having a large overall parameter count. This creates difficulties because the trained models become quite large, requiring substantial disk storage and computational resources due to their excessive number of layers. In this study, we present a COVID-19 classification approach employing a model with a limited number of params that nonetheless provides performance applicable to practical issues.

Our network comprises six layers of standard CNN (Convolutional Neural Network), kernel size for each CNN layer is 3x3 , kernel size of 3x3 is optimal for us as we aimed for a lightweight model. After each CNN layer, there is a subsequent batch normalization layer, and the ReLU activation function is applied(we call it CBR layer, see Figure 4). There are 8 kernels in first two CNN layers, 16 kernels in next two CNN layers and 32 kernels in last two CNN layers. There are total six layers of Average pooling with first 4 of pool size of 2x2, and fifth and sixth pooling layer comes after sixth CBR layer with fifth pooling layer of size 2x2 and sixth of size 4x4. Lastly our model has 2 Flatten layers which comes after last 2 pooling layers and then a concatenate layer which concatenates the two flatten layers and then comes two dense layers, The initial dense layer consists of 16 units and is subsequently followed by batch normalization and ReLU activation. The final layer serves as the classification layer with three units. To incorporate regularization, a single dropout layer with a rate of 0.3 is placed after the first dense layer.

Our model has total of 59,467(0.059 million) params, all are trainable parameters, our model's total size is 19.67 MB. Despite having significantly fewer parameters, our model delivers accuracy on par with models that possess a substantially larger parameter count. The comprehensive network architecture can be observed in Figure 4. Parameter count for each layer and final total parameter count is shown in figure 5.

