ENG 4001
Project Management Plan

COVID or flu? That’s the question!

Group: Abbott-2022s1-EEE-UG-13148

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1 Project aim and scope

The Coronavirus Disease 2019 (COVID-19) is a respiratory infectious disease caused by the SARS-CoV-2 virus. The COVID-19 outbreak has a significant global impact on health care, economy and lifestyle. Non-COVID-19 viral pneumonia is also a common respiratory infection caused by viruses, bacteria or fungi. Chest radiography is capable of identifying patients with COVID-19 or non-COVID-19 viral pneumonia. Both diseases affect and damage the human lungs and causes various similar symptoms, which makes it a difficult task for differential diagnosis using chest X-ray images.

The aim of this project, 'COVID or flu? That's the question!', is to explore advanced techniques for image classification to determine whether chest X-ray images from patients that have COVID-19 versus those with non-COVID-19 viral pneumonia can be differentiated. This project will involve designing and constructing Machine Learning (ML) models, that can extract specific features from chest X-ray images and then learn from it, to perform accurate classification.

The scope of this project involves identifying and selecting numerous effective ML methods, that can be used to perform classification on chest X-ray images, within the specified given timeframe of this project. The ML model's efficiency, relevancy to image classification problems, interpretability, and framework support availability, will all be analysed for selection.

This project requires analysis of chest X-ray images of patients that are diagnosed with COVID-19, non-COVID pneumonia and patients that are healthy. There is no need to perform experiments or contact health care centres for chest X-ray data as there exists numerous online datasets containing chest X-ray images of COVID-19, non-COVID pneumonia and healthy patients, that are free and publicly available.

For this project, there will be two datasets that will be used. COVID-19 Radiography Database is a database created by researchers from various Asian universities. The journal articles, 'Can AI Help in Screening Viral and COVID-19 Pneumonia?' by M. E. H. Chowdhury et al and 'Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images' by Rahman et al, has provided a 'Data Availability Statement,' allowing public use of their data [1][2]. The dataset constitutes of 3616 COVID-19, 1,263 non-COVID-19 viral pneumonia and 10,192 healthy X-ray images.

The University of Montreal has provided a dataset that consists of 137 COVID-19, 90 non-COVID-19 viral pneumonia and 90 healthy X-ray images. The journal article, 'COVID-19 Image Data Collection: Prospective Predictions Are the Future' by J. P. Cohen et al, also provided a 'Data Availability Statement,' allowing public use of their data [3].

There exist many variants of the COVID-19 virus. However, for this project the scope is only limited to the SARS-CoV-2 strain of the coronavirus, which was first identified in Wuhan, China, in December 2019.

2 Background

According to World Health Organisation (WHO), there has been a total of approximately 452.2 million COVID-19 cases and 6.3 million deaths, as of March 14, 2022[4]. The COVID-19 virus has caused an ongoing global pandemic and with newer variants being developed rapidly, the world is struggling to adapt. The first case of the COVID-19 virus was reported in December 2019, in Wuhan, Hubei Province, China, from where it began to transmit rapidly to the rest of the countries around the world [5].

For the diagnosis of COVID-19, various methods are used with the most common method being the Reverse transcription-polymerase chain reaction (RT-PCR) testing [6]. Although RT-PCR tests can be cost-effective, patients can expect a delay in testing and receiving results, especially during an outbreak. Numerous studies also concluded that RT-PCR testing has low sensitivity during the early stages of the infection, contributing to false-negative results [7][8][9]. Chest imaging using X-rays and computer tomography (CT) scans are protocols currently practiced by healthcare centres to patients, that show strong respiratory symptoms [10]. Contrast to other popular methods such as RT-PCR testing and Rapid Antigen Testing (RAT), the process of using chest imagine is very simple, fast and provides greater accuracy due to its high sensitivity during the early stages of the infection [11]. Non-COVID-19 pneumonia is still one of the leading causes of death [12]. According to WHO, chest imaging using X-rays is the best method for diagnosing pneumonia [13]. Over the recent years, there has been a significant development in the areas of Artificial Intelligence (AI) and ML. With increasing computational power and growing amount of quality available data, ML methods especially using deep learning approaches, have shown good performances on medical imaging diagnosis [14].

