Classification of Chest X-Rays: Project Report

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Abstract

Accurate interpretation of diagnostic imaging plays a crucial role in medical data science. This project focuses on the classification of respiratory conditions using chest X-Ray images, employing machine learning techniques. The dataset comprises moderate-resolution chest X-Ray images, presenting a five-class classification problem including Pneumonia, Tuberculosis, Lung Opacity, and Normal lungs. Through experimentation and preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), our research demonstrates the effectiveness of fine tuning pretrained models (resnet18, resnet50), for diagnosing respiratory illnesses accurately and efficiently at a accuracy of up to 95.5% on the test data. The project scope includes the integration of AI explainability tools, providing valuable insights into the model's decision-making process. Our findings contribute to advancing the understanding and application of machine learning in medical imaging, with implications for improving patient care and clinical decision-making.

1 Introduction

The field of medical data science is constantly advancing, and accurate interpretation of diagnostic imaging, such as chest X-Rays, is crucial. Chest X-Rays are commonly used to assess the condition of the lungs, heart, and chest wall. It not only takes pressure off healthcare professionals but also streamlines processes in medical settings, resulting in better patient outcomes (Satia et al., 2013). The focus of this study lies on a dataset featuring moderate-resolution chest X-Ray images, which presents a five-class classification problem. The categories include Pneumonia, Tuberculosis, Lung Opacity and Normal lungs, representing the some of the most prevalent respiratory infections encountered in clinical practice (Basu et al., 2021; Abdel-Aal et al., 2022). By applying machine learning techniques to medical imaging data, we aim to gain insights and practical experience that will contribute to our understanding of the application of machine learning in medical imaging. In detail, this report documents the methodology employed, the challenges faced throughout the process, the results attained, and the implications of these findings. Our project not only enhances our comprehension of machine learning's application in medical imaging but also offers insights that can benefit future endeavors in this domain.

2 Methodology

2.1 Conversion of NPZ files to PNG

The initial dataset consists of labeled chest X-Ray images. The images are stored in NumPy Zip (NPZ) format, which is not the most convenient for image processing tasks. Loading NPZ files into memory can be resource-intensive and potentially cause memory exhaustion (Pescador, 2024). Therefore, we opted to convert these NPZ files to the more commonly used PNG format. These allow us to load them lazily, which means the images are only loaded into memory as neeeded (Nanwani, 2021).

2.2 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is an image enhancement technique that has been widely used in various applications, including medical imaging, remote sensing, and computer vision. CLAHE operates on small regions in the image, called tiles, rather than the entire image. For each tile, it computes a histogram and redistributes the pixel intensities to enhance the contrast. To prevent amplifying the noise in homogeneous regions, CLAHE applies a contrast limiting step, where the histogram is clipped at a predefined threshold. CLAHE was chosen as the image enhancement technique for this project due to its ability to effectively improve the local contrast of images while avoiding the common pitfalls of global histogram equalization methods (Hana and Maulida, 2021). Global histogram equalization techniques can often result in over-enhancement, leading to unnatural-looking images with excessive contrast which can hinder the accuracy of classifiers. CLAHE addresses this issue by operating on small, localized regions of the image, rather than the entire image at once. This allows for more targeted contrast enhancement, preserving important details and structures (Hana and Maulida, 2021). Overall, the localized contrast enhancement, noise suppression, and adaptability of CLAHE make it a well-suited technique for improving the visual quality and interpretability of the images in this research.

2.3 Data Loading

When dealing with large datasets, it is important to have an organized approach to data loading (Suthakar et al., 2016). To accomplish this, a custom Data Loader was written to coherently load datasets and manage them. This enabled efficient batch processing during model training, with the added benefit of optimized memory usage and resource distribution for optimal model training performance.

2.4 Data Augmentation and Normalization

Data augmentation acts as a basic technique in machine learning, particularly in scenarios where the availability of training data is limited or when improving the efficiency and generalization capability of the model is required (Shorten and Khoshgoftaar, 2019). In our dataset, we employed rotation and flipping operations to introduce variability to the input data without compromising the integrity of the images. However, we refrained from using cropping as it could lead to the loss of vital diagnostic information.

