Detection of COVID-19 from X-rays using Hybrid Deep Learning Models

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Abstract In this paper, a hybrid deep learning model is proposed for the detection of coronavirus from chest X-ray images. The hybrid deep learning model is a combination of ResNet50 and MobileNet. Both ResNet50 and MobileNet are light Deep Neural Networks (DNNs) and can be used with low hardware resource-based Personal Digital Assistants (PDA) for quick detection of COVID-19 infection. The performance of the proposed hybrid model is evaluated on two publicly available COVID-19 chest X-ray datasets. Both datasets include normal, pneumonia and coronavirus infected chest X-rays. Results show that the proposed hybrid model more suitable for COVID-19 detection and achieve the highest recognition accuracy on both the datasets.

Keywords COVID-19 detection · MobileNet · ResNet50 · Hybrid model · Pneumonia · X-rays

1 Introduction

The unprecedented increase in the number of cases of the new respiratory disease, COVID-19 has left the healthcare sector frantic. Due to this sudden

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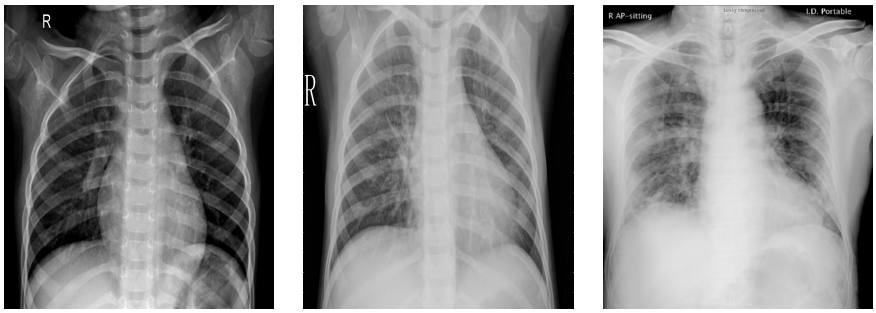
increase, many countries across the world are facing a shortage of resources to battle this pandemic. An important step towards mitigating this crisis is the quick and accurate detection of infected patients in order to utilize these limited resources wisely. The most effective tool for successfully identifying the infected patients is Polymerase Chain Reaction (PCR) testing. PCR tests are utilized to directly sight the presence of the COVID-19 antigen, instead of the body's invulnerable reaction, or antibodies. The tests can tell whether or not someone has the virus very early on, as they detect the viral RNA, which will be present in the body before symptoms start to appear or antibodies are formed [14]. However, this is a very complicated manual process that is extensively laborious, and time-consuming. Due to the sheer volume of reported cases, this process is in short supply.

It was established by early research [13, 19] that patients infected with COVID-19 display abnormalities in the radiography scans. As a result, detection of visual indicators associated with COVID-19 infection through chest radiography images (e.g., X-ray and CT scans) could be used as an alternative to PCR testing successfully. One of the biggest challenges in this avenue is the ability of radiologists to successfully identify and interpret the minute indicators of COVID-19.

In an attempt to overcome this restriction, we suggest a novel model based on deep learning which can recognize the indicators of these infections in the chest X-ray images with almost perfect accuracy. However, we wish to stress the fact that we are not proposing the employment of this model as a substitute to standard testing procedures for the detection of COVID-19, but merely a sorting tool for which can aid clinicians in improved screening.

2 Related work

Over the last few years, the quantity of medical information in machine-readable form has increased tremendously, notably in medical imaging. New



(a) Normal (b) Pneumonia (c) COVID-19

Fig. 1: Examples of Normal, Pneumonia infected and COVID-19 infected chest X-Ray images.

forms of neural networks have excelled at the task of identifying abnormalities from high-dimensional information, where previous generations of algorithms failed. Tasks like segmentation, detection, and classification from X-ray, CT scans, and MRIs have quickly become the "de facto" standard [16]. As additional proof, models dependent on neural networks command the leaderboard in most clinical imaging difficulties [28].

Various Deep Learning models have been deployed to detect the presence of respiratory diseases, particularly Pneumonia from chest X-ray scans [20, 21, 24, 26] in recent years. These models typically range from basic Convolution Neural Networks [27] to complex network architectures like DenseNet121 [20, 28]. A benchmark model for the detection of pneumonia from chest radiography images is CheXNet [20] which is built upon DenseNet121.

Keeping pace with the recent pandemic situation, several researchers have worked on machine learning and deep learning models. Machine Learning algorithms like Support Vector Machines (SVM) and Random Forest have been used by Alqudah et al. [3], to detect COVID-19 cases with an accuracy of 90.5% and 81%, respectively. Ghoshal and Tucker [9] suggested a model based on Bayesian CNN to detect COVID-19 from chest X-ray images and obtained an accuracy of 90%. CNN-based architectures have been proposed by various works [17, 18, 22, 23] that can be used effectively to identify the presence of COVID-19 infection from Chest Radiology images. The COVID-Net architecture, suggested by [23], is one of the first CNN-based models which identifies COVID-19 as well as bacterial and viral pneumonia while demonstrating significant sensitivity for COVID-19 detection. One disadvantage of this model is that it is an extremely resource-intensive model. COVIDAid model [17], which is built upon the CheXNet [20], performs great on the task of detecting COVID-19 from images, achieving 90.5% accuracy. Abbas et al. [2] proposed a DeTraC (Decompose, Transfer, and Compose) deep convolutional neural network for the classification of COVID-19 chest X-ray images and obtained an accuracy of 93.1% using this architecture. The Covidx-net model [11], proposes automatic detection of coronavirus infected persons using chest X-ray images using seven different transfer learning models. They obtained an average accuracy of 91% for COVID cases using VGG and DenseNet models.

Unsurprisingly, deep learning models [17, 18, 22, 23] perform better than machine learning models [3, 9] for the classification task. However, these DNN architectures are primarily built on heavy transfer learning models like DenseNet and VGG. They are deeper, slower, more complicated, and may not be suitable for personal digital assistants. In this paper, we utilize two light frameworks like MobileNet [12], and ResNet50 [10] and mold it according to our problem statement, for quick identification of COVID-19 infection. We have chosen two models - COVID-Net [23] and COVIDAid [17] as our baseline for an accurate comparison, as we have performed our experiments on the same data split as Covid-Net and COVIDAid models.

3 Methods

3.1 Datasets

Two versions of the COVIDx data proposed by [23] are used in this paper. The sample-wise distribution of both the datasets is mentioned in Table 1. For both datasets, we have applied 5-fold cross-validation to the training set. 10% of the training data has been used for validation in each fold. We have used the average accuracy obtained from each fold as the final accuracy.

