

COVID-19 Radiography Classification and Segmentation Using Deep Learning

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Introduction

Background

Since 2019, COVID-19 has been raging across the globe, and as a novel pneumonia, it has brought a tremendous disaster to humanity. In the battle against this virus, X-ray technology has played a crucial role. Compared to nucleic acid testing, X-rays can scan human lungs more quickly, especially for severe COVID-19 patients, whose X-ray images exhibit more typical features, helping doctors intuitively assess the progression and changes in the condition. However, despite the passage of time, COVID-19 continues to mutate, with new variants emerging and causing significant impacts in many countries, such as Japan, which is still deeply affected. In this context, the application of deep learning in X-ray image analysis has become particularly important, as it can significantly improve the efficiency and accuracy of image recognition, providing strong support for medical diagnosis.

In recent years, deep learning has made remarkable progress in the field of medical image analysis. For example, Wang et al. [5] proposed a convolutional neural network (CNN)-based method for X-ray image classification, which can efficiently distinguish pneumonia from normal lung images with an accuracy of over 92%. Additionally, Rahman et al. [6] demonstrated the superior performance of DenseNet and ResNet in COVID-19 detection tasks by comparing various deep learning models. Their research showed that deep learning can not only handle large-scale medical image data but also excel in multi-class classification tasks. Fang and Gong [7] further proposed a dual-ended multiple attention learning model (DMAL), which significantly enhanced the model's ability to analyze complex X-ray images by combining global and local features. These studies have laid a solid foundation for the application of deep learning in medical imaging.

Therefore, given the immense potential of deep learning in X-ray image analysis, we have decided to focus on this area as our research direction, aiming to develop an efficient and accurate COVID-19 X-ray classification model to provide a more reliable tool for medical diagnosis.

Problem Statement

Despite the advancements in deep learning, challenges remain in developing robust models for multi-class classification of chest X-rays. These challenges include class imbalance, overfitting due to limited data, and the need for models that can generalize well across diverse datasets.

This project aims to address these challenges by developing and evaluating deep learning models for the classification of chest X-rays into four categories: COVID-19, Normal, Lung Opacity, and Viral Pneumonia.

The second goal is to compare and analyze the performance of all the models we are going to use, find the pros and cons for those methods on the dataset.

Literature review

With the development of AI and machine learning, there are many works and models have been developed to solve this problem. There are many pre-trained models for people to use to detect COVID-19 and other lung diseases based on different medical image modalities. Thus, this project will be carried out in a more mature environment based on the works in the past.

In the traditional CNN architecture, some pre-trained models like VGG series, perform well on COVID-19 binary classification tasks. However, the overfitting risk may be caused by the complexity of the model in the four classification tasks. Enas M. F. El Houby [2] proposed a framework for chest X-ray image classification tasks based on deep learning to help in early diagnosis of COVID-19. This framework contains two phases, preprocessing phase and classification phase. For the preprocessing phase, it applied some image enhancement techniques to improve the pre-trained CNN models on classification phase. By looking at the results, this framework has achieved an excellent performance. An interesting point is that the dataset used in this research is the same one we will use.

Thanks to Sejuti Rahman and researchers with him [3], they compared and benchmarked 315 deep models in diagnosing COVID-19, normal, and pneumonia from X-ray images of a custom dataset created from four others. Their paper provides a comprehensive guideline for researchers in this field. It provides complete background knowledge and research ideas for researchers who are new to this field. Their results show that the best model is the combination of DenseNet201 and Quadratic SVM classifier. Therefore, the potential of model fusion is also verified.

Although most CNN models' accuracies are higher than 95%, there are still some weaknesses with these models. Yongxian Fang and Hao Gong found that these models only perform well on small datasets, and these models can only handle binary classification tasks and have high intractability on multi-classification tasks [4]. Thus, they propose the dual-ended multiple attention learning model (DMAL). In short, this model has two networks, one for capturing the global features and the other one captures the local features. Then, an integrated module will combine the information in these two networks and tell the model to focus on the information that is not easy to capture by CNN models.

materials and method

Dataset Overview

The COVID-19 Radiography Database [1], sourced from Kaggle, comprises 21,165 chest X-ray images categorized into four classes:

- **COVID-19:** 3,616 images
- **Normal:** 10,192 images
- **Lung Opacity:** 6,012 images
- **Viral Pneumonia:** 1,345 images

Additionally, the dataset includes segmentation masks for lung regions, which may be used for further analysis. The dataset's diversity and size make it suitable for training and evaluating deep learning models.

Methodology

1. Data Preprocessing

- All images are in Portable Network Graphics (PNG) format with a resolution of 299x299 pixels.
- Pixel values are normalized to facilitate model training.
- Techniques such as data augmentation and resampling are employed to address class imbalance.

2. Classification Models

- A basic CNN is implemented as a baseline for comparison.
- Advanced models, including pre-trained architectures (e.g., VGG, DenseNet) and model fusion techniques, are explored.
- Methods such as cross-validation and resampling are used to mitigate overfitting and improve generalization.

3. Evaluation Metrics

- Model performance is assessed using metrics such as accuracy, F1-score, precision, and confusion matrices.
- The robustness of the classifier is evaluated on both balanced and unbalanced test data.

Reference

[1] Rahman, T. (2020). *COVID-19 Radiography Database* [Data set]. Kaggle.
<https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database/data>

- [2] El Houby, E.M.F. COVID-19 detection from chest X-ray images using transfer learning. *Sci Rep* 14, 11639 (2024). <https://doi.org/10.1038/s41598-024-61693-0>
- [3] Rahman, S., Sarker, S., Miraj, M.A.A. *et al.* Deep Learning–Driven Automated Detection of COVID-19 from Radiography Images: a Comparative Analysis. *Cogn Comput* 16, 1735–1764 (2024). <https://doi.org/10.1007/s12559-020-09779-5>
- [4] Y. Fan and H. Gong, "An Improved COVID-19 Classification Model on Chest Radiography by Dual-Ended Multiple Attention Learning," in *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 1, pp. 145-156, Jan. 2024, doi: 10.1109/JBHI.2023.3324333.
- [5] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. (2017). ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2097-2106.
- [6] Rahman, T., Khandakar, A., Qiblawey, Y., Tahir, A., Kiranyaz, S., Abul Kashem, S. B., ... & Chowdhury, M. E. (2021). Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-ray Images. *Computers in Biology and Medicine*, 132, 104319.
- [7] Fang, Y., & Gong, H. (2024). An Improved COVID-19 Classification Model on Chest Radiography by Dual-Ended Multiple Attention Learning. *IEEE Journal of Biomedical and Health Informatics*, 28(1), 145-156.