The project contributes to the society mainly by providing an accurate differential diagnosis method to differentiate patients with COVID-19 and non-COVID pneumonia diseases. In comparison to non-COVID pneumonia, COVID-19 is highly transmissible and can display little to no symptoms, especially during the incubation period. Therefore, it is important to differentiate patients with COVID-19 and non-COVID pneumonia, to contain the spread of the COVID-19 virus and to assign appropriate medical treatments and measures.

Both diseases display similar symptoms affecting the lungs and similar characteristics in the chest X-ray images. Figure 1 illustrates an example of a COVID-19, non-COVID-19 viral pneumonia and a healthy patient's chest X-ray image.

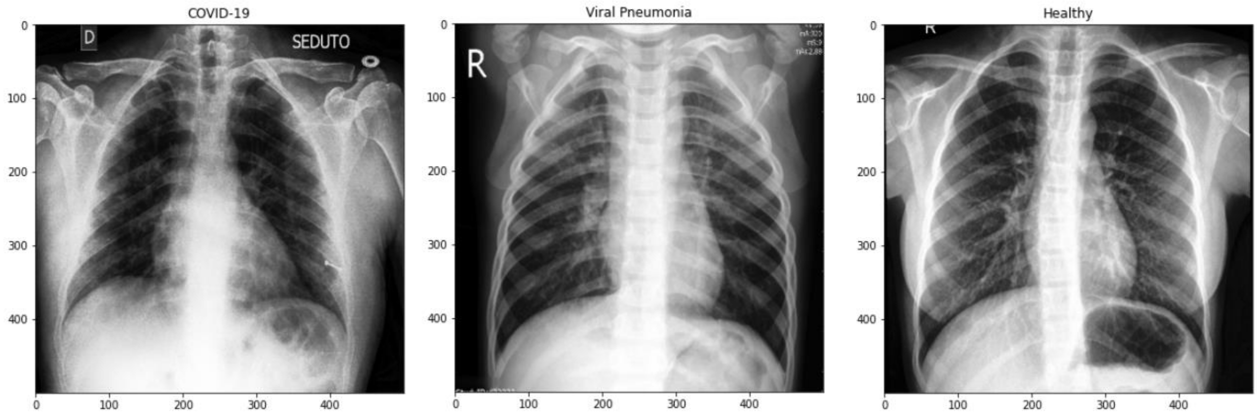


Figure 1: Chest X-ray image of COVID-19, Viral Pneumonia and Healthy patients from the University of Montreal dataset

Hence, differential diagnosis using chest X-ray images can be tedious, even for expert radiologists. Therefore, this project provides an alternative method to health care centres, using ML models to improve their accuracy of diagnosing COVID-19 and non-COVID-19 pneumonia diseases using X-ray images. Additionally, burdens and stresses induced on health care staffs during an outbreak, when there is a significant influx of patients will be reduced, due to the provision of highly accurate automated processes.

A great detail of work has been published already involving the use of ML methods for medical imaging analysis. However, there are still areas of improvement in the analysis, as it requires proficiency and incorporates a diverse range of techniques to improve, accelerate and generate an accurate diagnosis. Several studies have showed that deep learning methods, more specifically, Convolutional Neural Networks (CNNs), have achieved better performance on image classification problems in comparison to other traditional ML models [15][16][17]. In this project, existing studies will be used as a guide to verify the work being conducted. Furthermore, this project will also focus on exploring novel ML techniques with the aim of improving the accuracy of differential diagnosis.

