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Classification of COVID 19, Pneumonia and healthy lung on CXR images using Deep Transfer Learning Ensemble Framework with GRAD-CAM visualization

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Abstract:

COVID-19 and pneumonia both affect the human respiratory system and can cause symptoms ranging from mild respiratory issues to severe conditions. Radiological imaging techniques such as X-ray is really effective to diagnose these diseases.Though these patterns can overlap, on a chest X-ray, pneumonia typically shows localized consolidation in specific lung areas, while COVID-19 often presents with bilateral ground-glass opacities and patchy infiltrates in both lungs. Several deep learning techniques showed successful and effective results classifying medical images. In this paper, we worked with a customized dataset which contains 21,000 labeled chest X-ray images, including 7,000 images each for pneumonia, COVID-19, and normal cases. Several pre-trained networks have been used to develop the classification of the images. ViT outperformed most state-of-the-art models with a validation accuracy of 97%. We used Gradient-weighted Class Activation Mapping (Grad-CAM) to generate heat maps that show the regions of the X-ray image the model considers important for its prediction. This approach is reliable and robust for classifying these thoracic diseases from chest X-ray images. **Ensemble**

1. Introduction:

Pneumonia is a lung infection that can be serious and sometimes can be potentially life-threatening conditions specially for young children. For the elderly, and individuals with weakened immune systems. The risks associated with pneumonia include severe respiratory distress, complications like pleural effusion or sepsis, and, in some cases, long-term damage to the lungs.The mortality rate for pneumonia varies widely based on factors such as the patient's age, overall health, the type of pneumonia, and the quality and timeliness of medical care.Globally, pneumonia remains a leading cause of death in children under 5 years old, particularly in low-income countries.

COVID-19, caused by the SARS-CoV-2 virus, primarily affects the lungs, leading to inflammation, fluid buildup, and lung tissue damage. The term "corona" refers to a group of viruses that can cause severe respiratory illnesses in humans, although many are not highly dangerous. However, SARS-CoV-2, a new strain of the coronavirus, poses a serious threat to global health and has resulted in significant loss of life. First identified in Wuhan, China, in 2019, COVID-19 had infected over 507 million people worldwide by April 2022, with a death toll surpassing 6 million. Countries like the United States, India, Brazil, and several European nations have been hit hard, due to factors like healthcare systems, public health measures, population density, and the emergence of more contagious variants. These factors have contributed to the rapid spread of the virus, making COVID-19 one of the leading causes of death in many countries, including the United States, Spain, Italy, China, the United Kingdom, and Iran [1].

Pneumonia, which can be caused by bacteria, viruses, or fungi, also leads to inflammation and fluid accumulation in the lungs' air sacs. In both conditions, the inflammation and fluid interfere with normal breathing and oxygen exchange, leading to respiratory symptoms like coughing, shortness of breath, and chest pain. However, in the early stages of COVID-19, symptoms usually include fever, cough, fatigue, headache, muscle or joint pain. However, in severe cases, symptoms can intensify, leading to severe shortness of breath, persistent chest pain or pressure, and critically low oxygen levels. These severe cases may also involve respiratory distress, pneumonia, or acute respiratory distress syndrome (ARDS), depending on factors like age, general health, and the promptness of medical care.

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Ground-glass opacities (GGO) are common in COVID-19 but less frequent in regular pneumonia. In COVID-19, these spots usually appear on both sides of the lungs and near the edges, while in pneumonia, they are often found in one specific area or lobe of the lung. Another difference is that pneumonia tends to show thicker, more solid lung areas, while COVID-19 has a more scattered and spread-out appearance.

PCR testing for COVID-19 identifies the virus's genetic material from a sample, usually collected via a nasal or throat swab, by replicating the virus's RNA and transforming it into DNA. However, the process can be time-consuming, and some studies have shown a sensitivity of around 90.7% [2]. Detecting lung infection through X-ray images involves identifying specific patterns in the lungs that are indicative of the disease. Deep learning models help detect pneumonia and COVID-19 from chest X-rays by learning to recognize patterns specific to each condition. They are trained on labeled images, extract key features, and classify new X-rays as normal, pneumonia, or COVID-19. Radiologists and AI-based tools can assist in diagnosing these conditions faster from chest X-rays.

2. Related study:

In the paper [3] Gayathri J.L et. al. worked with chest x-ray images to detect COVID-19 with various pre-trained architectures for classification and they also used sparse encoder for feature selection, where the concatenation of InceptionResnetV2 and Xception provides the best performance with an accuracy of 0.9578 and an AUC of 0.9821. But due to insufficient number of images this can easily fall into overfittin, also they didn’t explore multi-class classification.

Linh T. Duong et. al. [4] experimented with both chest x-ray and lung CT images to classify COVID-19 and Pneumonia images.Differnt versions of Efficient and MixNet were used but EfficientNet-B0 (Acc. 96.64%) and EfficientNet-B3 (Acc. 95.82%) for two different X-ray datasets.

