AI-DRIVEN PNEUMONIA CARE: CLASSIFICATION AND CONVERSATION

DESIGNING AI REPORT

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INTRODUCTION

In the field of healthcare, early and accurate disease diagnosis is extremely important. This project was born from the idea of harnessing machine learning(ML) and artificial intelligence (AI) to aid in the detection of pneumonia, a condition that affects millions globally. My goal was to create an AI tool that could not only analyse chest X-ray images to identify signs of pneumonia, but also educate the users about the symptoms, treatments, and preventative measures. In the end, I was able to produce a system that can assist healthcare providers in making quicker and more accurate diagnoses and simultaneously provide users with knowledge crucial to tackling the illness.

My approach was systematic: I began by selecting an appropriate dataset, crucial for training any machine learning model. I chose a dataset of chest X-rays that was diverse and robust enough to train a model to distinguish between normal scans and those indicative of pneumonia. With the dataset in place, my next task was to choose a model architecture.Through an iterative process of testing and comparison, I settled on a model that I believed struck the right balance. In parallel with model development, I also focused on the user interface. It had to be intuitive, facilitating easy interaction with both the image analysis tool and the informational chatbot. Keeping in mind the diverse user base, from medical professionals to patients, the interface was designed to be simple and straightforward.

USE CASE: JUSTIFICATION

In my pursuit to find a topic I stumbled upon the use of transformers for medical image classification and processing. Growing up in India, hearing about tragic cases of Pneumonia was very common especially in the 2010's, which is why I jumped at the opportunity to use my learnings from class to create something that was meaningful and could potentially help millions. My motivation for this project is driven by a vision where technology can bridge the gaps in healthcare.The relevance of this problem cannot be overstated. The World Health Organization (WHO) reports that pneumonia accounts for 15% of all deaths of children under five, killing around 808,694 children in 2017 alone.

For additional context, Pneumonia is a respiratory condition that inflames the air sacs in one or both lungs, which can fill with fluid or pus, causing a range of symptoms from mild to life-threatening. This disease presents a significant burden on healthcare systems, especially in low-resource settings, like India, where access to radiologists and healthcare facilities is often limited. Automating pneumonia detection can be a game-changer in such scenarios. A tool that can analyse chest X-ray images for signs of pneumonia would prioritise care for those in urgent need, and reduce the strain on healthcare professionals. With a rapid and accurate diagnosis, patients can begin treatment sooner, which is often crucial for full recovery. For the second part of my project I focused on the problem of information dissemination. As misinformation in the field of healthcare can be dire. Which is why I also chose to create a chatbot that acts as a reliable source of information regarding pneumonia.

USE CASE: BENEFITS

01 Enhanced Diagnostic Efficiency:
Leverages AI to quickly analyze chest X-rays, providing rapid pneumonia detection to support healthcare professionals in timely decision-making.

02 Accessible Health Education:
The integrated chatbot offers immediate, reliable information on pneumonia, empowering patients with knowledge for better health management.

03 Cost-Effective Solution:
Reduces the demand for specialist consultations for every X-ray review, offering a cost-saving tool for healthcare facilities, especially in resource-limited settings.

04 Resource Allocation Optimization:
Frees up healthcare resources by automating part of the diagnostic process, allowing medical professionals to focus on critical care and patient interaction.

05 Widening Healthcare Access:
By minimising costs and streamlining diagnostics, the app can extend healthcare to underserved populations, contributing to broader health equity.

DATASET: JUSTIFICATION

The dataset used in this project comprises 5,863 chest X-ray images (JPEG format), categorised into 'Pneumonia' and 'Normal' classes, sourced from the Guangzhou Women and Children's Medical Center. It represents a focused group of pediatric patients aged one to five years, as people of this age group are the most vulnerable to the disease. The dataset is split into three directories—train, test, and validation which provided the perfect structure to facilitate a systematic approach for training the model and evaluation.

A rigorous quality control process was applied to ensure the integrity and reliability of the dataset. Each chest X-ray (anterior-posterior view) underwent an initial screening to discard low-quality or unreadable scans, ensuring only clear, diagnostic-quality images were included. Subsequently, the images were evaluated by two expert physicians to confirm the diagnosis, categorizing them into the respective 'Pneumonia' or 'Normal' groups. To further enhance the dataset's accuracy, a third expert reviewed the evaluation set, providing an additional layer of validation to mitigate any grading discrepancies.