This project can prove to be highly valuable to the medical imaging field, as it will implement existing and novel, traditional and deep learning ML methods to accurately diagnose COVID-19 and non-COVID-19 pneumonia using chest X-ray images. The ML models will undergo a validation process, to fine tune its model parameters, which will allow it to generalise to unseen data. For this project, the validation methods, Hold-out Validation, k-Fold Cross-Validation (k-Fold CV) and Leave-one-out Cross-Validation (LOOCV) will be considered. The Hold-out Validation method involves splitting the training data into separate training and validation sets. For example, 60% of the training data could be used for training the model and the remaining 40% of the training data would be used for validating the model. The k-Fold CV method involves splitting the data into k folds, then training the data on k-1 folds and validating the data on the remaining fold. LOOCV is a variant of the k-Fold CV method, where each single sample is used for validation, while the remaining data is used for training the model. For both k-Fold CV and LOOCV, the average of all the individual evaluations is computed to determine the final result.

The ML methods will be tested using newly found datasets and evaluated using a series of evaluation metrics, to determine the best performing model. Performance measures such as Accuracy, Recall, F1-Score and Precision will be used. The work completed on this project can be extended to classify other common COVID-19 variants for accurate diagnosis.

3 Technical objectives

The technical objectives for this project are summarised in Table 1. In addition to this table, a breakdown of the objectives selected using the SMART objective structure is provided in the Appendix.

Table 1: Objectives of the project and their key specifications and outcomes.

#	Objective description	Specifications	Deliverables / outcomes
1.	Perform image pre-processing and data augmentation on the dataset provided to prepare the dataset for training.	• Resize images to 300x300 pixel size. • Pixel value range will be normalised to the range 0 to 1. • Additional data will be generated by slightly modifying the existing training dataset.	• All X-ray images have been pre-processed and are ready for training the ML models. • Additional X-ray images generated via data augmentation to increase robustness of ML models.
2.	Design and construct ML models to differentiate between Covid-19 and flu in chest radiographic images.	• 80% of the dataset provided will be used to training the ML models. The remaining 20% will be used to validate and fine tune the ML models. • A baseline model will be generated and will serve as the standard metric, in which every other ML model is compared with and is expected to perform better than. • Various Convolutional Neural Network architectures will be trained to perform classification on X-ray images. • Hold-out validation, k-Fold Cross-Validation (k-Fold CV) and Leave-one-out Cross-Validation (LOOCV) will be used to determine the best hyperparameter values for the ML models (i.e., best settings).	• Several ML models capable of differentiating between Covid-19 and flu in chest radiographic images.
3.	Evaluate ML models to determine the best performing model.	• New 'un-seen' datasets will be used to test ML models. • Several evaluation metrics will be used to evaluate models.	• Accuracy, precision, and F-score quantities determined for each ML model. • Selection of best performing ML model that can differentiate between Covid-19 and flu in chest radiographic images.

The methodology that will be used to complete this project is outlined in Figure 2 below. The structure presented in this figure mirrors the structure of the technical objectives and their specifications as shown in Table 1 above.

