Project Proposal

A. Problem Statement and Application

The problem addressed in this proposal is the detection and classification of pneumonia using chest X-rays. Pneumonia is a dangerous infection of one or both lungs in which the air sacs are filled with pus and other liquids. Pneumonia is mainly caused by viruses, fungi, and bacteria. Pneumonia is a prevalent and potentially life-threatening lung infection, particularly affecting vulnerable populations such as children and the elderly [1]. The project aims to develop a robust and reliable system for pneumonia detection, with the potential to make a significant impact on healthcare delivery and patient outcomes.

The absence of doctors and diagnosis support systems worldwide has hurt the health organization. Furthermore, hospitals lack radiologists, particularly in rural regions, and doctors are under pressure to treat a large number of patients. As a result, nearly all cases are handled by a single physician, which frequently results in incorrect diagnosis. Neural networks can be utilized to increase diagnosis accuracy, but better tools are required to evaluate chest X-ray data. Artificial intelligence and deep learning are extensively utilized in medicine.

B. Image Dataset Selection

1. This dataset, which is further classified into two classes: Normal and Pneumonia contains 5863 X-ray images that were chosen from retrospective cohorts of pediatric patients from Guangzhou Women and Children's Medical Center, Guangzhou, aged one to five. Initially, every chest radiograph was screened for quality control by eliminating any scans that were of poor quality or were not readable. Before the images' diagnoses could be used to train the AI system, they were evaluated by two board-certified medical professionals [2].

2. There are 27811 X-ray images in this dataset, and they are further broken down into 5 classes. The comparatively small number of X-ray scans classified as Covid-19 infected and the increased risk of pneumonia in individuals with Covid-19 infection are the main reasons for choosing this dataset [3].

3. 112,120 X-ray images from 30,805 distinct patterns with disease labels are included in this dataset. The images are categorized into 15 groups based on various diseases. We have taken into consideration 25,000 images from all the categories for this project. We anticipate low accuracy because the majority of the images in the dataset have annotations, and there are relatively few images per label [4].

C. Possible Methodology

In this section, we will discuss CNN architectures, model training and evaluation metrics.

1. **CNN architectures:**

   We will be using the three most powerful pre-trained CNN models, ResNet [5], DenseNet [6], and Inception [7] to examine the X-ray dataset.

   (a) **ResNet:** It features residual connections and identifies mapping which helps the model to learn features more effectively and increases accuracy.

   (b) **DenseNet:** It employs dense connectivity patterns, facilitating feature reuse and propagation throughout the network, enhancing information flow and gradient flow during training.

   (c) **Inception:** This architecture family uses batch normalization to reduce internal co-variate shift which leads to accelerated deep network training [8].

2. **Model Training:**

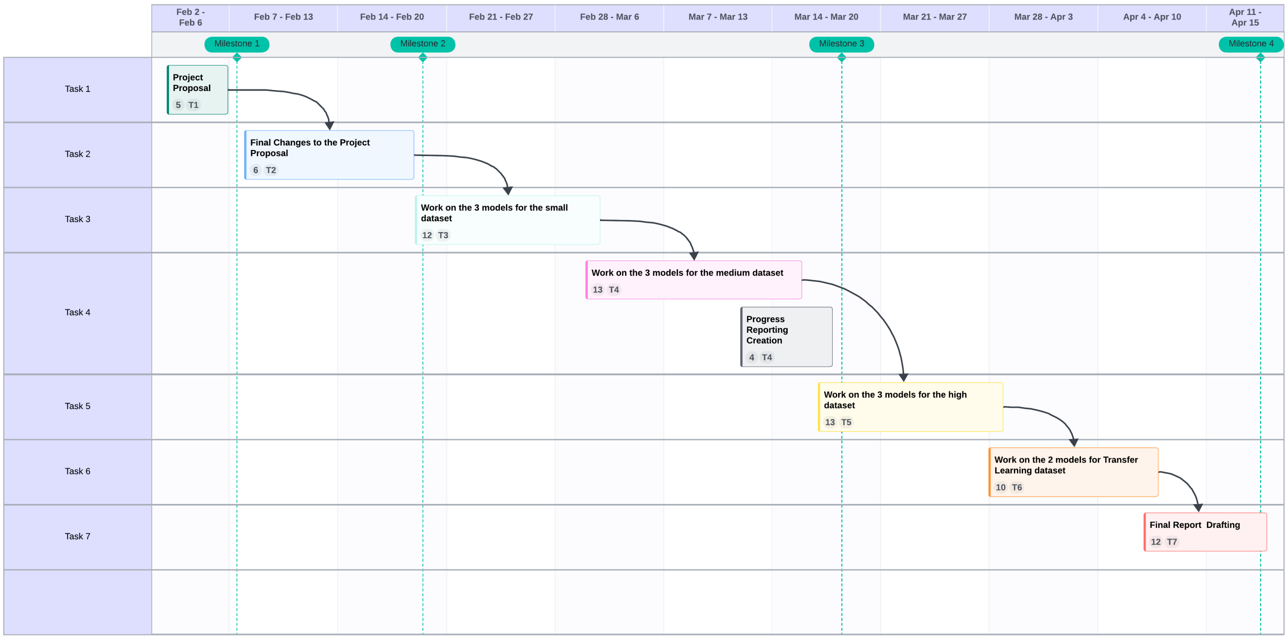
   In the training process, the dataset will be partitioned into three subsets: training, validation, and test sets. The training set will serve as the primary data source for training each CNN model. Subsequently, the models will be validated using the validation set to closely monitor their performance. We'll use various optimization techniques like adjusting the hyperparameters and using loss functions to fine-tune the model performance.

3. **Evaluation metrics:**

   We'll evaluate CNN and compare the accuracy based on the following evaluation metrics.

   - **Accuracy:** Measures the overall correctness of the model's predictions.
   - **Precision:** Indicates the proportion of true positive predictions among all positive predictions made by the model.
   - **F1-score:** Providing a balanced measure of the model's performance.
   - **AUC-ROC:** Evaluates the model's ability to discriminate between positive and negative instances across different threshold values.

Gantt Chart



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