Dataset	**Normal**	**Pneumonia**		**COVID-19**
		Bacterial	Viral	
Dataset 1	2786	1589	1498	76
Dataset 2	8851	6052		573

Table 1: Sample wise Dataset Distribution

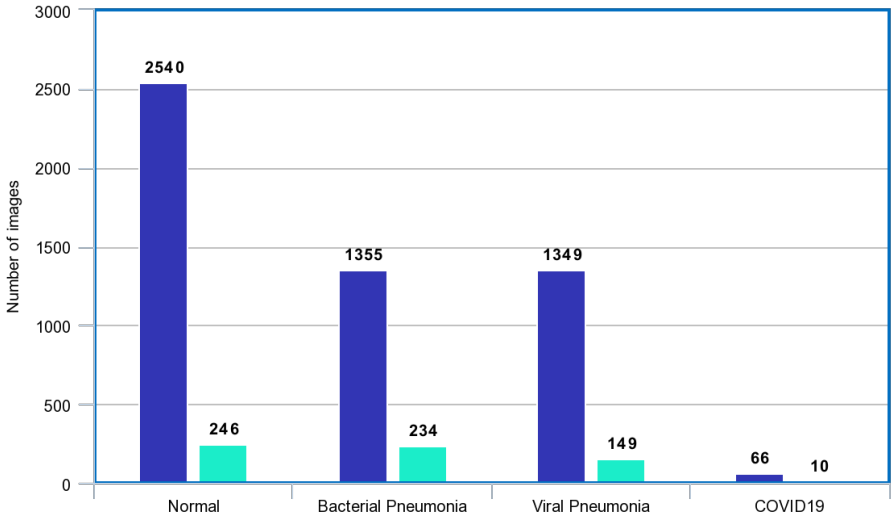
Dataset 1 The first version of the dataset consists of 5949 posterior chest radiography images divided into 4 classes - Normal, Bacterial Pneumonia, Viral Pneumonia, and COVID19. Two publicly available datasets 1) COVID chest X-ray dataset by [7], and 2) Kaggle chest X-ray images (pneumonia) dataset by [15] are combined to create this dataset. The train/test distribution of the classes is depicted in Figure 2a.

Dataset 2 The second version contains 15,476 posterior chest radiography images divided into 3 classes - Normal, Pneumonia, and COVID19 (see Figure 1). Five different open-source repositories have been combined to create the second version of the dataset - 1) COVID-19 Image Data Collection by [7], 2) Figure 1 COVID-19 Chest X-ray Dataset Initiative by [5], 3) ActualMed COVID-19 Chest X-ray Dataset Initiative by [6], 4) RSNA Pneumonia Detection Challenge dataset by [1], which used publicly available CXR data from [25], and 5) COVID-19 radiography database by [4]. The train/test distribution of the classes are shown in Figure 2b.

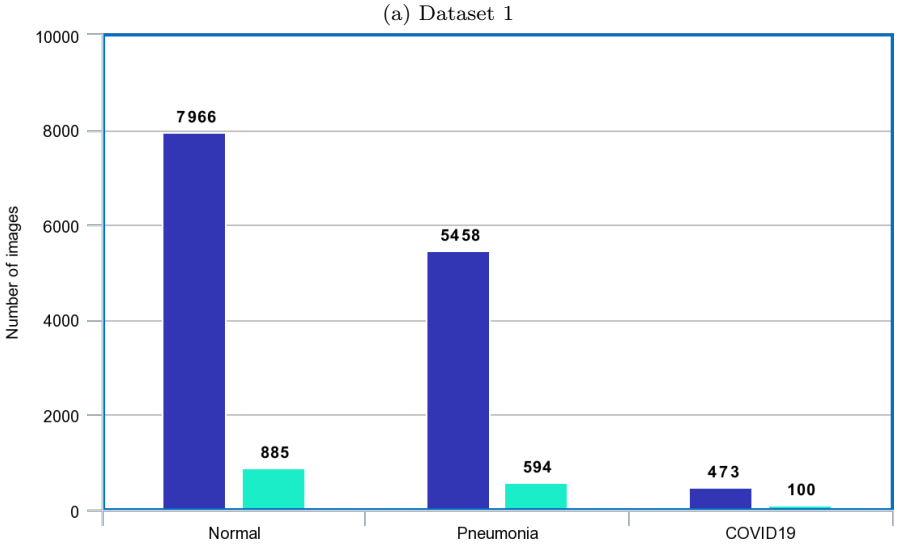
3.2 Deep Learning Architectures

The proposed hybrid model is a combination of ResNet50 and MobileNet, which are explained below in brief.

ResNet50 Proposed by [10], ResNet-50 is a light architecture of a Deep Convolutional Neural Network. It contains 50 layers, which, instead of learning



(a) Dataset 1



(b) Dataset 2

Fig. 2: Train-Test class-wise distribution of the Chest X-ray images.

unreferenced functions, reformulate as learning residual functions with reference to the layer inputs [10]. The ResNet model consists of a stack of comparable or 'residual' blocks. This block acts as a stack of convolutional layers. The output of a block is additionally connected with its own input through an identity mapping path. To preserve the time complexity per layer, the feature mapping is repeatedly down-sampled by strided convolution along with the increase in channel depth [10]. In the ResNet50 model, to allow for a re-

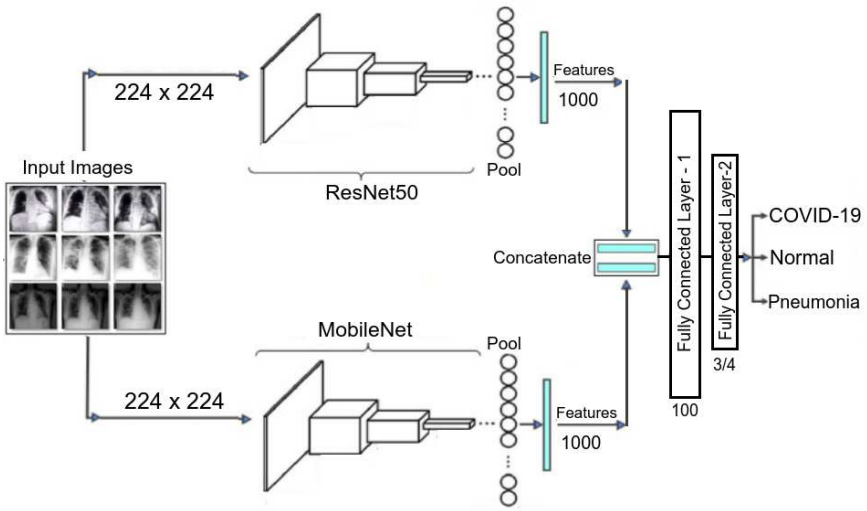


Fig. 3: Architecture of the proposed hybrid model

duced computational load while calculating the $3 * 3$ convolution, we have a 3-layer bottleneck block that uses $3 * 3$ convolutions to lower and consequently reestablish the channel depth.