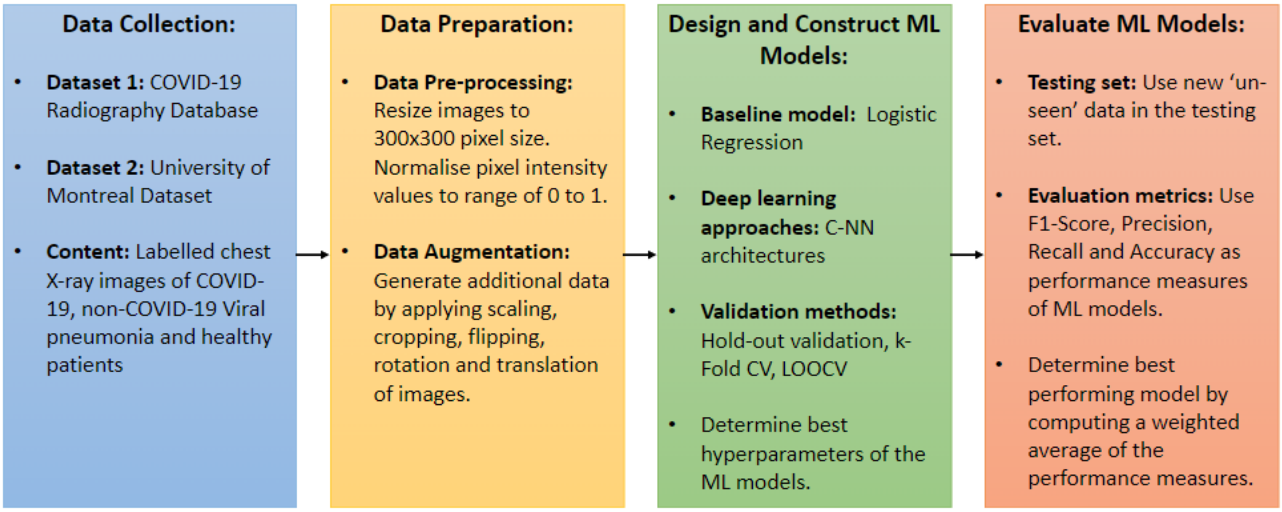
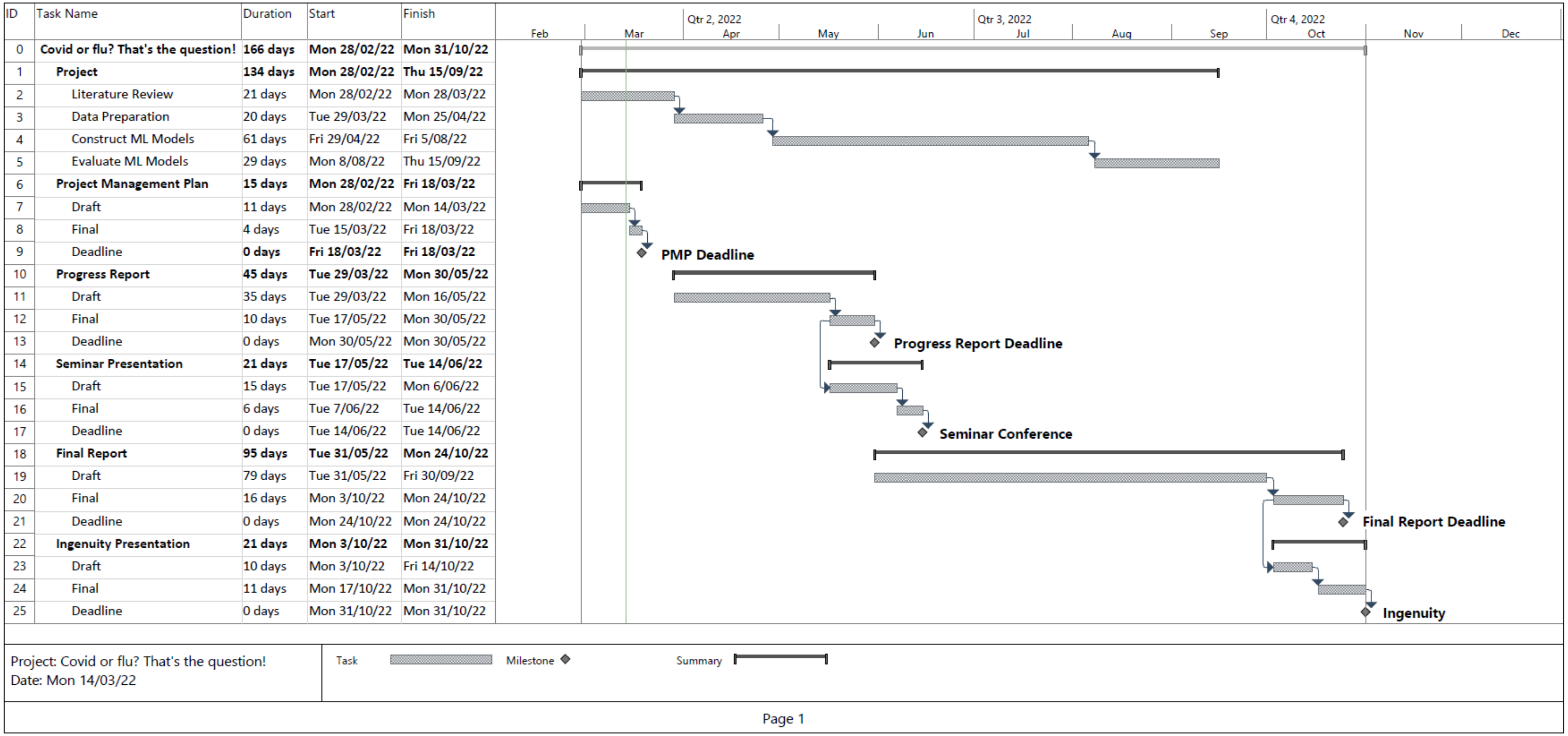