On the other hand normalization aims to standardize the scale of input data to a consistent range

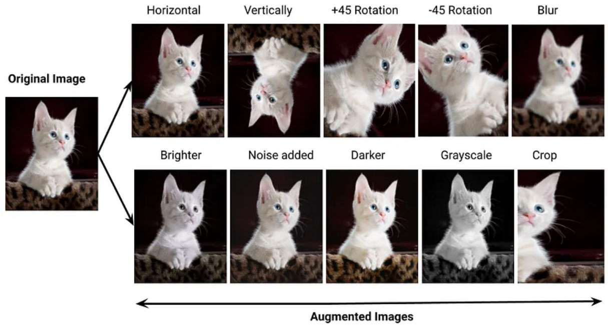


Figure 1: Data Augmentation shown on a sample image (Ostwal, 2023)

(Google for Developers, 2024). In our dataset, we adjust the pixel values of the images and the standard deviation. By introducing variations through rotation, flipping and normalization, we provided the model with a diverse training dataset, enabling it to better generalize and diagnose lung conditions from chest X-Ray images.

2.5 Model Definition

The model architecture is based on resnet18. Additionally resnet50 was tested. These models are pretrained convolutional neural networks with 18 or 50 layers respectively, trained on the imagenet-1k dataset (Microsoft, 2024a,b). The fully connected layers of the model were adjusted to fit the five-class classification problem. While resnet18 typically expects inputs with three color channels, the dataset exclusively utilizes grayscale images (Basu et al., 2021). To adjust for that the model was given 3 identical channels all containing the same gray scale image. After these modifications the model was then finetuned.

2.6 Explainability Analysis

AI models lack transparency in explaining their predictions. An Explainability Analysis offers insights into their decision-making process. Sometimes merely relying on classification accuracy isn't enough to assess a model's training. Understanding why a prediction was made can be essential for improving accuracy and identifying potential errors (Molnar, 2022). For that reason a Saliency Map and Grad-CAM was used to gain deeper insights into the model's decision-making process.

2.6.1 Saliency Map

The Saliency Map, introduced by (Simonyan et al., 2013), is a Pixel Attribution Method utilized in deep learning. It involves a forward pass of the image through the neural network, followed by the computation of gradients. These gradients are then visualized to create a map that highlights the pixels in the input image that contribute most significantly to the model's prediction (Simonyan et al., 2013; Molnar, 2022).

2.6.2 Grad-CAM

Grad-CAM, which stands for Gradient-weighted Class Activation Map, is a technique that utilizes the gradient of the neural network by employing backpropagation to the last convolutional layer. Through this process, Grad-CAM analyzes which regions in the feature map are activated, generating a heatmap that provides insights into how these activations influenced the decision-making. This heatmap, once generated, is then mapped back to the original image (Selvaraju et al., 2020; Molnar, 2022).

3 Results

3.1 CLAHE

Figure 2 provides an example of applying CLAHE to X-Ray images. The image with CLAHE has an enhanced contrast while maintaining important details. Furthermore, Figure 3 demonstrates the effect of CLAHE, showing a more evenly spread distribution of pixel intensities compared to the original image in order for the model to make more informed predictions.

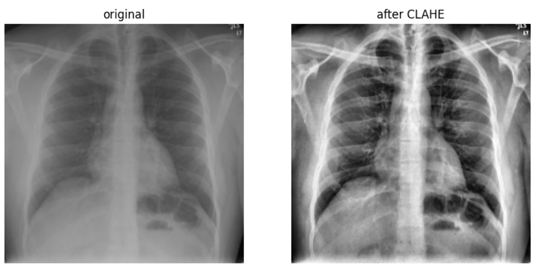


Figure 2: Chest X-Ray of healthy patient with CLAHE disabled and CLAHE enabled. With CLAHE, the contrast of the image is enhanced.

3.2 Finetuning resnet

Finetuning resnet18 resulted in faster iteration and training cycles, yet still achieving good accuracy. On the other hand, finetuning resnet50 demanded significantly more time for training, with performance just slightly above resnet18.