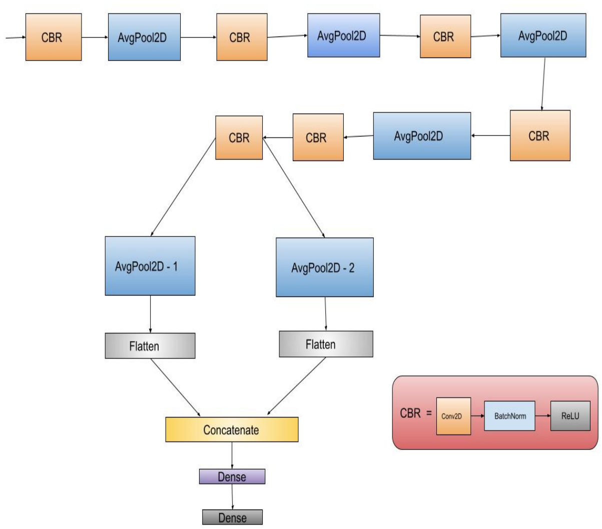

Fig. 4. The architectural diagram illustrating our model's structure

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1          [-1, 8, 256, 256]             224
       BatchNorm2d-2          [-1, 8, 256, 256]              16
              ReLU-3          [-1, 8, 256, 256]               0
         AvgPool2d-4          [-1, 8, 128, 128]               0
            Conv2d-5          [-1, 8, 128, 128]             584
       BatchNorm2d-6          [-1, 8, 128, 128]              16
              ReLU-7          [-1, 8, 128, 128]               0
         AvgPool2d-8            [-1, 8, 64, 64]               0
            Conv2d-9           [-1, 16, 64, 64]           1,168
      BatchNorm2d-10           [-1, 16, 64, 64]              32
             ReLU-11           [-1, 16, 64, 64]               0
        AvgPool2d-12           [-1, 16, 32, 32]               0
           Conv2d-13           [-1, 16, 32, 32]           2,320
      BatchNorm2d-14           [-1, 16, 32, 32]              32
             ReLU-15           [-1, 16, 32, 32]               0
        AvgPool2d-16           [-1, 16, 16, 16]               0
           Conv2d-17           [-1, 32, 16, 16]           4,640
      BatchNorm2d-18           [-1, 32, 16, 16]              64
             ReLU-19           [-1, 32, 16, 16]               0
           Conv2d-20           [-1, 32, 16, 16]           9,248
      BatchNorm2d-21           [-1, 32, 16, 16]              64
             ReLU-22           [-1, 32, 16, 16]               0
        AvgPool2d-23             [-1, 32, 8, 8]               0
        AvgPool2d-24             [-1, 32, 4, 4]               0
          Flatten-25                 [-1, 2048]               0
          Flatten-26                  [-1, 512]               0
           Linear-27                   [-1, 16]          40,976
      BatchNorm1d-28                   [-1, 16]              32
             ReLU-29                   [-1, 16]               0
          Dropout-30                   [-1, 16]               0
           Linear-31                    [-1, 3]              51
================================================================
Total params: 59,467
Trainable params: 59,467
Non-trainable params: 0
----------------------------------------------------------------
```

Fig. 5. All layers of our model, shape of their output and their parameter count

C. Training and Validation

Python was used as the programming language. We used pytorch deep learning framework for our model. In our model training process, we utilized the Adam optimizer along with a categorical cross-entropy loss function, commencing with an initial learning rate of 0.001. To dynamically adapt the learning rate, we employed a variable learning rate strategy, which decreases the rate by a factor of 0.2 if the validation loss doesn't show improvement for 5 consecutive epochs. Throughout the training, we used mini-batches of size 4 and conducted training for a total of 40 epochs.

We assessed our model's ultimate performance by employing a test set that was not employed during the training process, and included 2140 photos from the "Normal" class, 2253 images from the "Non-COVID" class, and 2395 images from the "COVID-19" class. To evaluate the effectiveness of the model, we employed the accuracy(Acc) metric, whose equation is provided below. And we used cross-entropy loss as loss function.

$$Acc = \frac{tp + tn}{tp + tn + fp + fn}$$

In simpler terms, accuracy is a measure of how many of the total samples a model correctly predicted. It's calculated based on various factors, including false negatives (fn), true positives (tp), true negatives (tn), and false positives (fp).

IV. Results and Discussion

Our model achieved an accuracy of 93.61% and the same F1 score when evaluated on unseen test data. Table 2 presents a performance comparison between our model and models that have been proposed in prior research, demonstrating that our model achieves comparable accuracy while requiring significantly fewer parameters. The table includes information on parameters (denoted as "Params") where "M" represents million.

TABLE II
COMPARISON BETWEEN OUR MODEL AND MODELS THAT HAVE BEEN PROPOSED IN PRIOR RESEARCH

Study	***Method***	***Params (M)***	***Accuracy***
Adbani et al. [11]	SPP-COVID-Net	0.86	94.6%
Wang et al. [7]	COVID-Net	11.75	92.4%
Hemdan et al. [10]	COVIDX-Net	20.55	90%
Ozturk et al. [9]	DarkCovidNet	1.16	87.02%
Ioannis et al. [12]	VGG-19	20.55	93.48%
Awasthi et al. [8]	Mini-COVIDNet	3.36	83.2%
Chakraborty et al. [13]	Corona-Nidaan	4.02	95%
Khan et al. [15]	CoroNet	33	89.6%
This work	**Ours**	**0.059**	**93.61%**

As our dataset is balanced so accuracy is good metric for evaluation, but still we also considered f1score metric for our model's performance, which is a good metric to show that model's performance for all classes is good, because if model doesn't perform good on any class this metric would not be good. To understand the f1score we need to look into precision and recall then f1score is just the harmonic mean of these two.

Precision - Precision is one of the metric to evaluate the model. In multiclass classification, there are more than two possible classes or labels. Precision for a specific class 'i' is defined as:

$$Pr[i] = \frac{tp[i]}{tp[i] + fp[i]}$$

In other words, it measures the ratio of correctly predicted instances of class i to all instances predicted as class i. Precision can be calculated for each class separately.

To compute the overall precision for multiclass classification, there are two ways:

Macro-Average Precision: In the macro-average precision approach, you compute precision for each class separately and then determine the average (mean) of these individual precision scores. This technique treats all classes equally and doesn't consider any imbalance in class sizes. Each class's contribution to the overall precision is the same, irrespective of how many samples are present in each class.