Figure 2: Methodology for X-ray image classification

4 Gantt Chart

A rudimentary Gantt chart for this project is displayed in Figure 3. This chart will be updated as the project progresses and new deliverables are identified. In addition to this Gantt chart, a Work Breakdown structure is also attached in the Appendix, which serves to further break this project down into more manageable tasks.



ID	Task Name	Duration	Start	Finish
0	**Covid or flu? That's the question!**	**166 days**	**Mon 28/02/22**	**Mon 31/10/22**
1	**Project**	**134 days**	**Mon 28/02/22**	**Thu 15/09/22**
2	Literature Review	21 days	Mon 28/02/22	Mon 28/03/22
3	Data Preparation	20 days	Tue 29/03/22	Mon 25/04/22
4	Construct ML Models	61 days	Fri 29/04/22	Fri 5/08/22
5	Evaluate ML Models	29 days	Mon 8/08/22	Thu 15/09/22
6	**Project Management Plan**	**15 days**	**Mon 28/02/22**	**Fri 18/03/22**
7	Draft	11 days	Mon 28/02/22	Mon 14/03/22
8	Final	4 days	Tue 15/03/22	Fri 18/03/22
9	Deadline	**0 days**	**Fri 18/03/22**	**Fri 18/03/22**
10	**Progress Report**	**45 days**	**Tue 29/03/22**	**Mon 30/05/22**
11	Draft	35 days	Tue 29/03/22	Mon 16/05/22
12	Final	10 days	Tue 17/05/22	Mon 30/05/22
13	Deadline	0 days	Mon 30/05/22	Mon 30/05/22
14	**Seminar Presentation**	**21 days**	**Tue 17/05/22**	**Tue 14/06/22**
15	Draft	15 days	Tue 17/05/22	Mon 6/06/22
16	Final	6 days	Tue 7/06/22	Tue 14/06/22
17	Deadline	0 days	Tue 14/06/22	Tue 14/06/22
18	**Final Report**	**95 days**	**Tue 31/05/22**	**Mon 24/10/22**
19	Draft	79 days	Tue 31/05/22	Fri 30/09/22
20	Final	16 days	Mon 3/10/22	Mon 24/10/22
21	Deadline	0 days	Mon 24/10/22	Mon 24/10/22
22	**Ingenuity Presentation**	**21 days**	**Mon 3/10/22**	**Mon 31/10/22**
23	Draft	10 days	Mon 3/10/22	Fri 14/10/22
24	Final	11 days	Mon 17/10/22	Mon 31/10/22
25	Deadline	0 days	Mon 31/10/22	Mon 31/10/22

Figure 3: Project Gantt Chart

5 Resources and procurement

The direct costs and in-kind resources required for this project are listed in Tables 2 and 3 respectively. Since the main focus in this project is to develop ML software, the direct costs involved are expected to be minimal. In the worst-case scenario, we may need to acquire additional RAM and GPU to process large datasets within a feasible timeframe. For the majority of this project, we will make use of the services such as MATLAB and Python software that are provided by the University of Adelaide.