MobileNet Proposed by [12], MobileNet is a deep learning model that is lightweight in nature. It uses depthwise separable convolutions i.e, it performs a single convolution on each color channel rather than combining all three and flattening it as in standard 2D CNN. This has the effect of filtering the input channels. The model performance increases due to these Depthwise Convolutions, and the input features are divided into two layers. Each layer is partitioned into the following layer by joining it with the output features until the procedure is finished. ReLU activation function is used between layers in MobileNet architecture [12]. Thus, it allows the non-linear outputs from the previous layer to be flattened and fed as input to the subsequent layer.

We believe that our architecture works well as it combines *identity mapping* of ResNet50, diminishing the vanishing gradient problem and boosting the gradient backward flow in the network, and *depthwise separable convolutions* of MobileNets, which increases model performance.

3.3 Implementation Details

Large volumes of data are required to train a neural network from scratch. As a result, due to the scarcity of openly available Chest X-Ray samples (especially of COVID-19), we conduct our experiments using two deep learning models, ResNet50 and MobileNet, pre-trained on the ImageNet [8] dataset. These models are used separately and their individual results are concatenated to produce results. This is followed by two fully connected layers. Our final classification layer consists of 3 classes in the case of Normal, Pneumonia, COVID19 configuration, and 4 classes where Pneumonia is split into Bacterial or Viral. The architecture of the model is detailed in Figure 3. This model is then trained on the COVID-19 dataset. Adam optimizer is used to update the neural network weights. We use early stopping on the lowest validation loss. The hyperparameters for training are: learning rate=1e-3, batch size=32, patience=15. The problem is treated as a Multi-Class Classification problem, where each sample belongs to one of the 3 or 4 classes. We use the categorical cross-entropy loss as given in (1).

$$L(y, \hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij}log(\hat{y}_{ij})) \tag{1}$$

The architecture was built and evaluated using the Keras, a python library for deep learning tasks which uses TensorFlow as a backend.

4 Results

Model	Dataset	Accuracy(%)				
		Fold-1	Fold-2	Fold-3	Fold-4	Fold-5
ResNet50	Dataset1	75.63	78.25	80.31	81.43	81.88
	Dataset2	90.80	92.52	89.70	91.67	90.97
MobileNet	Dataset1	82.50	85.35	81.23	83.08	84.14
	Dataset2	95.28	92.90	93.56	93.89	93.02
ResNet50 + MobileNet	Dataset1	82.86	83.52	85.89	84.73	84.76
	Dataset2	94.80	95.65	93.27	94.78	93.72

Table 2: 5-fold cross validation performances of the proposed model with other Baseline models on dataset 1 and 2.

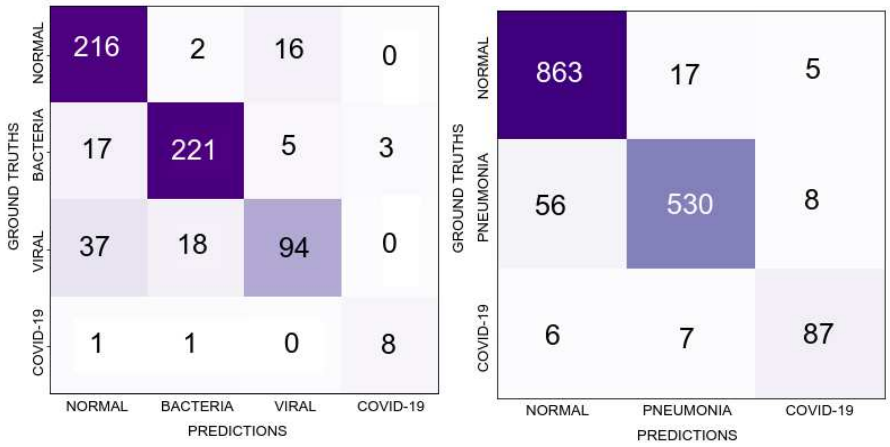
Performance metrics like accuracy and Area under ROC (AUROC) curves are used to carry out an experimental analysis. We have presented the fold-wise accuracy of two baseline models - ResNet50, and MobileNet, and our proposed hybrid model in Table 2. The overall accuracy in Table 3 is calculated as the average of accuracies obtained from each fold. Table 3 also presents the

Model	Dataset	Class	AUROC	Overall Accuracy(%)
ResNet50	Dataset1	Normal	0.96	79.50
		Bacterial Pneumonia	0.94	
		Viral Pneumonia	0.87	
		COVID-19	0.98	
	Dataset2	Normal	0.98	91.13
		Pneumonia	0.97	
		COVID-19	0.96	
MobileNet	Dataset1	Normal	0.97	83.26
		Bacterial Pneumonia	0.95	
		Viral Pneumonia	0.93	
		COVID-19	1.00	
	Dataset2	Normal	0.98	93.73
		Pneumonia	0.98	
		COVID-19	0.99	
ResNet50 + MobileNet	Dataset1	Normal	**0.98**	**84.35**
		Bacterial Pneumonia	**0.97**	
		Viral Pneumonia	**0.95**	
		COVID-19	**1.00**	
	Dataset2	Normal	**0.99**	**94.43**
		Pneumonia	**0.98**	
		COVID-19	**0.99**	

Table 3: Comparison of overall recognition Accuracy(%) and AUROC of the proposed model with other Baseline models on dataset 1 and 2.

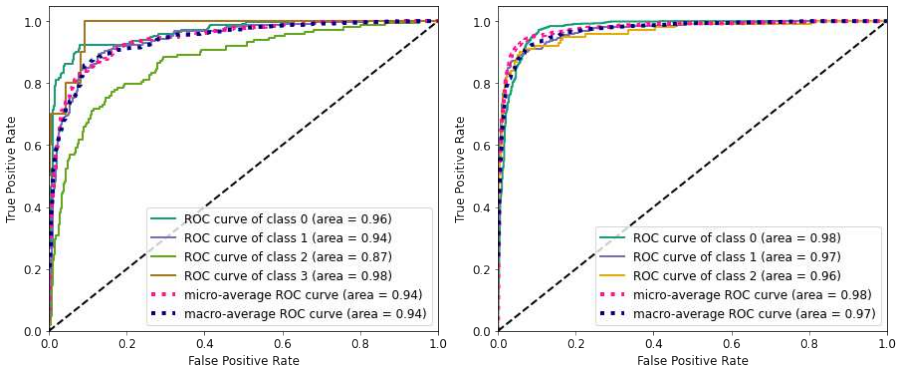
class-wise AUROC of each model. The class-wise ROC curves are presented in Figure 5.

