**Pneumonia Detection Task**

**Overview**

**This project focuses on the detection of pneumonia from chest X-ray images using Convolutional Neural Networks (CNNs) and Transfer Learning. The primary objective was to develop a robust and efficient model capable of classifying chest X-rays as 'Normal' or 'Pneumonia'.**

**Key Steps**

**1. Data Acquisition**

* **Dataset Source: Downloaded from Kaggle using the chest-xray-pneumonia dataset.**
* **The dataset was organized into train, test, and validation sets, each containing two subfolders for NORMAL and PNEUMONIA images.**

**2. Data Preprocessing**

* **Image Resizing: Resized all images to 224x224 pixels to maintain consistency with common pre-trained model input sizes.**
* **Normalization: Normalized pixel values to the range [0, 1] to aid in training convergence.**
* **Data Augmentation: Applied augmentation techniques like rotation, flipping, brightness adjustments, and zoom to increase dataset variability and reduce overfitting.**

**3. Data Splitting**

* **Divided the dataset into training, validation, and testing sets to ensure proper evaluation of the model.**

**4. Model Development**

* **Custom CNN: Built a custom CNN with multiple convolutional, max-pooling, and dropout layers to extract spatial features from images.**
* **Transfer Learning: Fine-tuned pre-trained models like EfficientNetB0 and EfficientNetB3 to leverage feature extraction from large ImageNet-trained networks.**
* **Activation Functions: Used ReLU activation for hidden layers and sigmoid activation for the binary classification output.**
* **Optimization: Utilized the Adam optimizer with a binary cross-entropy loss function.**

**5. Model Training**

* **Trained the models using the prepared training set, validating the performance on the validation set.**
* **Applied an early stopping mechanism to halt training if no improvements were observed in validation loss for 15 consecutive epochs.**

**6. Evaluation and Metrics**

* **Accuracy: Measured the accuracy of the model on the validation and test sets.**
* **Loss: Visualized the training and validation loss over epochs to detect overfitting.**
* **ROC-AUC: Evaluated the Area Under the Receiver Operating Characteristic Curve to assess classification performance.**
* **Confusion Matrix: Computed the confusion matrix to measure sensitivity, specificity, precision, and recall.**

**7. Results Comparison**

* **Augmented Data vs Non-Augmented Data: Compared the performance of the model trained on augmented data against non-augmented data.**
* **Observed significant improvements in model generalization due to the augmentation techniques applied.**

**8. Results**

* **Final Accuracy: The model achieved a testing accuracy of over 85%.**
* **Test Loss: The loss during testing was within an acceptable range, indicating no significant overfitting.**

**9. Future Enhancements**

* **Hyperparameter Tuning: Further tuning of learning rates, batch sizes, and optimizer selection.**
* **Ensemble Models: Combine predictions from multiple models to increase robustness.**
* **Explainability: Use Grad-CAM or similar methods to visualize important regions in X-ray images for better interpretability.**

**10. Tools and Libraries Used**

* **Languages: Python**
* **Libraries: TensorFlow, Keras, NumPy, Pandas, Matplotlib, Plotly, and Scikit-learn.**

**This project demonstrated the effectiveness of CNNs and Transfer Learning for medical image classification tasks, achieving strong performance on the Pneumonia Detection task.**

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