Gaffari Celik examined on several transfer learning models by keeping certain parameters constant on the same dataset [5] where the proposed model with combination of CovidDWNet+GB(Gradient Boosting) achieved 96.81% accuracy on chest X-ray images.

In study experimented by Xingsi Xue et. al. [6] investigates various deep learning techniques, including ResNet152, VGG16, ResNet50, and DenseNet121, for detecting COVID-19 and pneumonia in medical CT and radiography images. An enhanced VGG16 has achieved 99% accuracy and average F1-score 95%, to recognize three types of radiographic images.

Deepak Kumar Jain [7] et al. performed an experiment to classify regular, pneumonia, and normal X-ray images using Xception, Visual Geometry Group (16 & 19) with an accuracy of 98% which achieved by Xception model.

3. Methodology:

3.1 : Dataset and Experiment

3.1.1 : Dataset Compilation

Initially, the pandemic's sporadic nature resulted in the severely infected countries making only limited efforts to share clinical and radiography data publicly. Therefore, a database of chest X-ray images for COVID-19 positive cases, as well as Normal and Viral Pneumonia images, has been created by a team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh, in collaboration with medical doctors and collaborators from Pakistan and Malaysia[3.1, 3.2]. The database contains 3616 COVID-19 positive cases, 10,192 normal cases, 6012 lung opacity (Non-COVID lung infection), and 1345 viral pneumonia images and corresponding lung masks. X-rays have gradually become more accessible to the public. Like the **Chest X-ray (Covid-19 & Pneumonia)** dataset [3.3], it is divided into two folders (train, test), each of which contains three subfolders (COVID19, PNEUMONIA, NORMAL). The test data comprises 20% of the total 6432 x-ray images in the dataset. **COVID-19+PNEUMONIA+NORMAL**[3.5, 3.6]and **15K Chest X-Ray Images (COVID-19)** dataset [3.4] The Chest X-Ray Image dataset is a medical images directory structure that is divided into three subfolders (COVID, NORMAL, PNEUMONIA). This dataset contains 1626 COVID, 1802 NORMAL, and 1800 PNEUMONIA Chest X-ray (CXR) Images. Therefore, we modified those datasets to create COVID-PNEUMOINA-MRI-21k chest X-ray [3.7], which comprises more than 21,000 CXR images from three distinct classes:

1) 7,000 cases of COVID-19
2) 7,000 cases of non-COVID infections
3) 7,000 cases of normal (healthy) health

The dataset was generated by combining a multitude of publicly accessible datasets and repositories, each of which is dispersed and has a different format. A stringent quality control procedure guaranteed the dataset's quality by identifying and eliminating duplicates, images of extremely low quality, and overexposed images.

Input images (COVID_Pneumonia_Healthy)

Details of different data sources are given below:

COVID-19 Radiography Database [3.1, 3.2]: The COVID-19, normal, and other lung infection dataset have been released in stages. We have released 219 COVID-19, 1341 normal, and 1345 viral pneumonia chest X-ray (CXR) images in the initial release. In the initial update, the COVID-19 class has been expanded to include 1200 CXR images. The second update expanded the database to include

3616 COVID-19 positive cases, 10,192 normal cases, 6012 lung opacity (Non-COVID lung infection), and 1345 viral pneumonia images and corresponding lung masks.

Chest X-ray (Pneumonia & COVID-19): The dataset is divided into three folders (train, test, value) and includes subfolders for each image category (Pneumonia/Normal). There are 5,863 X-ray images (JPEG) and two categories (Normal/Pneumonia).

X-ray images of the chest (anterior-posterior) were selected from retrospective cohorts of pediatric patients aged one to five years at the Guangzhou Women and Children's Medical Center in Guangzhou. Chest X-ray imaging was conducted as part of the standard clinical treatment of all patients.

Initially, all chest radiographs were screened for quality control by removing any scans that were illegible or of low quality in order to analyze chest X-ray images. Two expert physicians subsequently evaluated the diagnoses for the images before being approved for AI system training. Additionally, a third expert reviewed the evaluation set to account for any grading errors.

