greatlearning

Learning for Life

INTERIM REPORT

1. Summary of problem statement, data and findings

**Problem Statement:**

Pneumonia is a serious respiratory condition that requires rapid and accurate diagnosis. Manual analysis of chest X-ray images can be time-consuming and error-prone, especially in resource-limited settings. Our objective is to build a deep learning-based system that can **classify chest X-ray images into three categories**:

* **Normal**
* **Lung Opacity (Pneumonia detected)**
* **No Lung Opacity / Not Normal**

**Dataset:**

The dataset used is derived from the **RSNA Pneumonia Detection Challenge**, which includes:

* Chest X-ray DICOM images
* Bounding box annotations for pneumonia regions
* Label metadata indicating the class (Normal, Lung Opacity, or No Lung Opacity)

**Key Findings:**

* Majority of lung opacity cases have clearly distinguishable patterns in the radiographs.
* Normal and “No Lung Opacity / Not Normal” classes are harder to distinguish without localization.
* There is a class imbalance with fewer "Normal" samples compared to "Lung Opacity".

1. Summary of the Approach to EDA and Pre-processing

**Exploratory Data Analysis (EDA):**

* **Image sample visualization:** Random chest X-rays across each class were visualized with bounding boxes (if present).
* **Class distribution:** A pie chart and bar plot confirmed **imbalance**, with “Lung Opacity” being the most frequent class.
* **Bounding box analysis:** For Lung Opacity images, multiple bounding boxes are often present, indicating severity.
* **Size distribution of bounding boxes:** Heatmaps showed that pneumonia regions are generally centralized in the lungs.

**Pre-processing Steps:**

* **DICOM conversion:** DICOM images were converted to pixel arrays using pydicom.
* **Resizing:** Images resized to 224x224 for uniform input to the CNN model.
* **Normalization:** Applied per-channel mean and standard deviation normalization.
* **Augmentation:** To combat class imbalance and improve generalization, applied transformations like:
  + Random horizontal flips
  + Rotation ±10°
  + Zoom and cropping

**Meaningful Features Identified:**

* Pneumonia presence is visually detectable in dense and irregular lung patterns.
* In “Lung Opacity” images, lesion density and location in lungs (mostly lower lobes) are common.
* Heatmap visualizations (Grad-CAM) show model focuses on actual infected regions when correctly classified.

1. Deciding Models and Model Building

**Basic CNN model:**

* **Architecture:** A simple Convolutional Neural Network with fewer layers.
* **Purpose:** Acts as a baseline to measure the performance of more advanced models.
* **Performance:**
  + **Accuracy:** ~66.31%
  + **Observations:** Balanced performance; particularly strong in identifying the **Normal** class (F1 = 0.7424).
  + **Limitation:** Struggles slightly with “No Lung Opacity / Not Normal” (F1 = 0.5837).

**Deeper CNN model:**

* **Architecture:** More convolutional layers and parameters to learn deeper features.
* **Performance:**
  + **Accuracy:** ~65.31%
  + **Observations:**
    - Best at detecting **No Lung Opacity / Not Normal** (Recall = 0.6664).
    - Slightly underperforms in overall accuracy compared to BasicCNN and MobileNetV2.
  + **Limitation:** Sacrifices precision on Lung Opacity to boost recall.

**MobileNetV2 (Pre-trained Model):**

* **Architecture:** Lightweight, pre-trained on ImageNet.
* **Purpose:** Uses transfer learning to achieve better generalization with less training data.
* **Performance:**
  + **Accuracy:** ~68.42% **(best overall)**
  + **Observations:**
    - Highest overall F1-score (0.6812), particularly strong in classifying **Normal** cases (F1 = 0.7812).
    - Transfer learning helps in extracting better features.
* **Why it performs best:**
  + Pre-trained features from ImageNet.
  + Fine-tuning adapts it well to the pneumonia dataset.
  + Balanced precision and recall across all classes.

**LeNet-5 Model:**

* **Architecture:** Classic CNN with limited depth.
* **Performance:**
  + **Accuracy:** ~62.55%
  + **Observations:** Performs relatively well for **Normal** (F1 = 0.7086), but weak for “No Lung Opacity / Not Normal” (F1 = 0.4968).
  + **Limitation:** Older architecture not well suited for complex classification tasks like chest X-ray interpretation.

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| **Model** | **Accuracy** | **Precision (Macro Avg)** | **Recall (Macro Avg)** | **F1-Score (Macro Avg)** |
| **Basic CNN** | 66.31% | 66.55% | 67.46% | 66.82% |
| **MobileNet** | **68.42%** | **68.60%** | **69.63%** | **69.00%** |
| **LeNet-5** | 62.55% | 62.47% | 64.65% | 62.51% |
| **DeepCNN** | 65.31% | 67.39% | 65.38% | 65.92% |

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| **Model** | **Observation** |
| **Basic CNN** | Good performance in predicting **Normal** cases (1409/1760), moderate confusion between **Lung Opacity** and **No Lung Opacity**. |
| **MobileNet** | Strong **Normal** class identification (1448/1767) and overall better balance across all classes. Less confusion across all axes. |
| **LeNet-5** | Lower performance on **No Lung Opacity**, indicating confusion with both other classes. |
| **DeepCNN** | Better at detecting **No Lung Opacity / Not Normal**, slightly weaker on **Lung Opacity** compared to MobileNet. |

1. How to improve your model performance?
2. **Data Preprocessing**

* Apply **data augmentation** (flips, rotations, brightness, etc.) to improve generalization.
* Ensure **pixel normalization** (0–1 range).
* Check **class imbalance**: Consider oversampling or using **Focal Loss** for better minority class performance.

1. **Feature Selection / Engineering**

* Not directly applicable for raw images, but:
  + Try **autoencoders or PCA** for dimensionality reduction.
  + Combine CNN features with **metadata** (e.g., age, gender) if available.

1. **Model Improvements**

* **Fine-Tune MobileNetV2 Further**
  + Unfreeze deeper layers and retrain using a **lower learning rate**.
* **Use Ensemble Models**
  + Combine predictions from **BasicCNN**, **DeeperCNN**, and **MobileNetV2** using majority voting or weighted averaging.
* **Redesign the Classifier Head**
  + Add **dense layers**, **dropout**, or **attention layers** after the base MobileNetV2 model.

1. **Training Enhancements**

* Use learning rate schedulers like:
  + **ReduceLROnPlateau**
  + **Cosine Annealing**
* **Early stopping** to prevent overfitting.
* Perform **grid/random search** for hyperparameter tuning:
  + Learning rate, dropout, filters, batch size, etc.

1. **Evaluation Metrics**

* Already evaluated using **Precision, Recall, F1-score**.
* Consider **Confusion Matrix** visualization to diagnose class-level misclassifications.
* Use **ROC-AUC** for further insights, especially if model is used in clinical decision-making.