Using the pre-trained ResNet50 model, we obtained an average accuracy of 79.50% and 91.13% on Dataset 1 and 2 respectively. The pre-trained MobileNet model classifies the images with an average accuracy of 83.26% and 93.73% on Dataset 1 and 2 respectively. The best result is obtained by concatenating the



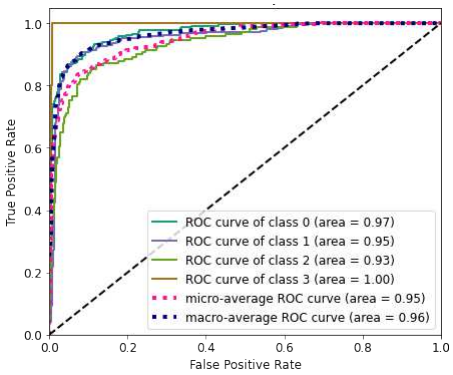
(a) Dataset 1 (b) Dataset 2

Fig. 4: Confusion Matrices of the Hybrid model on Dataset 1 and Dataset 2

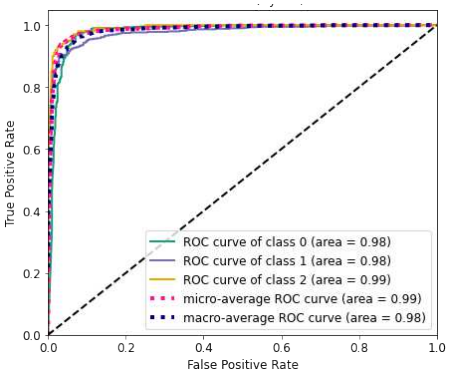


(a) Dataset 1 - ResNet50

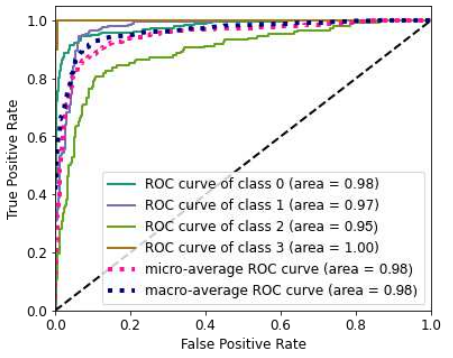
(b) Dataset 2 - ResNet50



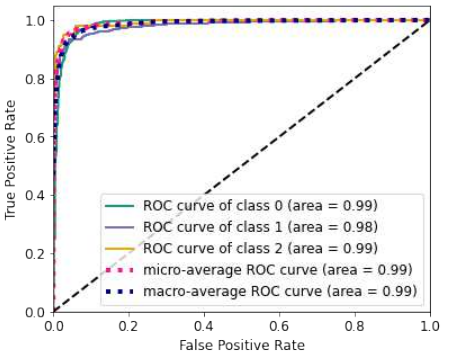
(c) Dataset 1 - MobileNet



(d) Dataset 2 - MobileNet



(e) Dataset 1 - Hybrid Model



(f) Dataset 2 - Hybrid model

Fig. 5: ROC curves obtained from the ResNet50, MobileNet, and Hybrid models. In Dataset1, classes 0, 1, 2, 3 refer to Normal, Bacterial Pneumonia, Viral Pneumonia and COVID-19 respectively; and in Dataset2, classes 0, 1, 2 refer to Normal, Pneumonia and COVID-19 respectively.

individual outputs of ResNet50 and MobileNet, before passing them through the fully connected layer. Using this hybrid approach, we obtain an average accuracy of 84.35% and 94.43% on Dataset 1 and 2 respectively. This architecture leads to the detection of COVID-19 from the radiography images with an AUROC (Area under ROC curve) of 1.00 for the 4-class classification and 0.99 for the 3-class classification. The confusion matrix obtained from the hybrid model, for both the versions of the datasets is shown in Figure 4. In dataset 1, it can be seen that a lot of bacterial and viral pneumonia is misclassified as each other (Figure 4a). This might be due to similar characteristics.

Table 4 shows the difference in the performance of the ResNet50 and MobileNet models, and the ResNet50 + MobileNet hybrid model proposed in this paper by T-test. There were statistically significant differences between both baseline models, and the hybrid model ($p < 0.5$).

Model	Dataset	T-test p value
ResNet50	Dataset1	0.0051
	Dataset2	0.0008
MobileNet	Dataset1	0.2495
	Dataset2	0.2696

Table 4: Comparison of performance baseline models and hybrid model by T-test

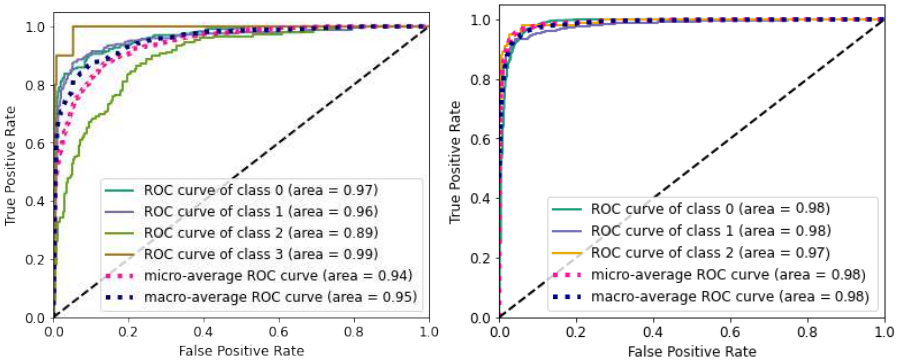
5 Discussion

We compare our model with COVIDAid [17] and Covid-Net [23]. Since we have used the same dataset and data split as the COVID-Net model, we use the values obtained from [23] as it is. In the same way, for COVIDAid, we evaluate their approach on the same data split as ours and obtain the accuracy, ROC curve, and Confusion Matrix. As shown in Table 5, we obtain higher accuracy than the COVID-Net and COVIDAid models on the same data split. It is worth pointing out that lightweight MobileNet slightly outperforms both complex COVID-Net and COVIDAid architectures. The combination of ResNet50 and MobileNet reasonably outperform COVID-Net and COVIDAid architectures. Hence, the hybrid model is more effective in coronavirus detection.

Figure 6a and 6b presents the AUROC obtained from the COVIDAid model. Comparing with the ROC with our proposed hybrid approach in Figure 5e and 5f, in 4 class classification, our model performs comparable to the COVIDAid model in Normal, Bacterial Pneumonia and COVID-19 classes, but performs significantly better in the Viral Pneumonia class. In 3 class classification, our model performs better in the Normal and COVID-19 classes than the COVIDAid model. This hybrid approach clearly establishes a higher baseline for detection of Pneumonia or COVID-19.

Model	Accuracy	
	Dataset1	Dataset2
COVID-Net	83.5	93.3
COVIDAid	82.47	93.41
Our model	**84.35**	**94.43**

Table 5: Comparison of Accuracy(%) of Baseline models.



(a) Dataset 1 - COVIDAid (b) Dataset 2 - COVIDAid

Fig. 6: ROC curves of our model compared to COVIDAid model. In Dataset1, classes 0, 1, 2, 3 refer to Normal, Bacterial Pneumonia, Viral Pneumonia and COVID-19 respectively; and in Dataset2, classes 0, 1, 2 refer to Normal, Pneumonia and COVID-19 respectively.