Table 2: Direct costs intended to be spent for the project.

#	Item	Lead time	Cost
1.	Random Access Memory (RAM)	1 week	$150
2.	Graphics Processing Unit (GPU)	1 week	$200
	Total		**$350**

Table 3: In-kind resources that will be used by the project.

#	Item	Source
1.	Licensing for MATLAB	The University of Adelaide
2.	Anaconda environment for Python	The University of Adelaide
3.	Python Interactive tool: Jupyter Notebook	The University of Adelaide
4.	Data consisting of Covid-19, Viral Pneumonia and Healthy X-ray images	The University of Adelaide
5.	Published Research Papers	The University of Adelaide
6.	Library/package extensions for Python	The University of Adelaide
7.	Online repository for code development: GitHub	The University of Adelaide
8.	Online repository for documentation: OneDrive	The University of Adelaide
9.	Online Python interactive environment: Google Colaboratory (free back-end GPUs)	Google
10.	Zoom	Zoom Video Communications

6 Project risks

The project risks are summarised in Table 4 below. The likelihood and consequence of each risk were estimated and the overall risk classified according to the Risk Matrix attached in the Appendix.

Table 4: Identified project risks, their inherent risk classifications before mitigation, and their mitigation measures.

#	Risk event	Impact	Likelihood / Consequence / Classification	Mitigation measures
1	University shut-down due to COVID-19.	May hinder team collaboration.	*Unlikely / Minor / Low*	Sharing platforms should be utilised for coding and technical reports. Communication must be maintained via an online channel.
2	Low quality data.	ML models would become ineffective.	*Unlikely / Major / Medium*	The training data should be investigated for any outliners or any obvious flaw that can risk the efficiency of the model.
3	Possible bias in the data.	Testing results would be biased.	*Possible / Major / High*	During training of ML models, only 80% of the provided data will be used, while the remaining 20% will be used to fine-tune the model to minimise the bias.
4	Underfitting the data due to small sample of training data.	ML models would generate poor accuracy results on training data and testing data.	*Possible / Major / High*	To overcome this, data augmentation will be used to increase the training data sample size.
5	Overfitting the data.	ML models will be incapable of generalising to unseen data.	*Unlikely / Major / Medium*	To minimise the risk, sufficient amount of data with high diversity will be used, so the there is enough variety in data for the ML models to be useful. Cross validation will also be utilised to introduce generality.
6	ML models producing incorrect accuracy measures due to poor evaluation.	The best performing ML model may be incorrectly determined.	*Unlikely / Major / Medium*	Use relevant evaluation metrics that are applicable to image classification type problems.
7	Uncertainty in planned works.	Milestones cannot be reached.	*Unlikely / Major / Medium*	Create contingency measures and allocate extra time and resources to complete tasks.

7 Communication

The primary form of communication in this group will be via an agreed upon communication channel (WhatsApp, Messenger etc.). This group chat will serve as a form of quick and casual communication between group members throughout the project. As such, group members are expected to monitor this chat at least twice a day to ensure that they remain up to date with the project. The primary mode of contact for the project supervisors will be via the university email address. This will mainly be used to share documents and organise times for meetings.

Formal meetings between the group members will take place at least once a fortnight depending on the urgency of the project and the availability of the group. These meetings will provide members with an opportunity to update the group on their progress and raise any concerns regarding the direction or timeline of the project. These meetings will typically be face-to-face and take place at the city campus of the University of Adelaide. Meetings with supervisors will be conducted on a case-by-case basis either for consultation or to present findings. These will take place online via Zoom. For each meeting, an individual will be appointed to record the meetings minutes. These minutes will be used to document the items discussed during the meeting and will serve as a record for each member to check their allocated tasks.

