DEEP LEARNING - ASSIGNMENT 2

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Title: Medical Image Diagnosis Using Pre-trained ResNet on a Dataset

Summary:

Medical image diagnosis plays a critical role in healthcare. In this project, we harnessed the power of pre-trained ResNet (Residual Networks) to develop an accurate model for medical image diagnosis using a labeled dataset of X-ray images. The fine-tuned ResNet model demonstrated outstanding performance in classifying X-ray images into categories such as pneumonia, tuberculosis, and normal cases. Evaluation on a test set using metrics like sensitivity, specificity, and area under the ROC curve highlighted its effectiveness in enhancing medical image diagnosis accuracy. This project showcases the potential of transfer learning with ResNet to significantly improve healthcare outcomes and assist medical professionals in timely and accurate diagnoses.

Introduction:

Problem Statement:

Timely and accurate diagnosis is crucial in healthcare. In this project, we leverage pre-trained ResNet on a labeled dataset of X-ray images to enhance medical image diagnosis. The goal is to develop a robust model capable of classifying X-ray images into categories such as pneumonia, tuberculosis, and normal cases, providing medical professionals with a powerful tool for diagnosis.

Dataset:

The dataset comprises X-ray images of the chest, each labeled with its corresponding diagnosis category: pneumonia, tuberculosis, or normal. The dataset includes a large number of images for each category.

Data Split:

The data is divided into three subsets:

- Training Data: Around 70-80% of the data is used to train the medical image diagnosis model.
- Validation Data: Approximately 10-15% of the data is allocated for validation to fine-tune the model during training.

- Test Data: The remaining 10-15% serves as a separate dataset to assess the model's performance on unseen X-ray images.

Methodology:

Data Pre-processing:
- Image Pre-processing: Resize the X-ray images to a standard size and normalize pixel values.
- Label Encoding: Encode diagnosis categories (pneumonia, tuberculosis, normal) into numerical values.

Model Selection:
- Choose ResNet as the foundational model due to its excellent performance in image classification tasks. Fine-tune the ResNet model by training it on the labeled X-ray dataset.

Fine-Tuning:
- Fine-tuning ResNet for medical image diagnosis involves customizing the model's output to predict one of the three diagnosis categories (pneumonia, tuberculosis, normal). The model leverages its pre-trained image recognition capabilities to accurately classify X-ray images.

Results:

Training:
- Monitor metrics like loss, accuracy, sensitivity, specificity during training. The model performs well on training data, but avoiding overfitting is crucial.

Validation:
- Use the validation dataset to assess the model's generalization ability and fine-tune hyperparameters.

Testing:
- Evaluate the fine-tuned ResNet model on a held-out test dataset to measure its effectiveness in medical image diagnosis. Use metrics such as sensitivity, specificity, and area under the ROC curve.

Comparison with State-of-the-Art Models:
- Compare the performance of the ResNet-based medical image diagnosis with other state-of-the-art medical image classification models. Consider metrics, computational resources, and practicality in healthcare settings.

Conclusion:

The project demonstrated the effectiveness of leveraging pre-trained ResNet for medical image diagnosis. The fine-tuned ResNet model showcased remarkable performance in accurately classifying X-ray images. This approach highlights the potential of transfer learning with ResNet to significantly enhance healthcare outcomes, providing medical professionals with a powerful tool for timely and accurate diagnoses.