6 Conclusion

In this paper, ResNet50, MobileNet, and a hybrid approach combining ResNet50 and MobileNet are used for the detection of COVID-19 from chest X-rays. The performance of the proposed model is evaluated on two publicly available datasets. Results show that our approach outperforms competitive COVID-Net and COVIDAid. It indicates that the proposed model has a significant contribution to the detection of COVID-19 infected chest Xrays. Proposed models for COVID-19 detection are light DNN as compared to other DNNs and can be used with low resource devices for quick identification of coronavirus.

Declarations

6.1 Funding

Not applicable

6.2 Conflict of interest

The authors declare that they have no conflict of interest.

6.3 Availability of data and material

The data that support the findings of this study are openly available and details regarding the same are mentioned in section 3.1.

6.4 Code availability

The code that supports the findings of this study is not openly available currently and will be made available after the publication of the work.

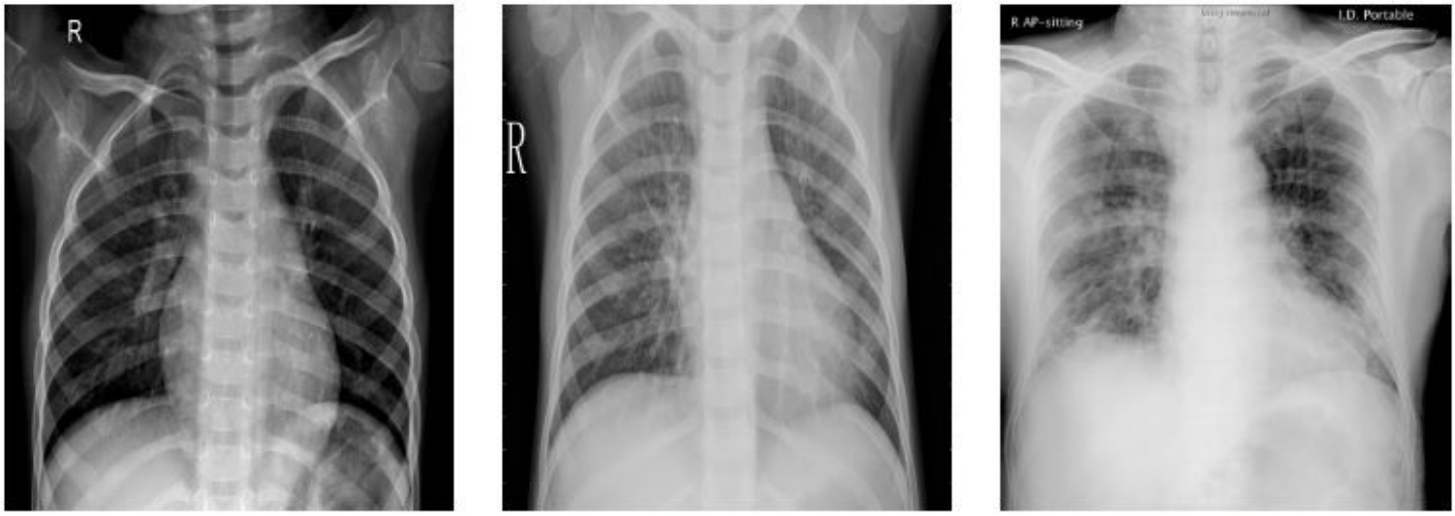
References

1. Rsna pneumonia detection challenge, 2018. URL `https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/data`.
2. Asmaa Abbas, Mohammed M. Abdelsamea, and Mohamed Medhat Gaber. Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network, 2020.
3. Ali Mohammad Alqudah, Shoroq Qazan, Hiam Alquran, Isam Abu Qasmieh, and Amin Alqudah. Covid-2019 detection using x-ray images and artificial intelligence hybrid systems.
4. Muhammad E. H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandaker Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al-Emadi, Mamun Bin Ibne Reaz, and T. I. Islam. Can ai help in screening viral and covid-19 pneumonia?, 2020.
5. Audrey Chung. Figure 1 covid-19 chest x-ray dataset initiative, 2020. URL `https://github.com/agchung/Figure1-COVID-chestxray-dataset`.
6. Audrey Chung. Actualmed covid-19 chest x-ray dataset initiative, 2020. URL `https://github.com/agchung/Actualmed-COVID-chestxray-dataset`.
7. Joseph Paul Cohen, Paul Morrison, and Lan Dao. Covid-19 image data collection. *arXiv 2003.11597*, 2020. URL `https://github.com/ieee8023/covid-chestxray-dataset`.
8. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*, 2009.
9. Biraja Ghoshal and Allan Tucker. Estimating uncertainty and interpretability in deep learning for coronavirus (covid-19) detection. *arXiv preprint arXiv:2003.10769*, 2020.

10. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun 2016. doi: 10.1109/cvpr.2016.90. URL http://dx.doi.org/10.1109/cvpr.2016.90.
11. Ezz El-Din Hemdan, Marwa A Shouman, and Mohamed Esmail Karar. Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images. *arXiv preprint arXiv:2003.11055*, 2020.
12. Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications, 2017.
13. Chaolin Huang, Yeming Wang, Xingwang Li, Lili Ren, Jianping Zhao, Yi Hu, Li Zhang, Guohui Fan, Jiuyang Xu, Xiaoying Gu, Zhenshun Cheng, Ting Yu, Jiaan Xia, Yuan Wei, Wenjuan Wu, Xuelei Xie, Wen Yin, Hui Li, Min Liu, and Bin Cao. Clinical features of patients infected with 2019 novel coronavirus in wuhan, china. *The Lancet*, 395, 01 2020.
14. Chloe Kent. Different paths to the same destination: screening for covid-19, 2020. URL https://www.medicaldevice-network.com/features/types-of-covid-19-test-antibody-pcr-antigen/.
15. Daniel S. Kermany, Kang Zhang, and Michael H. Goldbaum. Labeled optical coherence tomography (oct) and chest x-ray images for classification. 2018.
16. Alexander Selvikvåg Lundervold and Arvid Lundervold. An overview of deep learning in medical imaging focusing on mri. *Zeitschrift für Medizinische Physik*, 29(2):102 – 127, 2019. ISSN 0939-3889. URL http://www.sciencedirect.com/science/article/pii/S0939388918301181. Special Issue: Deep Learning in Medical Physics.
17. Arpan Mangal, Surya Kalia, Harish Rajgopal, Krithika Rangarajan, Vinay Namboodiri, Subhashis Banerjee, and Chetan Arora. Covidaid: Covid-19 detection using chest x-ray, 2020.
18. Ali Narin, Ceren Kaya, and Ziynet Pamuk. Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. *arXiv preprint arXiv:2003.10849*, 2020.
19. Ming-Yen Ng, Elaine YP Lee, Jin Yang, Fangfang Yang, Xia Li, Hongxia Wang, Macy Mei-sze Lui, Christine Shing-Yen Lo, Barry Leung, Pek-Lan Khong, Christopher Kim-Ming Hui, Kwok-yung Yuen, and Michael David Kuo. Imaging profile of the covid-19 infection: Radiologic findings and literature review. *Radiology: Cardiothoracic Imaging*, 2(1):e200034, 2020.
20. Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, and Andrew Y. Ng. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning, 2017.
21. Ekagra Ranjan, Soumava Paul, Siddharth Kapoor, Aupendu Kar, Ramanathan Sethuraman, and Debdoot Sheet. Jointly learning convolutional representations to compress radiological images and classify thoracic diseases in the compressed domain. 12 2018.