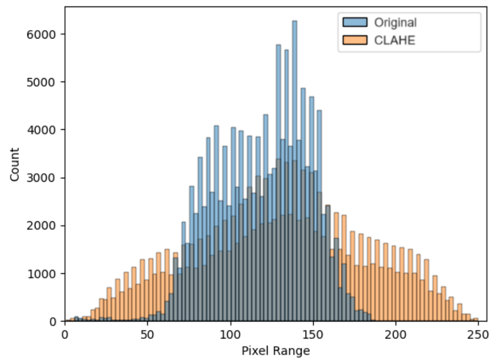


Figure 3: Pixel Distribution Chart with CLAHE and without CLAHE

Model	Epochs	Accuracy
finetuned resnet50	12	96.19%
finetuned resnet18	11	95.5%

Figure 4: Model Accuracy on test dataset of resnet18 and resnet50. Each model was trained for 12 Epochs or until the loss increased. resnet50 shows slightly better performance than resnet18.

Additionally, an experiment was conducted involving training cycles of resnet18 with and without CLAHE. Notably, without CLAHE, the loss began to rise by epoch 5. Comparing accuracies, it was observed that the model without CLAHE performed slightly better (95.95%) than with CLAHE (95.5%). Visualizations of Saliency and Grad-CAM in Figure 12 revealed a more focused activation on the lungs when CLAHE was applied.

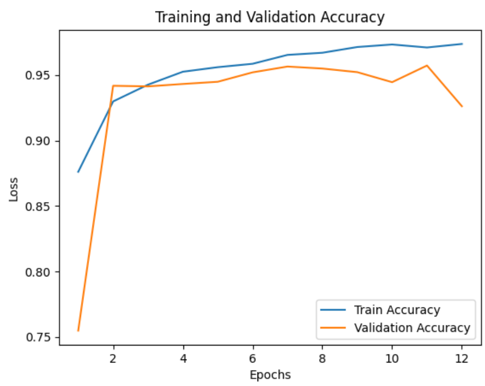


Figure 5: Train and validation accuracy plot for 12 epochs of resnet18 model with CLAHE enabled. The validation accuracy started dropping in epoch 12.

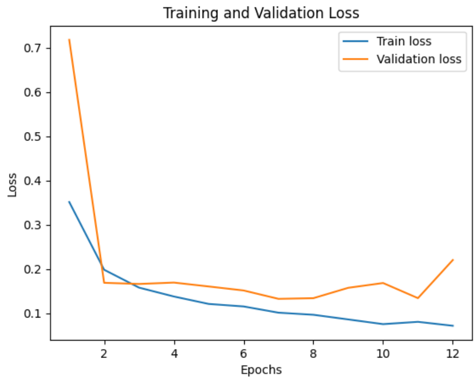


Figure 6: Train and validation loss plot for 12 epochs of resnet18 model with CLAHE enabled. The validation loss started increasing in epoch 12.

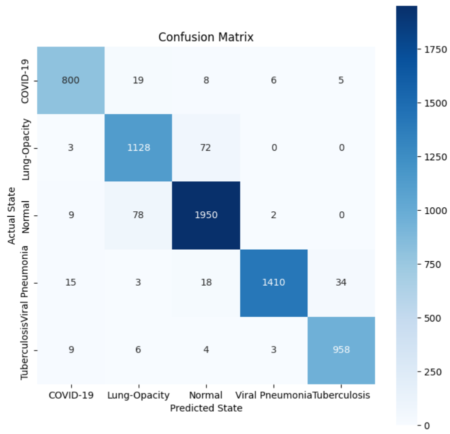


Figure 7: Confusion Matrix of resnet18 model at epoch 11 with CLAHE enabled. The most misspredictions appear to be between Lung-Opacity and the normal state.

3.3 Explainability Analysis

In the following section the Visualization of Saliency and Grad-CAM will be shown using the resnet18 model with CLAHE enabled. The chosen model yielded the best results in the considered explainability methods. One comparison between resnet50 and resnet18 can be seen in Figure 13.

3.3.1 Saliency

The Saliency Maps overlayed on the X-Rays showed a strong concentration on the area below the lungs with some shifts to the right or left, like in Figure 9 or concentrations on the whole area below the lungs, as to be seen in Figure 8. Furthermore some Saliency Maps showed a concentration along the center of the lungs.

