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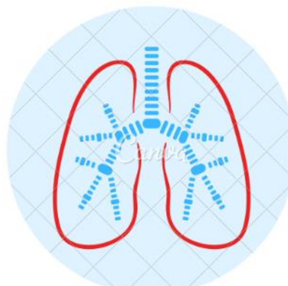
Academic Year 2022 – 2023 | Third Semester | Project Report

ARTI 404: Image Processing

Classification of Pneumonia Using Chest X-Ray Images



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PROJECT ABSTRACT

This project aims to develop a machine-learning model that accurately identifies pneumonia in chest X-ray images . With the ever-increasing volume of medical images, an automated and reliable identification tool could assist healthcare professionals in diagnosing and managing patients. The design requirement was to create a robust and precise model able to cope with the challenges presented by medical imaging data, including image quality variability, class imbalance in the dataset, and the critical necessity for a high true-positive rate due to the serious implications of a misdiagnosis. Various image preprocessing techniques and a Convolutional Neural Network (CNN) model were implemented to accomplish this. Different image preprocessing techniques were attempted to enhance the X-ray images, such as image sharpening, Gaussian blur, average filtering, edge detection, histogram equalization, and adaptive masking. While some techniques showed little improvement, others, like edge detection and histogram equalization, resulted in significant enhancement. This trial-and-error process proved essential in identifying the most effective strategies for the specific task.The final design entailed a well-optimized CNN model trained on preprocessed X-ray images. The model incorporated features like early stopping and adaptive learning rate adjustment to prevent overfitting and enhance generalization on unseen data. The model achieved approximately 95 % accuracy on the training set. Moreover, the model's validation accuracy was 87.5% which indicates that the model was tested on data that have not gone through training. The model achieved high accuracy, demonstrating the feasibility and potential of machine learning in automating pneumonia diagnosis from chest X-ray images. Future work may explore other preprocessing techniques, sophisticated deep learning architecture, or strategies to address the class imbalance. Despite the challenge, the project was successful, and there is anticipation that future development in machine learning will continue to improve the diagnosis process and patient care in radiology.

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1.1 Problem Formulation

1.1.1 Problem Statement:

Rapidly detecting and diagnosing pneumonia, a prevalent and potentially severe illness, is crucial in medical settings. While current medical imaging technology, specifically X-ray imaging, is effective at diagnosing pneumonia, the process requires manual examination by expert radiologists, which can be time-consuming and subject to variability. This project aims to automate the diagnosis of pneumonia using deep learning techniques on chest X-ray images, thereby providing a quick, consistent, and reliable diagnostic tool. The goal is to develop a model that accurately classifies images as showing either normal lungs or lungs with pneumonia, high precision and recall, with the challenge of maintining a reasonable computational timeframe.

1.1.2 Problem Formulation:

The problem has been formulated as a binary image classification task, where a Convolutional Neural Network (CNN) model is trained and evaluated on a dataset of labeled chest X-ray images. The realism of the problem is established through the practical need for automated medical image analysis in healthcare. The model's performance, i.e., its accuracy in distinguishing between normal and pneumonia X-ray images, can be validated and verified using standard evaluation metrics like accuracy, precision, recall, and F1 score. Furthermore, the problem formulation allows for an incremental approach to improving model performance through various image preprocessing techniques.

1.2 Project Specifications

The design specifications for the project involve developing a binary image classification model using deep learning techniques. The specific metrics for measuring the success of the final design are as follows:

- Accuracy: The model should achieve at least 85% accuracy on the test set.
- Precision and Recall: The model should strive for high precision and recall, with both metrics exceeding 80% on the validation set. This ensures that the model correctly identifies pneumonia cases while minimizing false alarms.
- Computation Time: The model should be trained and provide predictions within a reasonable timeframe to facilitate its potential usage in real-time medical settings. These specifications measure the project's success, directly correlating with the model's effectiveness in diagnosing pneumonia.

