**Internship Week 3 Report**

**Project: Pneumonia Detection Using Deep Learning (CNN & ResNet50)**

**1. Introduction**

Pneumonia is a serious lung infection that can be detected through chest X-ray (CXR) images. The goal of this week’s task was to build a deep learning model that can classify CXR images into Normal or Pneumonia.

We used the Chest X-ray Dataset from Kaggle (Paul Mooney’s dataset), which has become a benchmark dataset for medical image classification tasks.

The overall workflow included:

1. Understanding dataset structure
2. Preprocessing images
3. Building a baseline CNN model
4. Training and evaluating with different loss functions
5. Applying ResNet50 transfer learning
6. Fine-tuning and analyzing results

**2. Dataset Description**

We used the dataset **chest\_xray**, which consists of three main folders:

* **train/** → 5216 images (3883 Pneumonia, 1349 Normal)
* **val/** → 16 images (8 Pneumonia, 8 Normal)
* **test/** → 624 images (390 Pneumonia, 234 Normal)

**Observations about the dataset:**

* Highly imbalanced (Pneumonia cases are approximately three times more than Normal cases).
* Images are grayscale X-rays but stored in 3-channel (RGB).
* The dataset already provides a test split, ensuring fair evaluation.

**3. Data Preprocessing**

The following steps were applied:

* **Image resizing**: All images resized to 128 × 128 × 3 for consistency.
* **Normalization**: Pixel values rescaled to the [0,1] range.
* **Batching**: Batch size set to 32.
* **Data Generators**: Used ImageDataGenerator for training, validation, and testing.

At first, we used only rescaling. Later, data augmentation was introduced to improve generalization.

**4. Baseline CNN Model**

We started with a custom CNN built from scratch.

**Architecture:**

* Conv2D → Batch Normalization → MaxPooling
* Conv2D → Batch Normalization → MaxPooling
* Conv2D → Batch Normalization → MaxPooling
* Flatten → Dense(256, relu) → Dropout(0.5)
* Dense(1, sigmoid)

**Loss Function:**

* Initially used Binary Crossentropy.
* Then experimented with Focal Loss to handle class imbalance.

**Training Setup:**

* Epochs = 10
* Optimizer = Adam

**Results:**

* Accuracy: approximately 84–85%
* Weakness: The model struggled with Normal cases (low recall).

**5. Introducing Focal Loss**

Since the dataset is imbalanced, we tested Focal Loss.

* Formula emphasizes harder-to-classify samples.
* Parameters: γ = 2, α = 0.25

**Observations:**

* Accuracy remained around 85–86%
* Loss values became very small, leading to unstable training
* Conclusion: Focal Loss did not significantly improve performance in this setup

**6. Transfer Learning with ResNet50**

Next, we applied ResNet50 (pretrained on ImageNet) to leverage deep features.

**Architecture:**

* ResNet50 base (frozen layers, include\_top=False)
* Flatten → Dense(256, relu) → Dropout(0.5) → Dense(1, sigmoid)

**Training Strategy:**

1. Freeze ResNet50 layers and train only the dense head.
2. Later, unfreeze the last 30–50 layers and fine-tune with a smaller learning rate (1e-5).

**Results:**

* Test Accuracy: approximately 86%
* Pneumonia Recall: 95%
* Normal Recall: 71% (still weak)

**7. Evaluation**

We used:

* Confusion Matrix
* Classification Report
* ROC-AUC Curve

**Final Evaluation (ResNet50 + Focal Loss):**

* Accuracy: 86%
* Precision (Normal): 0.90
* Recall (Normal): 0.71
* Precision (Pneumonia): 0.85
* Recall (Pneumonia): 0.95

**Interpretation:**

* The model is strong at detecting Pneumonia.
* However, it often misclassifies Normal as Pneumonia (false positives).
* This is mainly due to class imbalance and frozen backbone layers.

**8. Key Changes Made and Their Rationale**

1. **Custom CNN → ResNet50**
   * CNN gave decent accuracy, but ResNet50 captured better features.
2. **Binary Crossentropy → Focal Loss**
   * Tried to address imbalance, but training became unstable.
3. **Added Class Weights**
   * Helped balance contributions of Normal vs Pneumonia classes.
4. **Unfreezing Last Layers of ResNet50**
   * Allowed the model to learn domain-specific medical features.
5. **Data Augmentation**
   * Increased diversity of Normal cases for better balance.

**9. Challenges Faced**

* **Imbalanced dataset**: Model favored Pneumonia over Normal.
* **Focal loss scaling**: Loss values shrank too much, leading to ineffective learning.
* **Validation split mismatch**: Required careful stratification to ensure balanced validation.

**10. Conclusions**

* The baseline CNN achieved around 85% accuracy.
* ResNet50 transfer learning improved robustness, reaching 86% accuracy with better Pneumonia detection.
* The model still struggles with Normal detection due to imbalance.

**Future Work:**

* Use binary crossentropy with class weights instead of focal loss.
* Apply stratified splits for better validation balance.
* Increase data augmentation for Normal cases.