Figure 8: Overlayed Saliency Map on Covid-19 X-Ray. The model has a strong focus on the center-right part below the lungs.

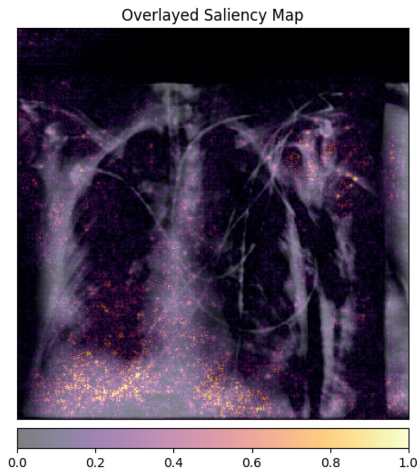


Figure 9: Overlayed Saliency Map on Lung-Opacity X-Ray. A strong concentration on the lower chest cavity can be observed.

3.3.2 Grad-CAM

The Layer Grad-CAM explainability method was applied on "layer4" of the resnet18 model. The Grad-CAM algorithm showed high focuses on the right, left or both lungs respectively to the given lung-diseases. On some images the model had a high focus on written text on the X-Rays like in Figure 11. Sometimes the model showed concentration on parts of the left or right shoulder.

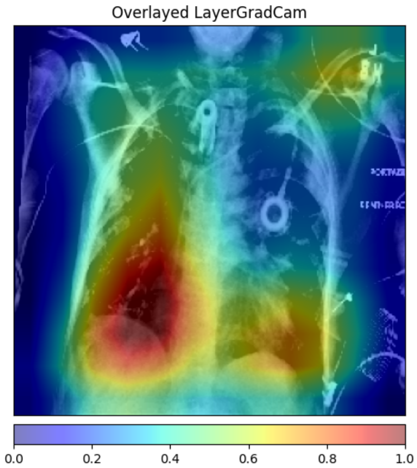


Figure 10: Overlayed Layer Grad-CAM on Lung-Opacity X-Ray. Attention is localized largely to the lower part of the left lung with a slight activation on the lowest part of the right lung and the right shoulder.

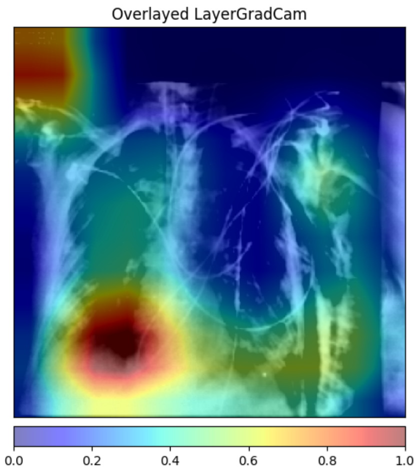


Figure 11: Overlayed Layer Grad-CAM on Covid-19 X-Ray. The model factors in the lowest part of the left lung as well as a text reading „Ocha." in the upper left corner in order to make the prediction.

4 Discussion

Through our experimentation with machine learning techniques on chest X-Ray images, we have achieved promising results in the classification of respiratory conditions, including Pneumonia, Tuberculosis, Lung Opacity, and Normal lungs. These findings underscore the potential and usefulness of machine learning algorithms to assist healthcare professionals in diagnosing respiratory illnesses accurately and efficiently.

By employing CLAHE, we effectively enhanced the local contrast of chest X-Ray images, the interpretability of subtle features and structures indicative of various respiratory conditions was made better. Additionally, the integration of AI explainability tools such as saliency maps and Grad-CAM has provided valuable insights into the decision-making process of our model.

The use of saliency maps allows us to visualize which regions of the input image are most influential in the model's decision-making process. By highlighting these salient regions, we gain a better understanding of the features that contribute to the classification of different respiratory conditions. Similarly, Grad-CAM enables us to generate heatmaps that depict the regions of the input image that are most relevant to a particular class prediction, providing further transparency into the model's internal mechanisms. Nevertheless, there were instances where Grad-CAM displayed heightened activations on non-relevant areas like text or shoulders instead of the lungs, suggesting potential inconsistencies. These findings need to be further investigated to identify any underlying factors contributing to the potential anomalies observed.