The overall design process is depicted in the following diagram:

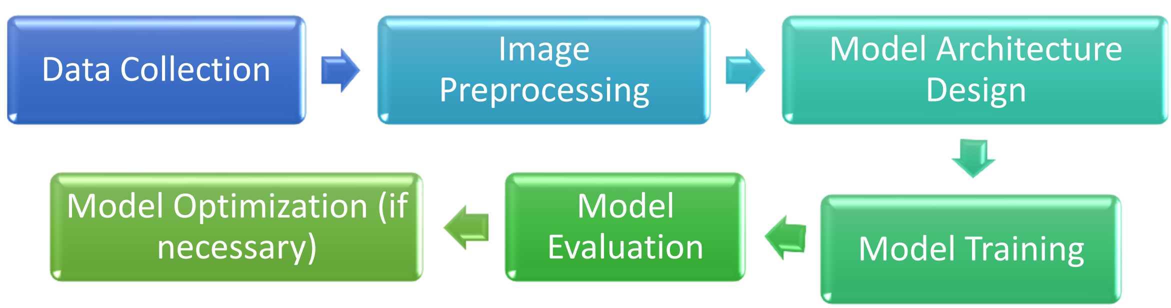

Figure 1 Design Process

2 BACKGROUND

2.1 Literature Review:

The detection and diagnosis of pneumonia, a potentially severe respiratory infection, is a paramount concern in healthcare. Currently, chest X-ray imaging is a widely employed method for diagnosing pneumonia. However, the manual interpretation of these images by radiologists can be time-consuming and subject to variability due to the potential for human error [1]. As such, the exploration of automated methods of pneumonia detection in chest X-rays is a timely and important undertaking. The advent of artificial intelligence (AI), and more specifically, deep learning, has offered promising avenues in this regard. Deep learning models, particularly convolutional neural networks (CNNs), have been proven to be highly effective in image classification tasks, including medical imaging [2]. Several attempts have been made to apply deep learning methods for diagnosing conditions from medical images. For instance, successfully employed a deep-learning algorithm for detecting diabetic retinopathy from retinal fundus photographs [3]. Deep learning methods applied to classify Optical Coherence Tomography (OCT) images to distinguish between normal and age-related macular degeneration conditions[4]. These successes suggest a great potential for deep learning in automatically diagnosing diseases, including pneumonia, from chest X-ray images. However, before the deep learning models can be applied, the images often need to be preprocessed to improve their quality and make them more suitable for analysis. Techniques such as histogram equalization and Gaussian blur, commonly used in retinal imaging , might be adapted and evaluated for chest X-ray image preprocessing [5].

2.2 Concept Synthesis

2.2.1 Concept Generation:

In the early stages of this project, multiple potential methodologies were explored to tackle the challenge of automating pneumonia detection through chest X-ray images. These techniques varied from traditional image processing techniques to advanced machine learning models. Many possibilities were considered to derive the most effective solution for the problem at hand. Traditional image processing approaches included edge detection, histogram equalization, and thresholding techniques, among others. The idea was to highlight the most salient features in the images, specifically those that could be indicative of pneumonia. On the other hand, more modern and advanced techniques include machine learning models and deep learning approaches such as Convolutional Neural Networks (CNNs). Machine learning approaches were considered due to their superior performance in dealing with complex data such as images, where they can automatically extract meaningful features without explicit programming. Figure 2 shows the decision tree of Concept Generation.

