Project Abstract

Title: *Interpretable Deep Learning (AI) for Pneumonia Detection in Chest X-Rays*

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**Problem Statement**

Detecting pneumonia from chest X-ray images is critical for timely treatment, especially in low-resource settings where radiologist availability is limited. Manual examination of X-rays is time-consuming and subject to human error. This project aims to automate pneumonia detection using deep learning techniques to improve diagnostic efficiency and accuracy.**Dataset**

I will use the **NIH Chest X-ray Dataset**, which contains over 100,000 labeled chest X-ray images across 14 disease categories, including pneumonia. The dataset is publicly available and widely used for medical imaging research.

**Proposed Techniques to be Used**

I will use **Convolutional Neural Networks (CNNs)** with **Transfer Learning** leveraging a pre-trained ResNet50 model, fine-tuned on the pneumonia classification task. The model will be implemented using **TensorFlow and Keras** for efficient experimentation and deployment.

**Steps to Complete the Project**

* **Data Preprocessing:** Load and preprocess X-ray images (resize, normalization, augmentation).
* **Data Splitting:** Divide data into **training, validation**, and **test** sets.
* **Model Development:** Build and fine-tune the ResNet50 CNN model.
* **Model Training:** Train using appropriate hyperparameters and callbacks.
* **Evaluation:** Assess model performance using accuracy, precision, recall, and AUC.
* **Visualization:** Generate Grad-CAM visualizations to interpret model predictions.
* **Reporting:** Document methodology, results, and analysis for submission.

**Expected Output/Results**

We expect the deep learning model to achieve **over 90% classification accuracy** in detecting pneumonia on unseen chest X-ray images. The project aims to provide a reliable, automated screening tool to assist healthcare professionals in rapid diagnosis, reducing manual workload and improving early detection rates in clinical settings.

**Key Benefits**

* Faster diagnosis in resource-limited environments.
* Reduced dependency on manual radiologist examination.
* Interpretable AI predictions for clinical trust.

**1. Start with the Real-World Problem**

Emphasize the clinical relevance:

* Pneumonia is a leading cause of death globally, especially in children and elderly populations.
* In low-resource settings, radiologist shortages delay diagnosis.
* Manual X-ray interpretation is prone to variability and human error.

**Justification**: “This project addresses a critical healthcare gap by automating pneumonia detection, aiming to reduce diagnostic delays and support clinicians with reliable AI-driven insights.”

**2. Highlight the Dataset’s Credibility**

* NIH Chest X-ray Dataset is large-scale, diverse, and publicly vetted.
* Contains over 100,000 images labeled across 14 conditions, making it ideal for transfer learning.

**Justification**: “Using a trusted, high-volume dataset ensures our model is trained on clinically representative data, enhancing generalizability and robustness.”

**3. Explain the Technical Choices**

* ResNet50 is a proven architecture for medical imaging tasks.
* Transfer learning allows faster convergence and better performance with limited labeled data.
* TensorFlow/Keras enables reproducibility and deployment readiness.

**Justification**: “We chose ResNet50 for its depth and residual connections, which help preserve feature integrity in medical images. Transfer learning accelerates training and improves accuracy.”

**4. Showcase Interpretability**

* Grad-CAM visualizations reveal which regions of the X-ray influenced the model’s decision.
* This builds trust with clinicians and supports regulatory transparency.

**Justification**: “Interpretability is key in medical AI. Grad-CAM overlays allow us to validate that the model focuses on clinically relevant lung regions, not artifacts.”

**5. Present Results with Context**

* Achieving >90% accuracy is significant, but also show precision, recall, and AUC.
* Compare with baseline models or manual diagnosis benchmarks if available.

**Justification**: “Our model consistently detects pneumonia with high accuracy and recall, outperforming baseline classifiers and aligning with clinical expectations.”

**6. Connect to Broader Impact**

* Reduces radiologist workload.
* Enables faster triage in emergency settings.
* Can be integrated into mobile or cloud-based diagnostic tools.

**Justification**: “This project isn’t just academic — it’s a step toward scalable, accessible AI-assisted diagnostics that can save lives in underserved regions.”

**🗣️ Sample Presentation Line to Tie It All Together**

“By combining a robust dataset, a proven CNN architecture, and interpretability tools like Grad-CAM, we’ve built a model that not only detects pneumonia with high accuracy but also explains its decisions. This project demonstrates how deep learning can support real-world clinical workflows, especially where expert resources are scarce.”

If you’d like, I can help you build a slide deck outline or script your opening and closing remarks. Want to add a visual comparison of Grad-CAM overlays for normal vs pneumonia cases? That would really drive home the interpretability angle.

**How to Say “Achieving >90% Accuracy” with Justification**

**1. Reference Your Test Set Performance**

You likely evaluated your model on a held-out test set of chest X-ray images. If your final model gave:

* **Accuracy**: 91.3%
* **Precision**: 89.7%
* **Recall**: 92.5%
* **AUC**: 0.94

Then you can say:

“On the unseen test set, our model achieved 91.3% accuracy, with strong precision and recall, indicating reliable performance in detecting pneumonia.”

This grounds your claim in actual numbers.

**2. Compare with Baselines**

If you trained a simple CNN from scratch or used logistic regression as a baseline, and they achieved ~70–80% accuracy, you can say:

“Compared to baseline models that plateaued around 78% accuracy, our fine-tuned ResNet50 surpassed 90%, demonstrating the effectiveness of transfer learning.”

This shows improvement and validates your approach.

**3. Contextualize with Literature or Manual Diagnosis**

If published studies or radiologist benchmarks report ~85% accuracy for manual diagnosis, you can say:

“Our model’s performance aligns with — and in some cases exceeds — reported radiologist-level accuracy, offering a scalable alternative for rapid screening.”

This adds clinical relevance.

**4. Use Visuals to Reinforce the Claim**

Include:

* A confusion matrix
* ROC curve
* Grad-CAM overlays showing correct activation

These visuals help your audience trust the numbers.

**🗣️ How to Say It in Your Presentation**

“We achieved over 90% classification accuracy on the test set, with an AUC of 0.94 and recall above 92%. These metrics confirm that our model reliably detects pneumonia and generalizes well to unseen data. Compared to baseline models and manual diagnosis benchmarks, our approach offers a robust, interpretable, and scalable solution for clinical deployment.”

Note: 35 Epoch Start at 1:40 am

**Interpreting the Class Weights**

| **Class** | **Label** | **Weight** | **Meaning** |
| --- | --- | --- | --- |
| **Normal** | 0 | 1.94 | Heavily weighted — model is penalized more for misclassifying Normal cases |
| **Pneumonia** | 1 | 0.67 | Less weighted — model is penalized less for misclassifying Pneumonia cases |