**Report: RSNA Pneumonia Detection with DenseNet201**

**Objective**

Develop a deep learning model to classify chest X-rays as **Normal** or **Pneumonia** using the RSNA dataset, addressing **overfitting** and **class imbalance** while improving generalization.

**Dataset Overview**

* **Source**: RSNA Pneumonia Detection Challenge.
* **Class Distribution**:
  + **Normal**: ~75% (4135 samples).
  + **Pneumonia**: ~25% (1202 samples).
* **Image Resolution**: 1024x1024 → Resized to **224x224** for DenseNet compatibility.

**Model Architecture**

**Base Model: DenseNet201 (pretrained on ImageNet).**

* **Input Shape**: (224, 224, 3).
* **Fine-Tuning**:
  + **Frozen Layers**: First 200 layers (generic feature retention).
  + **Trainable Layers**: Last 53 layers (task-specific adaptation).

**Custom Head:**

python

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Sequential([

SpatialDropout2D(0.5), # Reduces overfitting in convolutional features

GlobalAveragePooling2D(), # Downsamples spatial dimensions

Dense(64, activation='relu', kernel\_regularizer=l2(0.01)), # L2 regularization

Dropout(0.5), # Additional regularization

Dense(1, activation='sigmoid') # Binary classification output

])

**Loss & Optimizer:**

* **Loss**: BinaryFocalCrossentropy(gamma=2.0) → Penalizes misclassified Pneumonia cases.
* **Optimizer**: AdamW(learning\_rate=1e-4, weight\_decay=1e-4) → Weight decay for gradient stability.

**Training Results**

**Metrics:**

| **Metric** | **Train** | **Validation** |
| --- | --- | --- |
| **AUC** | 0.80 | 0.60 |
| **Loss** | 0.40 | 0.90 |

**Classification Report:**

| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
| --- | --- | --- | --- | --- |
| **Normal** | 0.94 | 0.74 | 0.83 | 4135 |
| **Pneumonia** | 0.49 | 0.84 | 0.62 | 1202 |
| **Accuracy** | - | 0.77 | - | 5337 |

**Key Observations:**

1. **Overfitting**: Large gap between train/val AUC (0.8 vs. 0.6) and rising val loss.
2. **Class Imbalance**: High Pneumonia recall (84%) but low precision (49%) → Too many FPs.

**Identified Issues**

1. **Overfitting**:
   * Validation loss increases after epoch 5.
   * Model memorizes training data due to insufficient regularization.
2. **Class Imbalance**:
   * Weighting skewed toward majority class (Normal).
3. **Data Pipeline**:
   * Limited augmentation diversity (only flips/brightness).

**Planned Improvements**

**1. Enhanced Regularization**

* **SpatialDropout2D(0.5)**: Drops entire feature maps instead of individual neurons.
* **L2 Regularization (0.01)**: Penalizes large weights in the dense layer.
* **Freeze More Layers**: Only last 53 layers trainable (first 200 frozen).

**2. Class Imbalance Mitigation**

* **Focal Loss**: Focuses training on hard-to-classify Pneumonia cases (gamma=2.0).
* **Class Weights Adjustment**: Increase weight for Pneumonia (e.g., {0: 1, 1: 5}).

**3. Advanced Augmentation**

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img = tf.image.random\_rotation(img, 0.2) # ±20° rotation

img = tf.image.random\_crop(img, (180, 180, 3)) # Random crop + resize

**Expected Outcomes**

| **Metric** | **Before Fixes** | **After Fixes (Expected)** |
| --- | --- | --- |
| **Validation AUC** | 0.60 | **0.75–0.80** |
| **Pneumonia F1** | 0.62 | **0.70–0.75** |
| **Validation Loss** | 0.90 | **0.55–0.65** |

**Next Steps**

1. **Grad-CAM Visualization**: Validate if the model focuses on lung regions.
2. **Test-Time Augmentation (TTA)**: Improve robustness by averaging predictions over augmented samples.
3. **Hyperparameter Tuning**: Optimize dropout rate, L2 penalty, and focal loss gamma.

**Conclusion**

This revised pipeline addresses overfitting and class imbalance through **stronger regularization**, **focal loss**, and **advanced augmentation**. Expected improvements include a **15–20% boost in validation AUC** and better generalization. Future work will focus on model interpretability and deployment.