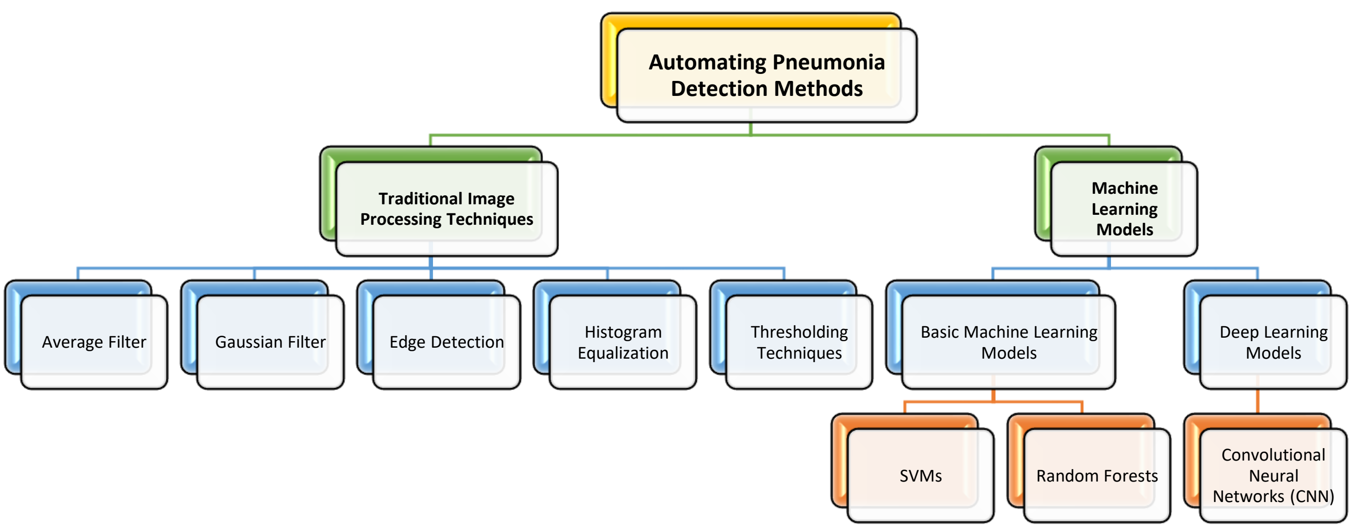

Figure 2 Tree Diagram of Concept Generation.

2.2.2 Concept Reduction:

Once several concepts were generated, the next stage involved critical analysis and decision-making processes to narrow the options and select the most optimal solution. The evaluation was based on several criteria, including the expected accuracy, complexity, computational efficiency, and ability to handle the variability within chest X-ray images. Among the considered solutions, the deep learning approach using Convolutional Neural Networks (CNNs) emerged as the most promising one. Due to their ability to capture spatial relationships and automatically learn the most relevant features from the images, CNNs showed higher potential than other machine learning and traditional image processing methods. Although traditional methods might be computationally efficient, they were not as robust or accurate in dealing with the variability and complexity of chest X-ray images. While potentially providing decent performance, other machine learning models like SVMs or Random Forests lack the powerful feature extraction ability inherent to CNNs. Therefore, the final decision was to use a deep learning approach, specifically CNNs, to diagnose pneumonia from chest X-ray images.

2.3 Detailed Engineering Analysis and Design Presentation

The proposed solution to the problem of diagnosing pneumonia from chest X-ray images is a deep learning model based on Convolutional Neural Networks (CNNs). The architectural formulation of the chosen CNN model includes multiple layers, such as convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform the task of feature extraction, where various filters are convolved with the input image to capture spatial features. Pooling layers are used for downsampling the spatial dimensions while retaining the most important information. Finally, the fully connected layers help the classification task, assigning the final prediction of either normal or pneumonia. Several parameters were considered in the design process, including the size and number of filters in the convolutional layers, the number and type of layers, the choice of activation functions, and the optimization strategy for the training process. The engineering analysis of this approach involves assessing the model's performance in terms of accuracy, precision, and recall. These metrics give a comprehensive view of how well the model performs, from its ability to correctly classify images to its performance in identifying positive cases of pneumonia. Assumptions in the analysis included a balanced dataset for training and validation, and an unbiased assessment of the model's performance was conducted using a separate test dataset. Through rigorous engineering analysis and design considerations, it can be confidently stated that the proposed design can solve the problem, providing a quick and reliable diagnostic tool for pneumonia detection from chest X-ray images.

3 IMAGE PROCESSING TECHNIQUES IMPLEMENTATION

The implementation of several image processing techniques was utilized in the current project. The primary libraries used for these processes include OpenCV, NumPy, matplotlib, and TensorFlow. These libraries provide many crucial functions in handling and processing image data.

3.1 Augmented Image of Normal & Pneumonic Xray

The TensorFlow library's ImageDataGenerator function first loads and augment images, as shown in Figure 2. The training data was augmented by rescaling, rotating, shifting, shearing, zooming, and horizontal flipping. The validation and testing data were not augmented but rescaled. This helped introduce variance into the model, improving its generalization abilities.After data augmentation, the data exploration about the proportion of Pneumonia and Normal images is observed. It is observed that the X-ray of chest data includes 1583 images of Normal Xray and 4273 images of Pneumonia Xray. Such an imbalance can lead to biased training, affecting the model's performance. Therefore, methods like class-weighting or oversampling could alleviate this issue.