These AI explainability tools not only enhance the interpretability of our model but also facilitate trust and adoption by healthcare professionals. By providing insights into how the model arrives at its predictions, we can better understand its strengths and limitations, thereby improving its utility as a diagnostic tool in clinical practice.

While our project has yielded promising results, it is not without limitations. One notable weakness is the reliance on a single dataset, which may introduce biases and limit the generalizability of our findings. Future efforts should aim to validate our findings on larger and more diverse datasets to ensure the robustness of our proposed approach.

The project's outlook involves several avenues for future research and development. Exploring alternative image enhancement techniques or combinations thereof could further enhance the model's performance.

Moreover, investigating the incorporation of clinical metadata, such as patient demographics, symptoms, and medical history could provide valuable context to aid in diagnosis and improve the model's accuracy. Integrating other AI explainability techniques, such as occlusion sensitivity could provide complementary insights into the model's decision-making process.

In terms of practical application, deploying the developed model in real clinical settings would be a crucial step towards validating its effectiveness and assessing its impact on patient care. This would involve collaboration with healthcare professionals to ensure seamless integration into existing workflows and to evaluate its performance in real-world scenarios.

In conclusion, our project demonstrates the efficacy of machine learning techniques in analyzing chest X-Ray images for the classification of respiratory conditions. The integration of AI explainability tools such as saliency maps and Grad-CAM enhances the interpretability of the model and fosters trust in its predictions by viewers of the predictions. While further research is needed to address limitations and enhance the robustness of our approach, our project shows promising possibilities for the development of automated diagnostic tools to support clinical decision-making in the field of radiology.

References

Abdel-Aal, A., Lisspers, K., Williams, S., Adab, P., Adams, R., Agarwal, D., Barnard, A., Bouloukaki, I., van Boven, J. F. M., Chavannes, N., Dickens, A. P., van Gemert, F., Escarrer, M., Haroon, S., Kayongo, A., Kirenga, B., Kocks, J. W. H., Kotz, D., Newby, C., McNulty, C., and ... Jordan, R. E. (2022). Prioritising primary care respiratory research needs: results from the 2020 international primary care respiratory group (ipcrg) global e-delphi exercise. *NPJ primary care respiratory medicine*, 32(1):6.

Basu, A., Das, S., Ghosh, S., Mullick, S., Gupta, A., and Das, S. (2021). Chest x-ray dataset for respiratory disease classification. Harvard Dataverse.

Google for Developers (Accessed: 1.05.2024). Normalization, machine learning. https://developers.google.com/machine-learning/data-prep/transform/normalization.

Hana, F. M. and Maulida, I. D. (2021). Analysis of contrast limited adaptive histogram equalization (clahe) parameters on finger knuckle print identification. *Journal of Physics: Conference Series*, 1764(1):012049.

Microsoft (Accessed: 1.05.2024a). resnet-18. https://huggingface.co/microsoft/resnet-18.

Microsoft (Accessed: 1.05.2024b). resnet-50. https://huggingface.co/microsoft/resnet-50.

Molnar, C. (2022). *Interpretable machine learning: A guide for making black box models explainable*. Christoph Molnar, Munich, Germany, second edition edition.

Nanwani, R. (2021). Lazy loading images – the complete guide. https://imagekit.io/blog/lazy-loading-images-complete-guide/.

Ostwal, P. (2023). Data augmentation for computer vision. https://pranjal-ostwal.medium.com/data-augmentation-for-computer-vision-b88b818b6010.

Pescador (Accessed: 1.05.2024). Sampling from disk. https://pescador.readthedocs.io/en/stable/example3.html.

Satia, I., Bashagha, S., Bibi, A., Ahmed, R., Mellor, S., and Zaman, F. (2013). Assessing the accuracy and certainty in interpreting chest x-rays in the medical division. *Clinical medicine (London, England)*, 13(4):349–352.