22. Fatima M Salman, Samy S Abu-Naser, Eman Alajrami, Bassem S Abu-Nasser, and Belal AM Alashqar. Covid-19 detection using artificial intelligence. 2020.
23. Linda Wang and Alexander Wong. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images, 2020.
24. X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3462–3471, 2017.
25. Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M. Summers. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jul 2017. URL `http://dx.doi.org/10.1109/CVPR.2017.369`.
26. Weng X., Zhuang N., Tian J., and Liu Y. Chexnet for classification and localization of thoracic diseases., 2017. URL `https://github.com/arnoweng/CheXNet/`.
27. Jadhav S.M. Yadav S.S. Deep convolutional neural network based medical image classification for disease diagnosis. *J Big Data 6*, 2019. URL `https://doi.org/10.1186/s40537-019-0276-2`.
28. Li Yao, Eric Poblenz, Dmitry Dagunts, Ben Covington, Devon Bernard, and Kevin Lyman. Learning to diagnose from scratch by exploiting dependencies among labels, 2017.

Figures



(a) Normal (b) Pneumonia (c) COVID-19

Figure 1

Examples of Normal, Pneumonia infected and COVID-19 infected chest X-Ray images.

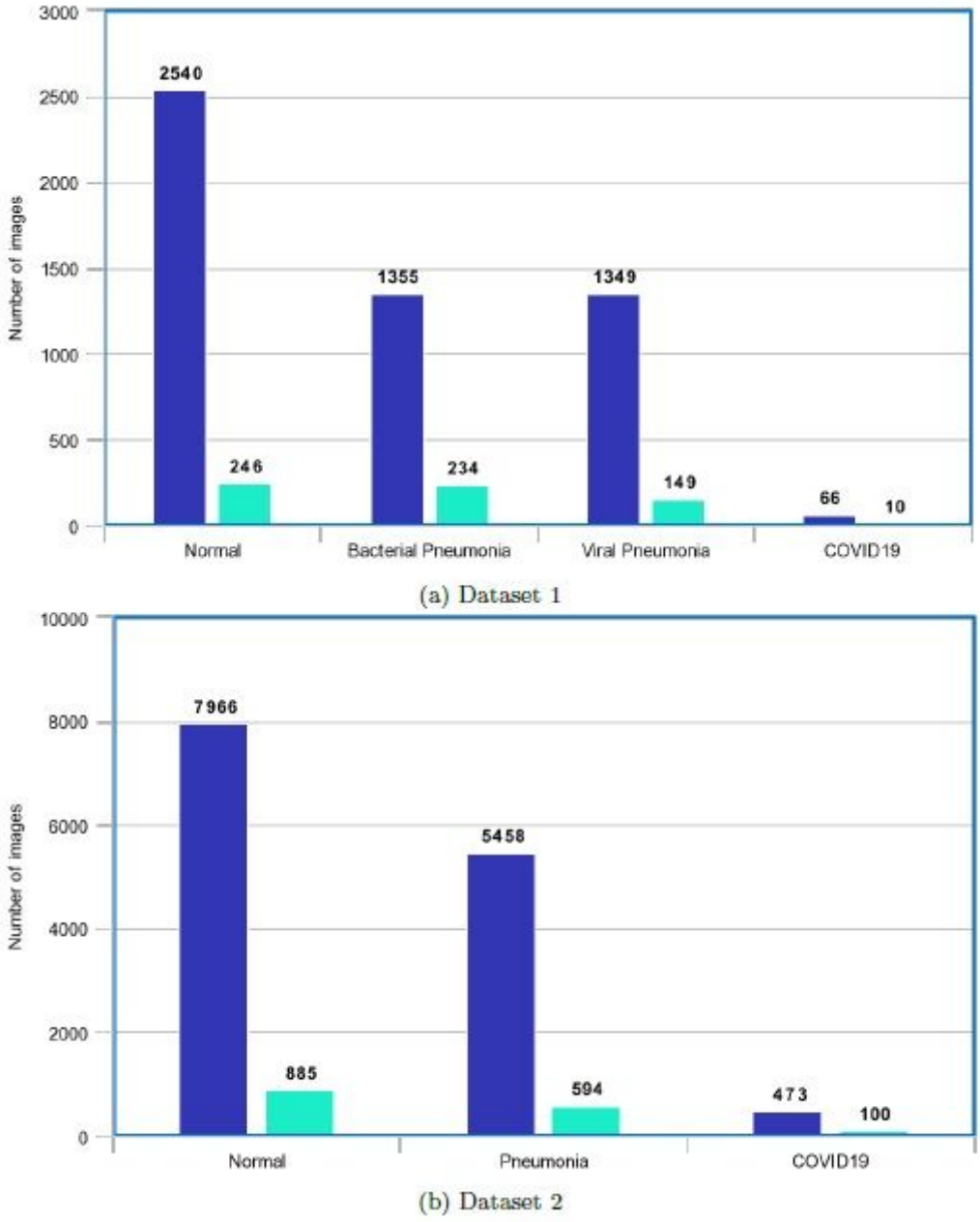


Figure 2

Train-Test class-wise distribution of the Chest X-ray images.