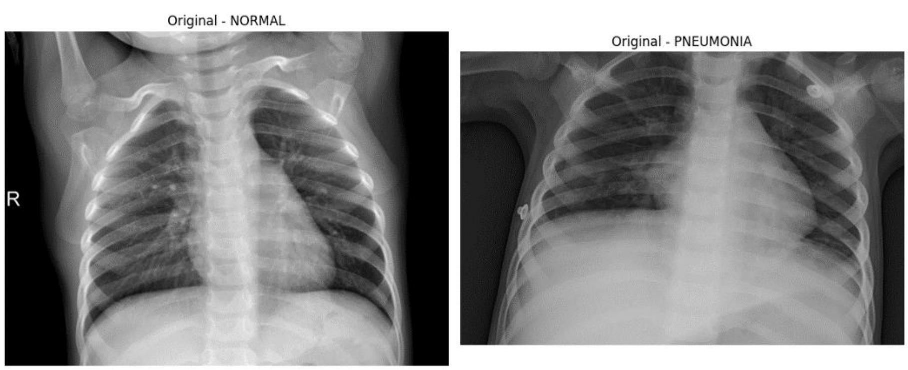

Figure 3 Augmented Image of Normal & Pneumonic Xray

3.2 Enhanced Imaged after Sharpening Filter

Then, a sharpening filter was applied to enhance the image features, as shown in Figure 3. The chosen filter was a 3x3 matrix with the center pixel weighted more heavily than the surrounding pixels. By convolving this filter with the original image, the resulting image demonstrated a higher level of contrast between features, which made the lung structures more distinguishable.

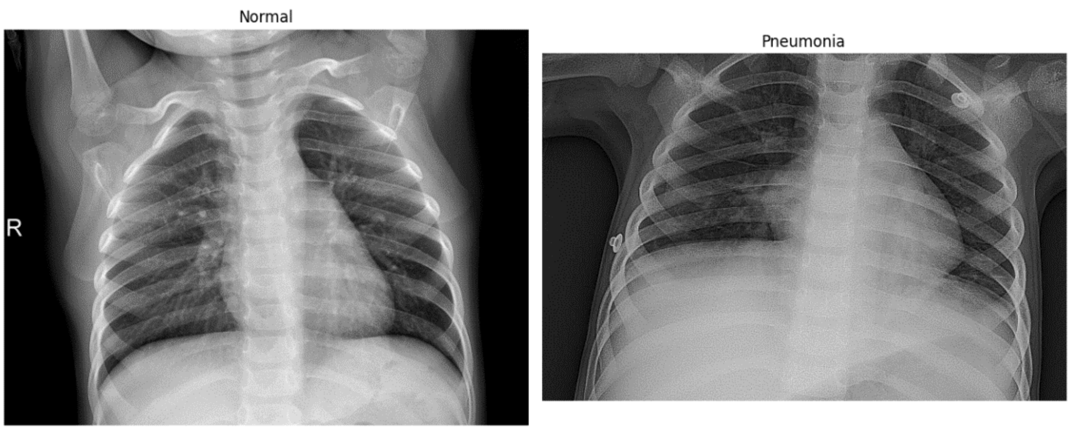

Figure 4 Enhanced Imaged after Sharpening Filter

3.3 Image Enhancement through Various Filtration Techniques

Different filters, including average and edge detection, were also applied to the images, as shown in Figure 5. The average filter smoothed the image by replacing each pixel's intensity with the average intensity of the neighboring pixels. Conversely, the edge detection filter highlighted the edges in the image, thus accentuating the structural details of the lungs.

