

Computer Vision

Project proposal

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**Section: A2**

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**Introduction**

**Problem Statement**

The detection and diagnosis of COVID-19 have become critical challenges in the healthcare sector, particularly due to the rapid spread of the virus and the need for timely and accurate diagnosis. Traditional methods like PCR tests are reliable but time-consuming. X-ray imaging offers a faster alternative for diagnosis but requires advanced classification systems to identify COVID-19 accurately from other types of pneumonia and healthy cases. The core problem addressed in this project is the need for reliable and accurate identification of COVID-19 from lung X-ray images. The goal is to classify images into three classes: COVID-19 positive, pneumonia, and healthy. This classification is crucial for assisting healthcare professionals in making quick and accurate diagnoses, especially in resource-constrained settings.

**Significance of the Project**

Developing a robust and accurate COVID-19 detection system based on lung X-rays can significantly enhance the diagnostic process, providing quicker results and facilitating timely treatment. This project aims to leverage advanced computer vision and deep learning techniques to create a system capable of distinguishing between COVID-19, pneumonia, and healthy lung conditions. By improving the accuracy and reliability of this classification, the project will contribute to more effective management of the pandemic, enabling better allocation of medical resources, reducing the burden on healthcare systems, and ultimately saving lives.

**Dataset**

The dataset used in this project comprises lung X-ray images categorized into three classes: COVID-19 positive, pneumonia, and healthy. The images are sourced from publicly available datasets and will be preprocessed to have a uniform size of 64x64 pixels. The dataset will be split into training and testing sets to facilitate model training and evaluation. Preprocessing steps will include normalizing the pixel values to a range of 0 to 1 to improve model performance and convergence during training.

**Tools and Techniques**

To address the classification problem, three different CNN architectures will be utilized:

1. **Custom CNN**: This sequential model will include three convolutional layers followed by max-pooling layers and two dense layers. The model will be designed to capture various levels of feature abstractions from the input images.
2. **ResNet50**: This pre-trained ResNet50 model, excluding its top layer, is known for its deep architecture that includes residual blocks, which help in training very deep networks by addressing the vanishing gradient problem.
3. **VGG16**: This pre-trained VGG16 model, also excluding its top layer, is characterized by its simplicity and uniform architecture, making it effective for image classification tasks.

Each model will be fine-tuned on our dataset to adapt the pre-trained weights to the specific task of classifying COVID-19, pneumonia, and healthy lung images.

**Model Definitions**

* **Custom CNN**: The custom CNN architecture will be defined using the Keras library. It will include convolutional layers with ReLU activation, followed by max-pooling layers to reduce the spatial dimensions of the feature maps. The final dense layers will be used for classification.
* **ResNet50**: The ResNet50 model will be loaded with pre-trained weights from the ImageNet dataset, excluding the top fully connected layers. Custom dense layers will be added for our classification task, and the pre-trained layers will be frozen initially. Fine-tuning will be performed by unfreezing some of the top layers of the ResNet50 base model to allow the network to learn domain-specific features while retaining the benefits of the pre-trained features.
* **VGG16**: Similar to ResNet50, the VGG16 model will be loaded with pre-trained weights and customized by adding dense layers for classification. The pre-trained layers will also be frozen initially. Fine-tuning will be performed by unfreezing some of the top layers of the VGG16 base model to allow the network to adapt more specifically to the task of COVID-19 detection.

**Fine-Tuning Process**

Fine-tuning involves unfreezing a few of the top layers of the pre-trained model and training them alongside the newly added dense layers. This allows the model to adjust the higher-level features to be more relevant to our specific task. The steps are as follows:

1. **Initial Training**: Train the model with the pre-trained base frozen to get the initial training results.
2. **Unfreeze Layers**: Unfreeze the top layers of the base model.
3. **Fine-Tuning**: Continue training the model with a very low learning rate to fine-tune the weights of the unfrozen layers.

**Evaluation Metrics**

The models' performance will be evaluated using accuracy and loss metrics on both the training and testing datasets. These metrics will provide insights into how well the models have learned to classify the images and their effectiveness in generalizing to new data.

* **Custom CNN Evaluation**: The custom CNN's training and testing accuracy, along with loss metrics, will be recorded and analyzed to determine its performance.
* **ResNet50 Evaluation**: The ResNet50 model's performance will be evaluated similarly, focusing on its ability to leverage pre-trained features for accurate classification and the improvements brought by fine-tuning.
* **VGG16 Evaluation**: The VGG16 model's accuracy and loss metrics will also be analyzed to compare its performance against the other two models and assess the impact of fine-tuning.

**Plotting Results**

The training and testing accuracy and loss for each model will be plotted to visually compare their performance across the epochs. This will help in understanding the training dynamics and identifying which model performs best.

**Conclusion**

Based on the evaluations, the project aims to determine the most effective model for diagnosing COVID-19 from lung X-ray images. The model with the highest testing accuracy and lowest loss will be considered the best performing. This project highlights the importance of model selection, initial training, and fine-tuning in achieving optimal performance for image classification tasks. The findings can be applied to enhance diagnostic systems in various applications, contributing to advancements in healthcare and improving the management of infectious diseases.