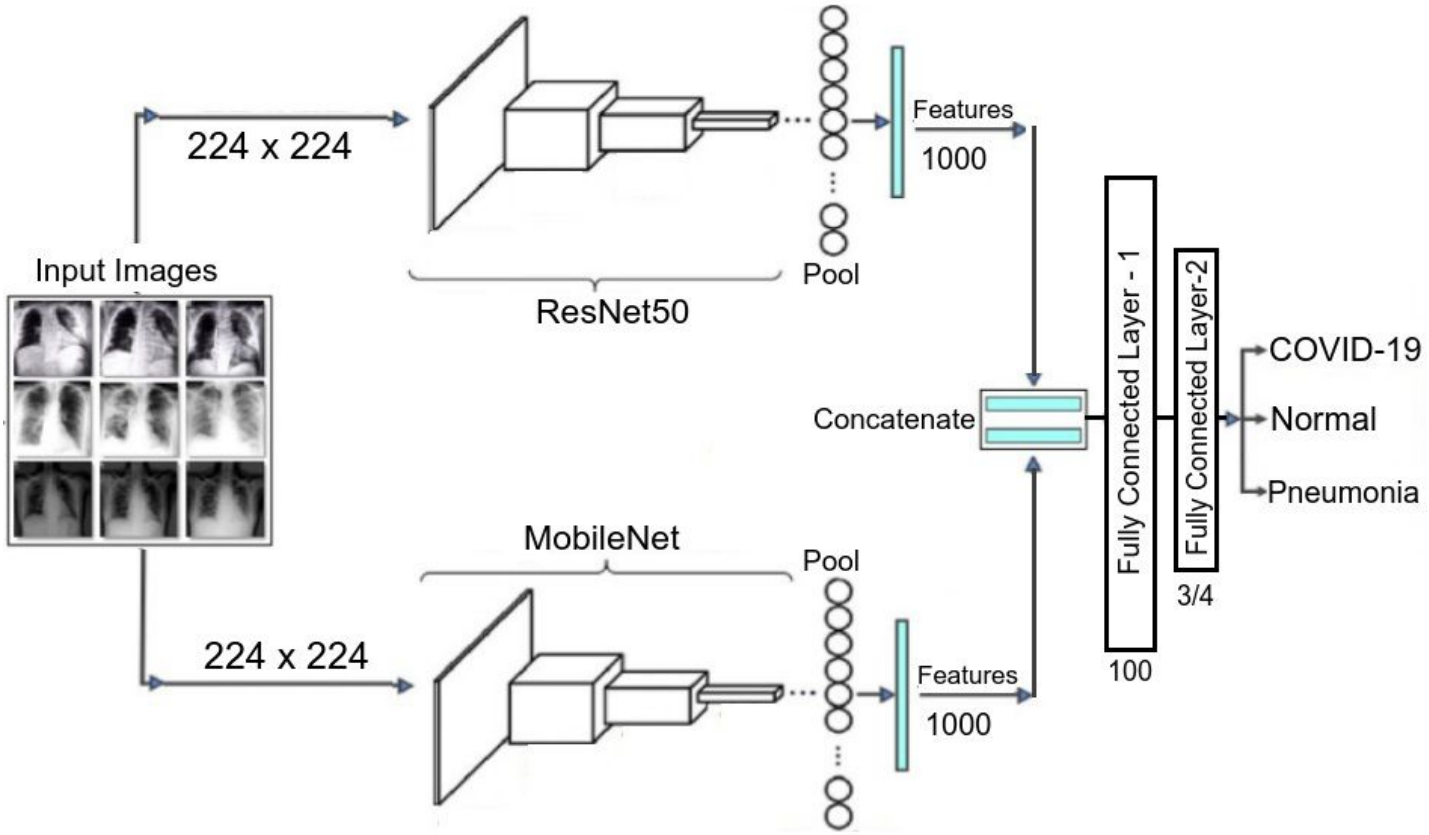


Figure 3

Architecture of the proposed hybrid model

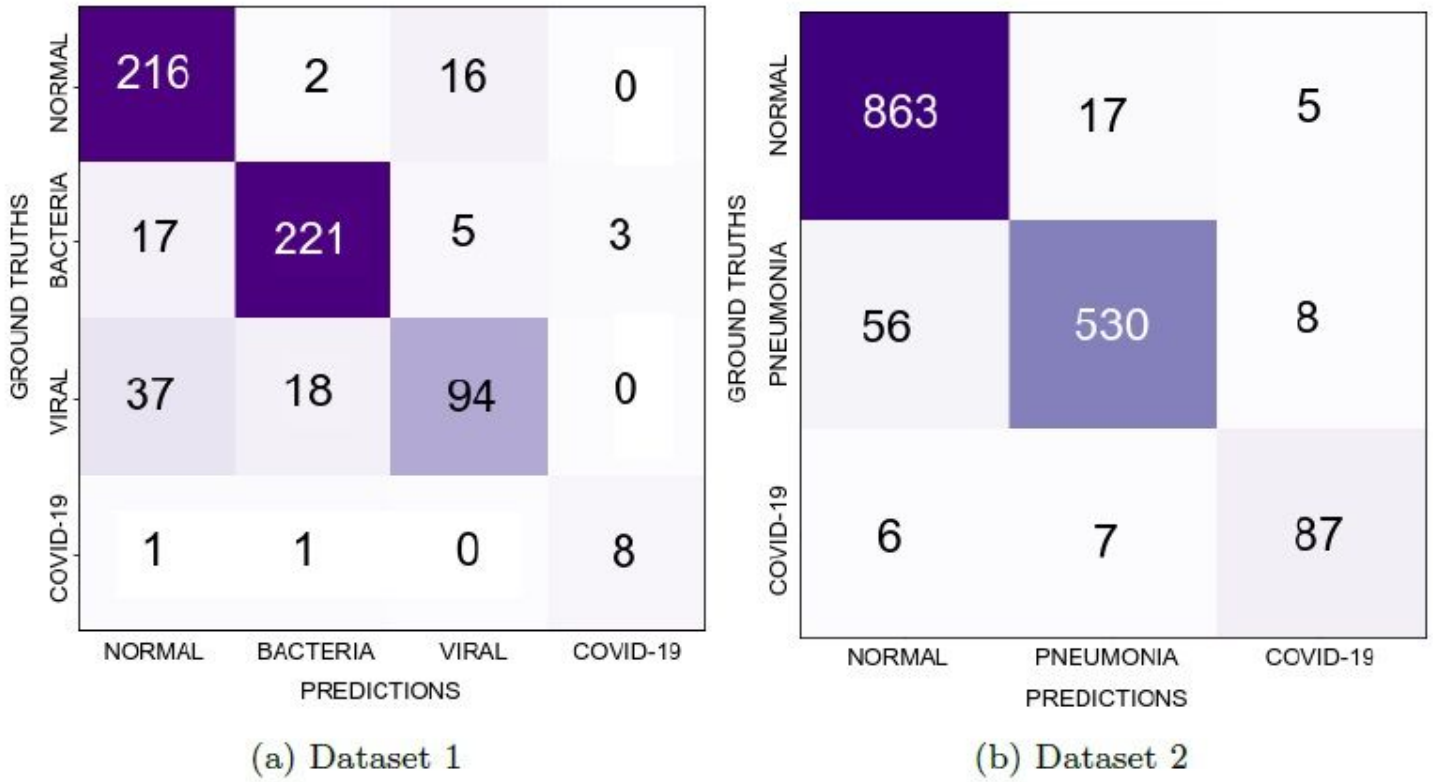


Figure 4

Confusion Matrices of the Hybrid model on Dataset 1 and Dataset 2

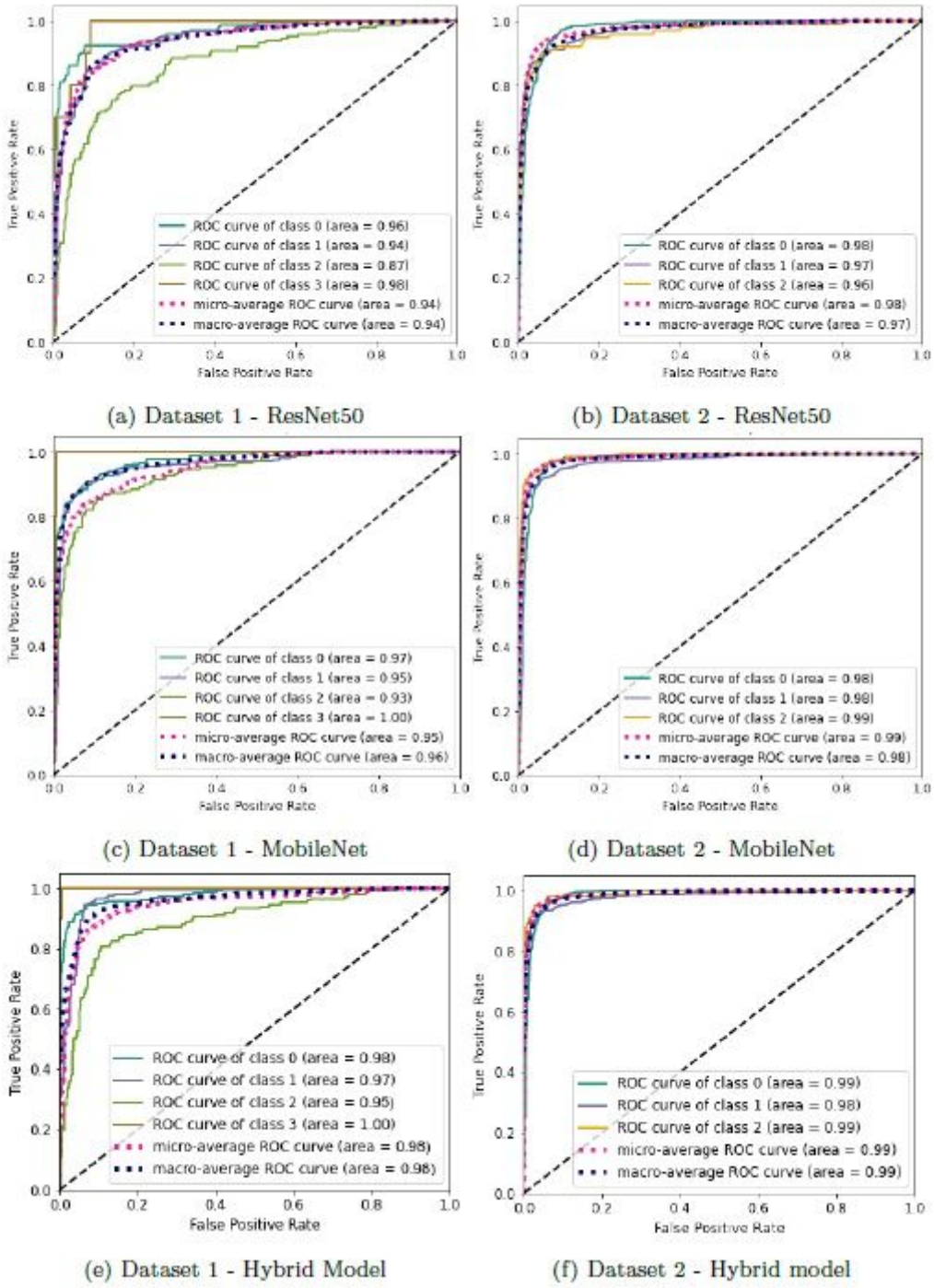
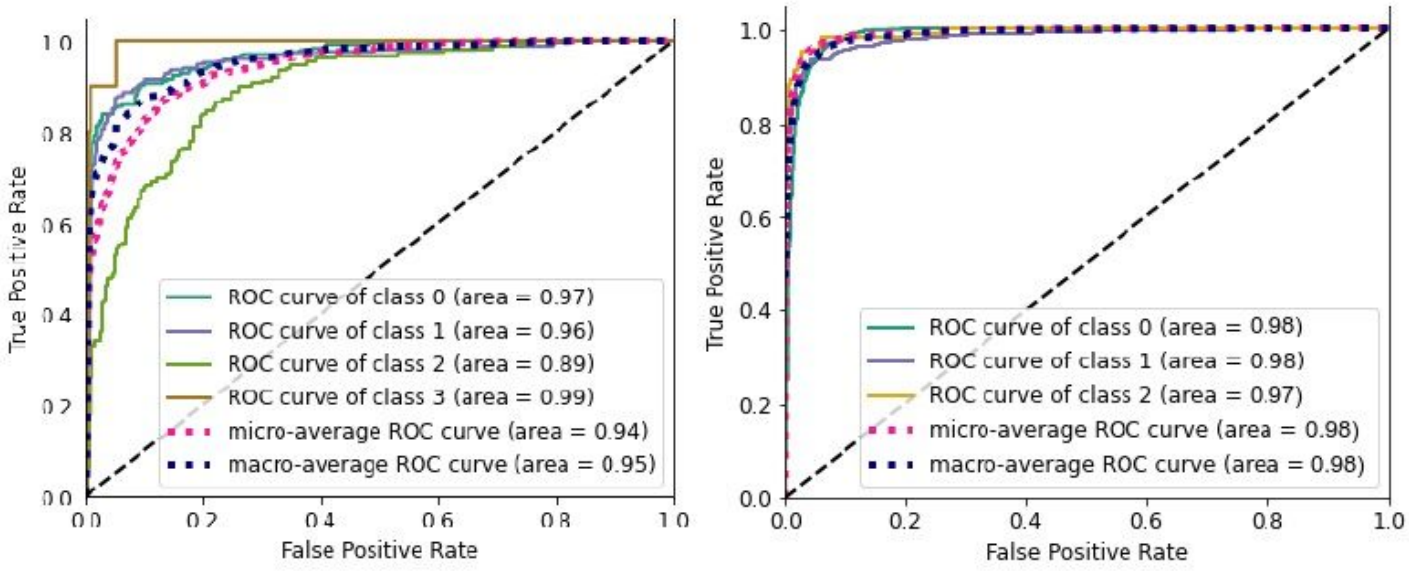


Figure 5

ROC curves obtained from the ResNet50, MobileNet, and Hybrid models. In Dataset1, classes 0, 1, 2, 3 refer to Normal, Bacterial Pneumonia, Viral Pneumonia and COVID-19 respectively; and in Dataset2, classes 0, 1, 2 refer to Normal, Pneumonia and COVID-19 respectively.



(a) Dataset 1 - COVIDAid (b) Dataset 2 - COVIDAid

Figure 6

ROC curves of our model compared to COVIDAid model. In Dataset1, classes 0, 1, 2, 3 refer to Normal, Bacterial Pneumonia, Viral Pneumonia and COVID-19 respectively; and in Dataset2, classes 0, 1, 2 refer to Normal, Pneumonia and COVID-19 respectively.