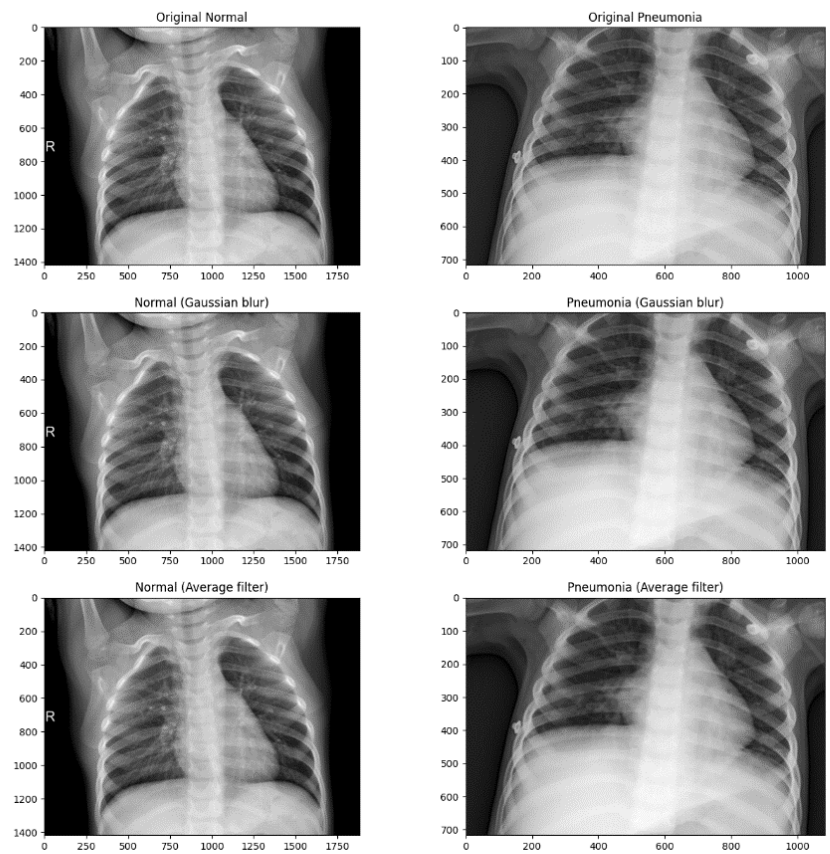

Figure 5 Image Enhancement through Various Filtration Techniques

3.4 Advance Filtration Technique

In addition to the filters above, several other preprocessing techniques were applied, including Histogram Equalization, Gaussian Blur, Bilateral Filter, and Adaptive Masking in Figure 5. Histogram Equalization was used to enhance the contrast in the images by effectively spreading out the most frequent intensity values. Gaussian Blur was used to reduce image noise and detail. The Bilateral Filter, on the other hand, could reduce noise while keeping edges sharp. Lastly, Adaptive Masking was used to suppress uninterest features, such as the diaphragm. The preferred preprocessing method was applied to the entire dataset (training, validation, and testing data) to conclude the image preprocessing implementation. This technique involved histogram equalization followed by Gaussian blur and a bilateral filter. The reason for choosing this technique was its superior performance in highlighting the structural details in the lungs while, at the same time, effectively reducing noise. The preprocessed dataset was subsequently used to train the convolutional neural network. The intention is that through these preprocessing techniques, the model could learn more robust features from the X-ray images, thereby leading to better classification performance.