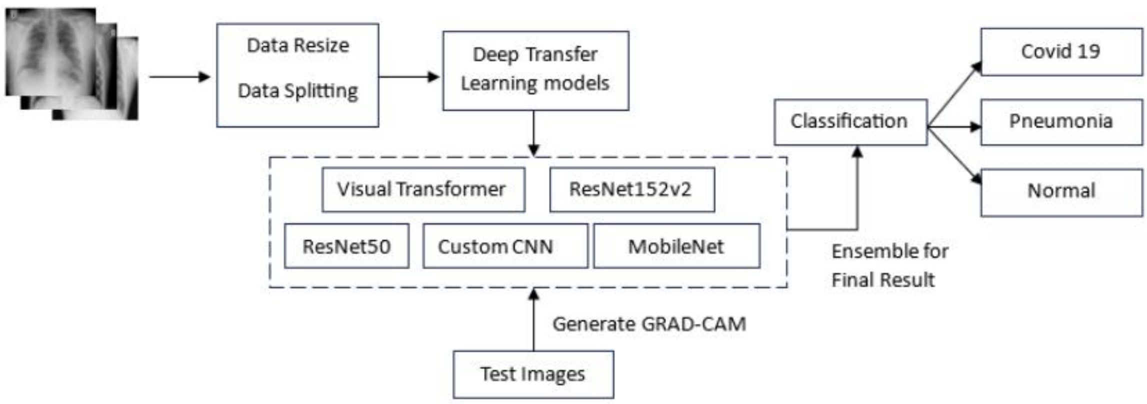
COVID-19+PNEUMONIA+NORMAL: The COVID-19+PNEUMONIA+NORMAL dataset is a medical image directory structure divided into three subfolders (COVID, NORMAL, and PNEUMONIA). It contains chest X-ray (CXR) images.

COVID-19: 1626 images
COMMON: 1802 images
1800 images of PNEUMONIA

Database	Types	Count of CXR's/ Class	Training Dataset		
			Training Image	Validation Image	Test Image
Our Custom Dataset	Covid-19	7000	4900	1050	1050
	Pneumonia	7000	4900	1050	1050
	Normal	7000	4900	1050	1050
COVID19+PNEUMONIA+NORMAL [3.5, 3.6]	Covid-19	1626	1138	244	244
	Pneumonia	1800	1249	271	270
	Normal	1802	1261	271	270

3.2 : Training Models

3.2.1 : Deep Transfer Learning Models
3.2.2 : ViT



About Hyperparmeter + GRADCAM

3.3 : Experimental Setup :

The hardware for this experiment comprises 8GB Nvidia GEFORCE RTX 4060 and 16 GB RAM. We built the pre-trained networks using NumPy, the TensorFlow framework, Sklearn, the Matplotlib graph charting tool, the Seaborn data visualization tool, Python 3.10 with the TensorFlow framework.

3.4 : Performance Evaluation matrix: Theory +Formula

4. Result and Discussion:

GRAD-CAM result figures:

Ensemble (Except ViT)

Model	Types	Dataset 1				Dataset 2			
		Precision	Recall	F1 - Score	Accuracy	Precision	Recall	F1 - Score	Accuracy
Mobile Net	Covid-19	0.99	0.99	0.99	0.9914	1.00	0.99	1.00	0.9758
	Pneumonia	0.99	1.00	1.00		0.99	0.94	0.97	
	Normal	0.99	0.98	0.99		0.94	1.00	0.97	
ResNet 50	Covid-19	0.98	0.99	0.99	0.9883	1.00	1.00	1.00	0.9860

	Pneumonia	0.99	1.00	0.99		0.98	0.98	0.98	
	Normal	0.99	0.98	0.98		0.98	0.98	0.98	
ResNet 152	Covid-19	0.99	0.98	0.98	0.9876	1.00	1.00	1.00	0.9783
	Pneumonia	1.00	1.00	1.00		0.97	0.97	0.97	
	Normal	0.98	0.98	0.98		0.97	0.97	0.97	
Custom CNN	Covid-19	0.95	0.96	0.96	0.9638				
	Pneumonia	0.99	0.99	0.99					
	Normal	0.95	0.95	0.95					
Ensemble (Except ViT)	Covid-19	0.9943	0.9952	0.9948	0.9956				
	Pneumonia	0.9981	0.9990	0.9986					
	Normal	0.9943	0.9924	0.9933					
Visual Transform (ViT)	Covid-19	0.94	0.95	0.94	0.9524				
	Pneumonia	0.98	0.99	0.98					
	Normal	0.94	0.92	0.93					

Heatmap (Ensemble +Best Model) figures

ROC curve (MobileNet +Ensemble) graphs

Comparison table

5. Conclusion

Early detection is helpful to prevent spread. Automatic and AI based and real-time detection is getting popular but the main limitation is the limited number of CXR images.

Data Availability:

This Pneumonia_Covid_21k chest X-ray images created during the current study is available in the following kaggle repository: https://www.kaggle.com/datasets/asadujjaman/covid-pneumoina-mri-21k-chest-x-ray

Reference:

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[3.5] S. Shastri, I. Kansal, S. Kumar, K. Singh, R. Popli, and V. Mansotra, "CheXImageNet: a novel architecture for accurate classification of Covid-19 with chest x-ray digital images using deep convolutional neural networks," *Health Technol. (Berl.)*, vol. 12, no. 1, pp. 193–204, 2022.

[3.6] S. Kumar *et al.*, “LiteCovidNet: A lightweight deep neural network model for detection of COVID-19 using X-ray images,” *Int. J. Imaging Syst. Technol.*, vol. 32, no. 5, pp. 1464–1480, 2022.

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