Weighted Average Precision: In the weighted average precision approach, you compute precision for each class separately and then determine an average by considering the weights associated with each class. These weights are usually based on the number of samples in each class. This method addresses class imbalance by assigning higher importance to classes with more samples. It offers a more precise depiction of overall precision, especially when dealing with rare classes.

In a multiclass image classification scenario, precision provides insights into how well the model performs for each individual class and overall. It helps to assess the performance in each category.

Recall - Recall, also known as sensitivity or true positive rate, is a crucial performance metric in multiclass image classification. It quantifies a model's ability to correctly identify all instances of a particular class among all instances that belong to that class.

In multiclass image classification, more than two classes, and we are interested in measuring how well the model performs for each individual class. Recall for a specific class 'i' is calculated a same as precision, but here false negatives is used instead of false positives.

In other words, recall measures the ratio of correctly predicted instances of class 'i' to all instances that actually belong to class 'i.' It tells us how well the model captures instances of a specific class.

To calculate the overall recall, there are two ways:

Macro-Average Recall: The macro-average recall approach involves computing the recall for each class separately and then finding the average (mean) of these individual recall values. This technique treats all classes equally and doesn't consider any imbalance in class sizes. Each class's contribution to the overall recall is the same, regardless of how many samples are in each class.

Weighted Average Recall: In the weighted average recall method, you calculate the recall for each class individually and then take a weighted average of these recall scores, where the weights are typically determined by the number of samples in each class. This method takes into account class imbalance by giving more weight to classes with more samples. It provides a more accurate representation of the overall recall when some classes are rare.

F1 score - The F1 Score, often referred to as the F1 measure or F1 score, is a popular and important metric in machine learning, particularly for classification tasks. It merges precision and recall into a single metric, offering a well-rounded evaluation of a model's effectiveness, particularly useful when working with datasets that have imbalanced class distributions, good F1 score shows our model's performance is excellent across all classes. The F1 Score is especially useful when you need to find a trade-off between precision and recall. So a good F1 score also shows our model's precision and recall is excellent. Overall F1 score can be calculated in two ways, macro-average and weighted average F1 score, method is same as described above for precision, just use F1 score in place of them.

The F1 Score is:

$$F1\_Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

Figure 6 shows full classification report, showing every metric classwise and also overall.

	precision	recall	f1-score	support
COVID-19	0.9748	0.9687	0.9717	2395
Non-COVID	0.9096	0.9241	0.9168	2253
Normal	0.9212	0.9121	0.9166	2140
accuracy			0.9361	6788
macro avg	0.9352	0.9350	0.9351	6788
weighted avg	0.9362	0.9361	0.9361	6788

Fig. 6. Classification report on test set

The accuracy of our method for detecting the COVID-19 class is 98%. Detecting whether an individual has COVID-19 is a critical task, and it's crucial not to overlook any COVID-19 cases. Our model achieves an impressively high level of accuracy when it comes to identifying COVID-19 cases, ensuring dependable detection, while also maintaining a good level of accuracy for the other two classes. You can find our model's correct prediction count for each class on the test data in the Confusion Matrix shown in Figure 7.

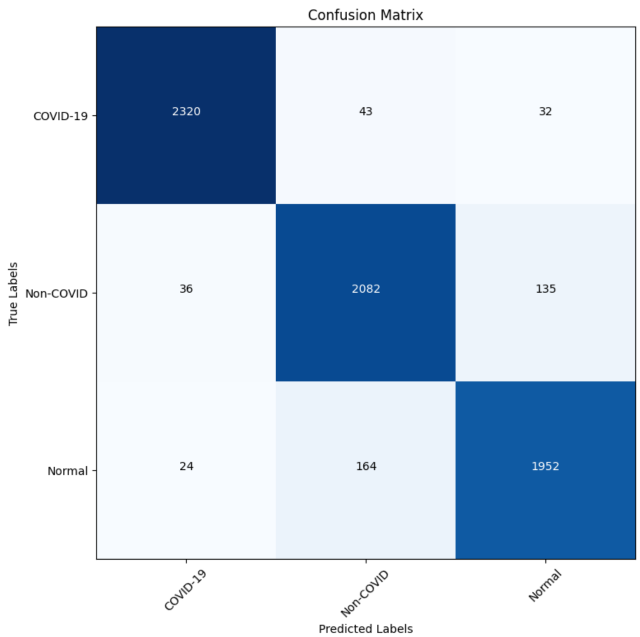

Fig. 7. The test set's confusion matrix depicting the predictions made by our lightweight model

From the results this can be seen when compared with other models our model gives excellent performance in terms of combined effect of parameter count and accuracy.

V. Conclusions

A robust AI-based COVID-19 diagnostic system that can attain excellent sensitivity and specificity, or precision and recall, on edge/mobile devices is highly demanded. Such AI-based tools for COVID-19 diagnosis have the potential to make screening tests more cost-effective and efficient for widespread, real-time testing. We proposed an exceptionally lightweight CNN model from scratch specifically designed for COVID-19 detection using CXR images, Chest X-ray (CXR) pictures are more easily obtainable when compared to chest computed tomography (CT) images, especially in less economically developed regions where CT machines are prohibitively costly. Our model underwent training on a comprehensive and varied dataset comprising the three categories mentioned in the dataset section above. Remarkably, even though our model is compact in size, it managed to attain accuracy levels similar to those of previously suggested algorithms for COVID-19 detection, all while utilizing far fewer parameters. F1 score shows our model is performing greatly for every class. This particular feature positions our model as an excellent choice for implementation on less powerful devices such as edge devices with limited processing capacity, devices having less compute are also not much expensive so this is cost effective too. Also, our model is very helpful for the healthcare system, which has a constrained budget. Also, real-time COVID-19 detection can be very helpful; this is where our model can provide great value. Through a comparison with other existing methods, we observed that our model delivers similar accuracy levels while having total model size of 19.67 MB and only 0.059 million total parameters, which is far fewer than others. This small size and low parameter count enable our model to be incorporated into mobile applications for efficient COVID-19 detection while maintaining high accuracy. In conclusion, our model provides a rapid, precise, and cost-efficient solution for detecting COVID-19.

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