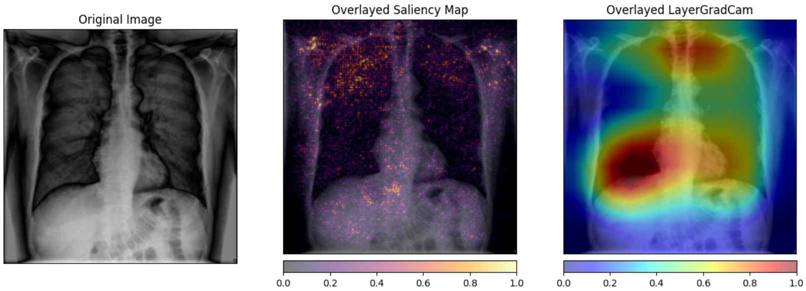
Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., and Batra, D. (2020). Grad-cam: Visual explanations from deep networks via gradient-based localization.

Shorten, C. and Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1):60.

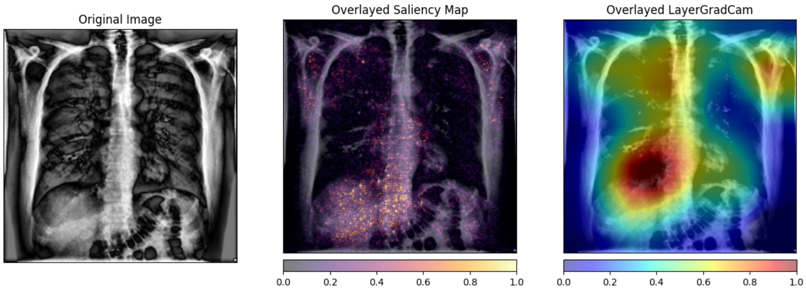
Simonyan, K., Vedaldi, A., and Zisserman, A. (2013). Deep inside convolutional networks: Visualising image classification models and saliency maps.

Suthakar, U., Magnoni, L., Smith, D. R., Khan, A., and Andreeva, J. (2016). An efficient strategy for the collection and storage of large volumes of data for computation. *Journal of Big Data*, 3(1):21.

Appendices

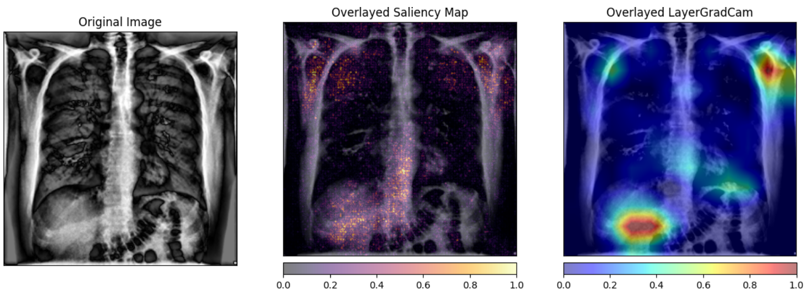


(a) Finetuned resnet18 with CLAHE disabled

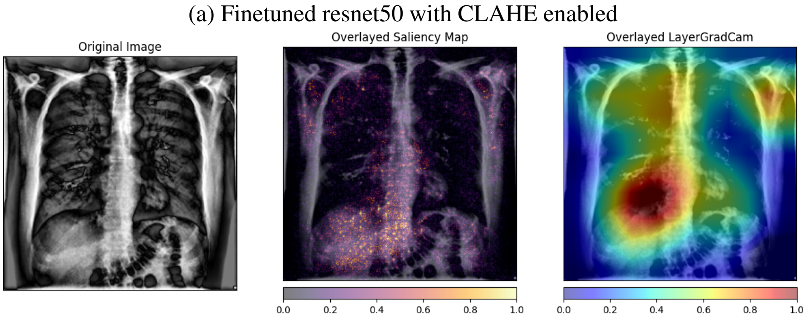


(b) Finetuned resnet18 with CLAHE enabled

Figure 12: X-Ray of Covid19 with overlayed Layer Grad-CAM and Saliency Map with CLAHE disabled (12a) and CLAHE enabled (12b) of finetuned resnet18. CLAHE images seemed to have a more localized attention.



(a) Finetuned resnet50 with CLAHE enabled



(b) Finetuned resnet18 with CLAHE enabled

Figure 13: X-Ray of Covid19 with overlayed Layer Grad-CAM and Saliency Map of finetuned resnet50 (13a) and finetuned resnet18 (13b). Resnet18 shows a higher localization on the lung area in comparison to resnet50.