Lung Disease Clasification - Applied Artificial Intelligence Project

Anonymous COMP6721 submission

Paper ID Group-Q

1. Problem Statement and Application

The destruction caused by COVID-19 created a need for diagnosis that is reliable and fast [21]. Chest X-ray acquisition is easy but needs to be evaluated by expert radiologists [15]. We propose that a deep CNN model can help diagnose new diseases much faster and accurately. We plan to create models that will classify multiple lung diseases like COVID-19 and Atelectasis. This will allow us to reduce the turn-around-times for diagnosis of new diseases. There are a number of challenges that we foresee, the datasets are highly imbalanced so we will have to take corrective measures. Images from different X-Ray scanners have different radiographic contrast [13] this could have a negative impact on our model's results. We will try different models to solve this problem and present a detailed comparison of the results. After evaluating the results, we will choose the best model in terms of both efficiency and accuracy.

Our novelty will be producing an explainable model as well as a custom CNN that we plan to create which could get us better results than the existing architectures. We also plan on releasing the best performing model, trained on all images to serve as the base model for other problems.

2. Image Dataset Selection

We chose chest X-Ray datasets (Tab. 1) that have varying disease types to ensure that our models are robust. The main concern while selecting the datasets was the number of images per class as most datasets were highly skewed. We rejected datasets where the images were compressed and noisy as this can lead to mis-diagnosis [18]. This will help reduce the time spent in the pre-processing stage.

3. Possible Methodology

As our datasets are from different sources, we will explore different pre-processing techniques like histogram equalization and Gaussian blur [6] in PyTorch using functions like normalize and gaussian_blur [14] to make training easier for our CNN. We will explore several neural network architectures like VGG 16 [17], Inception V3 [19], Resnet [9], and produce our own Custom CNN model as

Dataset	No. of Images	Classes	Image Size
Pneumonia, COVID-19 [16] [4] [5]	10,192 (Normal) + 3,616 (COVID-19) + 1,345 (Pneumonia)	3	299 x 299
Pneumonia [11] [20]	1,583 (Normal) + 1,493 (Viral Pneumonia) + 2,780 (Baterial Pneumonia)	3	224 x 224
Chest X-Ray8 [22] [23]	60,190 (Normal) + 16,610 (Infiltration) + 8,284 (Atelectasis)	3	1024 x 1024

Table 1. Shortlisted Datasets.

well with different depth, size of kernel, strides and types of layers. To train our models, we will use cross-entropy loss and experiment with optimizers [8] like Stochastic Gradient Descent, Adam, AdaDelta [10] etc. to select the optimizer that gives us a lower loss with less epochs. To ensure that our model does not get stuck at a local minima, we will try different learning rate decay methods. While training, we will tweak different hyperparameters like epoch, activation functions, and batch size to ensure that we get a well performing model. As the size of our dataset is small, we plan on experimenting with data augmentation using techniques like changing contrast and image flipping as well as transfer learning to improve our results. To find the best hyperparameters, we will perform ablation studies and try to make use of Bayesian hyperparameter optimization [1].

Given that our datasets are highly imbalanced, we will try to use class weights and data augmentation for minority class [2]. For evaluation, we will explore different metrics like confusion matrix, ROC Curve and F-Measure [3]. We will also consider the FLOPs of our models as one of the key metrics. To explain the results of our models, we plan on using SHAP [12] and GradCAM [7] which will help us diagnose our models and also help end users gain more confidence in our model's decisions.

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TASK	PROGRESS	START	END	Week 1 (12-09-22)	Week 2 (19-09-22)	Week 3 (26-09-22)	Week 4 (03-10-22)	Week 5 (10-10-22)	Week 6 (17-10-22)	Week 7 (24-10-22)	Week 8 (31-10-22)	Week 9 (07-11-22)	Week 10 (14-11-22)	Week 11 (21-11-22)	Week 12 (28-11-22)
Research															
Finding and evaluating datasets	100%	12-09-22	09-10-22	█	█	█	█								
Finding and evaluating models	100%	19-09-22	09-10-22		█	█	█								
Reporting															
Writing proposal	100%	03-10-22	09-10-22				█								
Writing progress report	0%	07-11-22	13-11-22									▒			
Writing the final report	0%	21-11-22	04-12-22											▒	▒
Development															
Exploring and pre-processing datasets	0%	10-10-22	23-10-22					█	▒						
Developing training pipeline	0%	10-10-22	23-10-22					█	▒						
Developing evaluation pipeline	0%	17-10-22	30-10-22						▒	▒					
Developing explainability pipeline	0%	17-10-22	30-10-22						▒	▒					
Creating visualizations	0%	21-11-22	04-12-22											▒	▒
Model training and evaluation															
Training Models	0%	24-10-22	20-11-22							▒	▒	▒	▒		
Evaluating Models	0%	31-10-22	20-11-22								▒	▒	▒		
Finding the best hyperparameters	0%	31-10-22	20-11-22								▒	▒	▒		

