Pneumonia Detection Using Chest X-Ray Images

1. Objective

The objective of this project is to develop a deep learning model capable of detecting pneumonia from chest X-ray images. The model classifies X-ray images into two categories: pneumonia-positive or pneumonia-negative.

2. Dataset Description

- **Source:** Kaggle dataset: *Chest X-Ray Images (Pneumonia)* by Paul Timothy Mooney.
- **Structure:**
    - The dataset is divided into three subsets: training, validation, and testing.
    - Each subset contains images organized into two directories: `NORMAL` and `PNEUMONIA`.
- **Preprocessing:**
    - Images were resized to 224x224 pixels.
    - Pixel values were normalized to the range [0, 1].

3. Methodology

3.1 Data Preprocessing

- The dataset was loaded using `kagglehub` to download directly from Kaggle.
- Images were resized and normalized for compatibility with the MobileNetV2 model.
- Training images were augmented using the following techniques:
    - Random rotation
    - Width and height shifts
    - Shear and zoom transformations
    - Horizontal flipping
- Validation and testing images were preprocessed with rescaling only.

3.2 Model Development

- **Architecture:** MobileNetV2, a lightweight pre-trained CNN, was used as the base model.
- **Transfer Learning:**
    - The base model, pre-trained on ImageNet, was fine-tuned for this binary classification task.
    - Additional layers included a global average pooling layer, a dense layer with 256 units, a dropout layer, and a sigmoid output layer.
- **Optimization:**
    - The model was compiled using the Adam optimizer.

    - The binary crossentropy loss function was used to handle the binary classification problem.

3.3 Training and Evaluation

- The model was trained for 10 epochs using the training dataset.
- Validation performance was monitored during training.
- The test dataset was used for final evaluation.

4. Results

4.1 Model Performance

- **Classification Report:**
    - Precision, Recall, F1-Score, and Accuracy were computed for the test dataset.
- **ROC-AUC Score:**
    - The model achieved a high area under the ROC curve, indicating robust discrimination between positive and negative cases.

4.2 Importance of Data Augmentation

- Augmentation helped the model generalize better and mitigated overfitting, especially given the limited dataset size.

5. Challenges

1. **Class Imbalance:**
    - The dataset had more pneumonia-positive samples compared to normal ones.
    - Careful monitoring of metrics like ROC-AUC and F1-Score was necessary to ensure balanced performance.
2. **Variability in Images:**
    - Chest X-ray images varied in quality, contrast, and resolution.
    - Robust preprocessing ensured consistent inputs to the model.

6. Insights

- MobileNetV2’s lightweight architecture made it ideal for quick training and inference while maintaining high accuracy.
- Transfer learning significantly reduced training time and improved performance on a small dataset.
- Evaluation metrics like ROC-AUC provided a more comprehensive view of model performance, especially in the presence of class imbalance.

7. Future Work

1. **Hyperparameter Tuning:**
    - Optimize learning rate, dropout rates, and batch size to improve accuracy.
2. **Ensemble Models:**
    - Combine predictions from multiple pre-trained architectures to boost robustness and reduce misclassifications.
3. **Deployment:**
    - Deploy the model in a real-world application for clinical testing and integration.

8. Tools and Technologies

- **Libraries:** TensorFlow/Keras, NumPy, KaggleHub, Scikit-learn
- **Hardware:** Google Colab with GPU acceleration