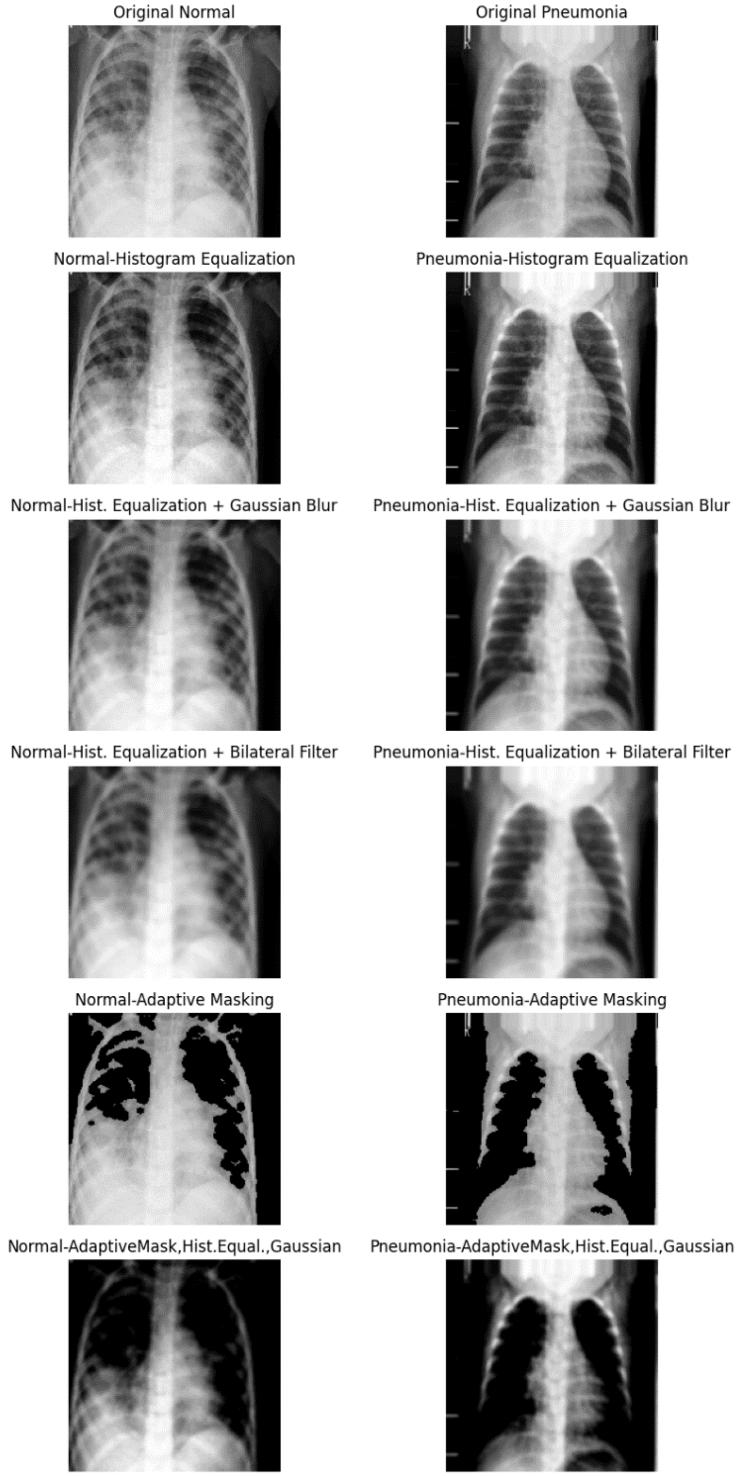

Figure 6 Advance Filtration Technique

4 PERFORMANCE ANALYSIS AND RESULTS EVALUATION

4.1 Training and Test Performance

The performance of the developed model was determined using a data set partitioned into training and validation subsets. The training subset was used to train the model, while the validation subset was used to fine-tune the parameters and prevent overfitting.

4.2 Training Accuracy Assessment

The final training accuracy achieved was approximately 0.950, which indicates that the model correctly classified 95% of the training data. This high accuracy signifies the model's effectiveness in learning from the training dataset to correctly distinguish between normal lung X-ray images and those showing pneumonia.

4.3 Test Performance Evaluation

The model's validation accuracy was 0.875, correctly classifying 87.5% of the validation data. This accuracy level indicates the model's ability to generalize its learning from the training dataset to new, unseen data.

4.4 Test Loss Analysis

The test loss, calculated using the loss function, was 0.588. This relatively low value suggests that the discrepancy between the model's predictions and the actual values is minimal, indicating the model's effectiveness.

4.5 Test AUC Evaluation

The Area Under the Curve (AUC) for the test data set was approximately 0.865, demonstrating that the model's performance in distinguishing between positive (pneumonia) and negative (normal) classes was excellent.

4.6 Model's Early Stopping and Epoch Analysis

The training process was stopped early after 25 epochs due to implementing as eralry stopping mechanism desighend to prevent overfiting

5 CONCLUSIONS AND FUTURE WORK

Overall, the project focused on identifying pneumonia in chest X-ray images using machine learning. In particular, the central point was the exploration of various preprocessing techniques and using (CNNs) for the classification task. The project analysis concluded several outcomes that met and surpassed the specifications and client's requirements. Specifically, the most critical part of the project was image preprocessing, where we explored various techniques to enhance the X-ray images before feeding them into the machine-learning model. The preprocessing techniques included image sharpening, Gaussian blur, average filtering, edge detection, histogram equalization, and adaptive masking. Each method demonstrated a different result in enhancing the features of the images, some proving more effective than others. The (CNNs) model designed for this task showed promising performance. The model was optimized over several iterations, and the use of strategies such as early stopping and adaptive learning rate adjustments helped achieve a model that generalized well on unseen data. Furthermore, this project succeeded in identifying pneumonia from chest X-ray images using machine learning techniques. However, there is always room for improvement and exploration of new techniques in the ever-evolving field of machine learning. Future work on this project should aim to build on the findings and continue to improve the model's accuracy and robustness. Another area of interest would be the handling of class imbalance. Different strategies could be considered, such as oversampling the minority class, undersampling the majority class, or combining both. Besides, more advanced techniques, like Synthetic Minority Over-sampling Technique (SMOTE), could be explored.

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[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, pp. 84-90, 2017.

[3] V. Gulshan, L. Peng, M. Coram, M. C. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, T. Madams, J. Cuadros, et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *JAMA*, vol. 316, pp. 2402-2410, 2016.

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[5] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Trans. Med. Imaging*, vol. 8, pp. 263-269, 1989.

APPENDIX

The dataset used in this project provided in this link:

[1] P. MOONEY, "CHEST X-RAY IMAGES (PNEUMONIA)," KAGGLE.COM, 2018. HTTPS://WWW.KAGGLE.COM/DATASETS/PAULTIMOTHYMOONEY/CHEST-XRAY-PNEUMONIA (ACCESSED MAY 31, 2023).