Deliverables markers: D1, D2 (around weeks 4–5), D3 (around week 9), D4 (week 12)

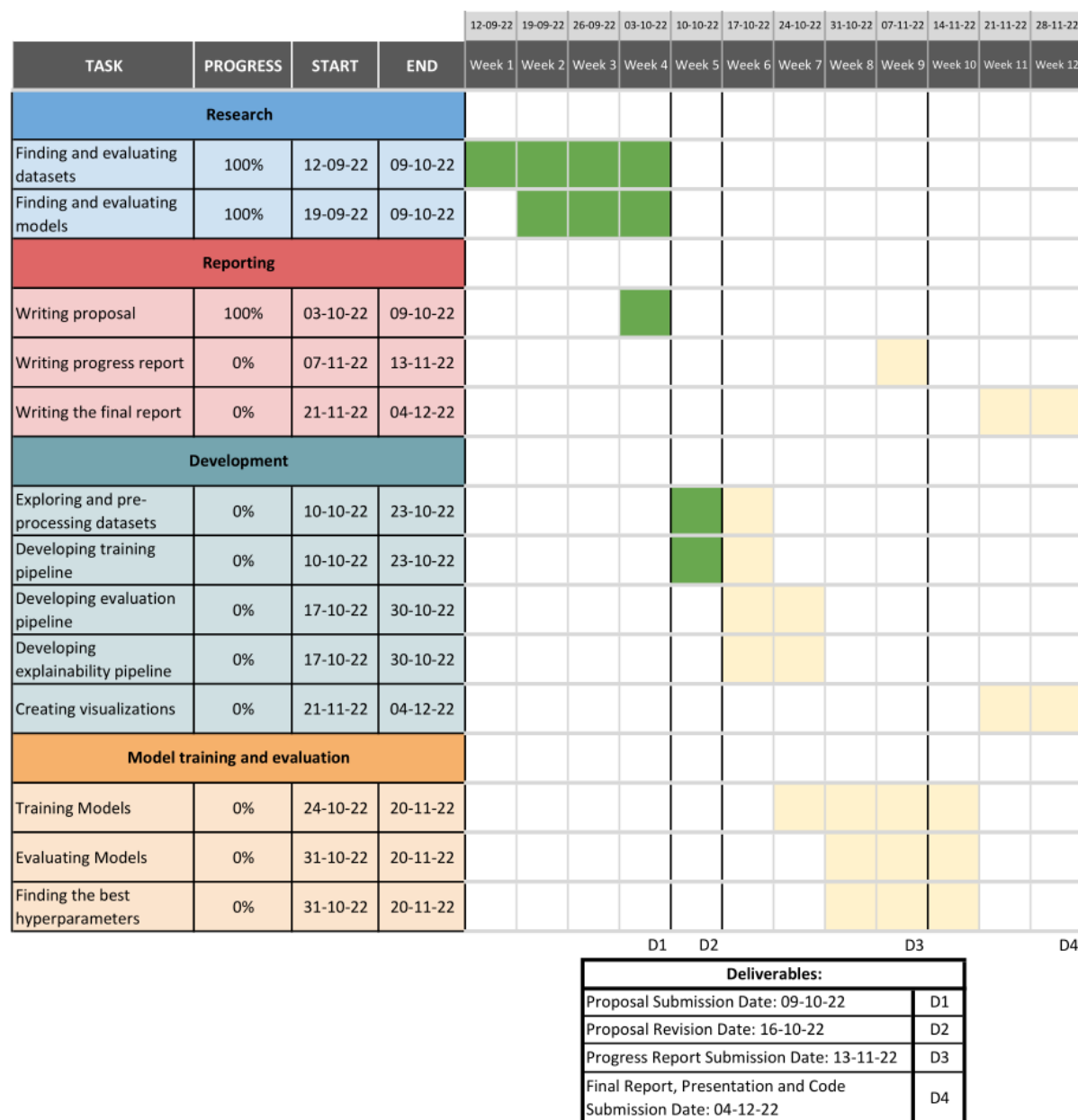| Deliverables:	
Proposal Submission Date: 09-10-22	D1
Proposal Revision Date: 16-10-22	D2
Progress Report Submission Date: 13-11-22	D3
Final Report, Presentation and Code Submission Date: 04-12-22	D4

Figure 1. The Gantt chart above portrays how our project will progress. The deliverables have been mentioned as well. We will work prarallely on different parts of the project as shown in the gantt chart. Different team members will work on different tasks like building the ML pipeline and building the data pre-processing pipeline at the same time. After the deveopment and training is complete, we will take up different sections of the final report and presentation to complete it in time for the final submission on 04-12-22.

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