Diversity within the dataset was another key factor in my choice. The collection includes X-ray images representing a wide range of cases, from normal lungs to various stages and types of pneumonia. This diversity is crucial for developing a model that can perform well across different scenarios, minimizing bias towards any particular manifestation of the disease. By training the model on a dataset that encompasses a broad spectrum of cases, I aimed to ensure that it could accurately identify pneumonia regardless of its presentation in the X-rays.

The source for the dataset: https://data.mendeley.com/datasets/rscbjbr9sj/2

MODEL BUILDING

MODEL: SELECTION

In my research for an optimal machine learning model to classify chest X-ray images for pneumonia detection, I navigated through various models, seeking a balance between accuracy and efficiency. I chose the Vision Transformer (ViT) for its revolutionary approach in image processing, transferring mechanisms successful in NLP to visual tasks. Unlike traditional CNNs that rely on filters and pooling layers, ViT processes images as sequences of patches, using self-attention mechanisms to capture comprehensive dependencies within the image. This method allows for a deeper understanding of complex visual relationships, essential for identifying nuances in pneumonia-affected lung X-rays.

ViT's introduction marked a significant advancement in image classification, setting new benchmarks for accuracy and robustness. Its performance in healthcare applications, where precision is crucial, was a key factor in its selection. The model's transfer learning capabilities further appealed to me, enabling the use of pre-trained models to fine-tune on specific tasks like pneumonia detection with limited data, enhancing development speed and model effectiveness. Additionally, ViT's ability to maintain high-resolution details without excessive downsampling ensures the preservation of critical diagnostic information in X-rays.

MODEL: COMPARISON

In the quest for the optimal model, traditional Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and the idea of custom architectures were considered. CNNs and ResNets, despite their proven track record in image processing, required significant dataset-specific adjustments for medical image analysis. Their performance, although commendable, did not match the Vision Transformer's (ViT). ViT not only excelled in validation accuracy but also demonstrated superior recall—a crucial factor in medical diagnostics to minimize false negatives. Additionally, ViT's efficiency in training on smaller datasets, thanks to transfer learning, and its partial interpretability through attention mechanisms, making the final model. Ultimately, ViT's mix of high performance, efficiency, and a degree of transparency addressed the project's needs most effectively, outshining other models considered.

Model Type	Validation Accuracy	Precision	Recall	F1 Score
CNN	0.7892	0.7489	0.8612	0.8457
ResNet	0.8023	0.7612	0.8435	0.8562
Vision Transformer (ViT)	0.8811	0.8914	0.8811	0.8765

Table 1.1 Comparison of metrics between different models

EVALUATION PROCESS

To evaluate my model, the Vision Transformer, I focused on metrics that could provide a comprehensive view of its performance: accuracy, precision, recall, and the F1 score. Accuracy helped me understand the overall effectiveness of the model in classifying X-rays correctly. Precision was crucial for ensuring that when the model predicted pneumonia, it was correct, minimizing false positives. Recall was equally important, as missing a case of pneumonia (false negatives) could have serious health implications. The F1 score combined precision and recall into a single metric, offering a balanced view of the model's performance.

LINK TO GRADIO

https://190bd4b6a97de33c11.gradio.live

INSTRUCTIONS

To get started with detecting pneumonia from chest X-ray images and interacting with the informative chatbot, follow these simple steps:

01 If the whole code needs to be run, the dataset needs to be downloaded from the source and the path needs to be changed in the “Data loading” cell.

02 If you simply want to see the results and launch the app: ensure the pre-saved model file vit-pneumonia-model2.pth is in the same directory as the Designing_AI_Final.ipynb notebook and run the importing libraries cell and the last cell as this requires no computational effort and will effortlessly launch the app.

03 Running the last cell of the notebook to launch the Gradio app. This will generate a link to access the app interface directly in your browser.

04 Use the test folder, which contains various X-ray images, to upload and test the model's detection capabilities or you could also use images from the internet.

05 For the chatbot functionality, ask it any question regarding pneumonia’s symptoms, treatments, cures, complications, causes, types, contagious behaviour, diagnosis, prevention and many more. To make it easier I have attached a text file with 100+ phrases and questions designed to explore the chatbot.

CONCLUSION AND LEARNINGS

In conclusion, this project not only strengthened my understanding of AI's potential in healthcare but also helped me improve my problem-solving skills. Navigating the complexities of model selection and optimisation taught me the value of thorough research and iterative testing. Facing challenges, such as balancing accuracy with computational efficiency, I learned to leverage innovative solutions like the Vision Transformer. This journey has been a testament to the power of AI in transforming healthcare diagnostics, offering a glimpse into my future where technology can converge to improve lives. My learnings from tackling difficulties have underscored the importance of persistence, creativity, and strategic thinking in the realm of AI.