Each member will also be responsible for updating their individual sections of the Wiki page that has been set up for this project. This will be primarily used by the supervisor to check what each member has accomplished for that week as well as their goals for the following week. All collaborative documents (including useful sources and/or links) will be stored on the OneDrive repository system, which has already been shared with the group. This will ensure that each member has access to the most recent documentation, which will help.

8 Software

After analysing the specifications and existing studies regarding the project, various programming languages and frameworks were explored by the team. Each team member's proficiency and technical expertise in the programming languages and frameworks, were evaluated when making the final selection. The two main programming languages used for image classification problems are MATLAB and Python. All team members were proficient in MATLAB, due to their exposure in the programming language from previous undergraduate courses. However, Python is the most popular programming language for ML related problems, due to its support for many scientific packages, and a large open source community. The team will aim to learn the programming language, Python, by completing several online courses and by analysing existing code on image classification problems. Anaconda is a distribution of the Python programming language for scientific computing and comes with a lot of pre-installed libraries/packages. The university provides the Anaconda environment for free to all university students. For code development, the Anaconda environment will be utilised by the team members. Google Colaboratory is an online Python interactive environment, that is free and publicly available. It allows users to collaborate efficiently, when performing code development. The team will use the Anaconda environment and Google Colaboratory environments interchangeably. The University of Adelaide, also provides access to GitHub, which is an online repository to store copies of working code. The team will also utilise GitHub, to collaborate efficiently.

9 References

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10 Appendices

10.1 Appendix 1: Breakdown of technical objectives using the SMART structure

Table 5: SMART structure for Technical Objective 1

Objective	**Perform image pre-processing and data augmentation on the dataset provided to prepare the dataset for training.**
Specific	Conduct image pre-processing and augment the given data, so that training of the models can be performed.
Measurable	The X-ray images will be reduced to the required dimensions (300x300 pixel size) of the ML models, with pixel intensity values ranging from 0 to 1. For training the models, additional data that are different to the training set will be generated.
Attainable	Pre-processing is an essential step implemented by mainly all ML projects, thus there exists many methods for it, in image classification problems. Many literatures have shown the use of data augmentation techniques to increase data for small-sized datasets.
Relevant	By performing pre-processing and data augmentation, it will mitigate the effect of underfitting and will increase the accuracy and efficiency of ML models.
Time	Goal is to finish this objective by 25/04/2022.

Table 6: SMART structure for Technical Objective 2

Objective	**Design and construct ML models to differentiate between Covid-19 and flu in chest radiographic images.**
Specific	ML models will be designed and constructed to perform differential diagnosis on X-ray images to diagnose COVID-19 or Viral Pneumonia.
Measurable	The training accuracy of the ML models will provide indications to whether they are suitable for further evaluations using the testing set.
Attainable	The concept of this project is recently established, but implementations of ML models for image classification applications are widely available and have been proven to be successfully by many studies.
Relevant	The ML models designed and constructed will be later used for further evaluation using newer data.
Time	Goal is to finish this objective by 05/08/2022.

Table 7: SMART Structure for Technical Objective 3

Objective	**Evaluate ML models to determine the best performing model.**
Specific	The constructed ML model will be tested and evaluated to find the model that satisfies the required criteria of the project.
Measurable	The best performing model would display better performance measures (i.e., accuracy, precision) than other ML models.
Attainable	There are existing implementations of evaluation metrics for image classification problems, provided by Python libraries.
Relevant	This objective will determine if ML models can be successfully used to differentiate patients with COVID-19 and non-COVID-19 pneumonia.
Time	Goal is to finish this objective by 15/09/2022.

10.2 Appendix 2: Work Break Down Structure Explanation

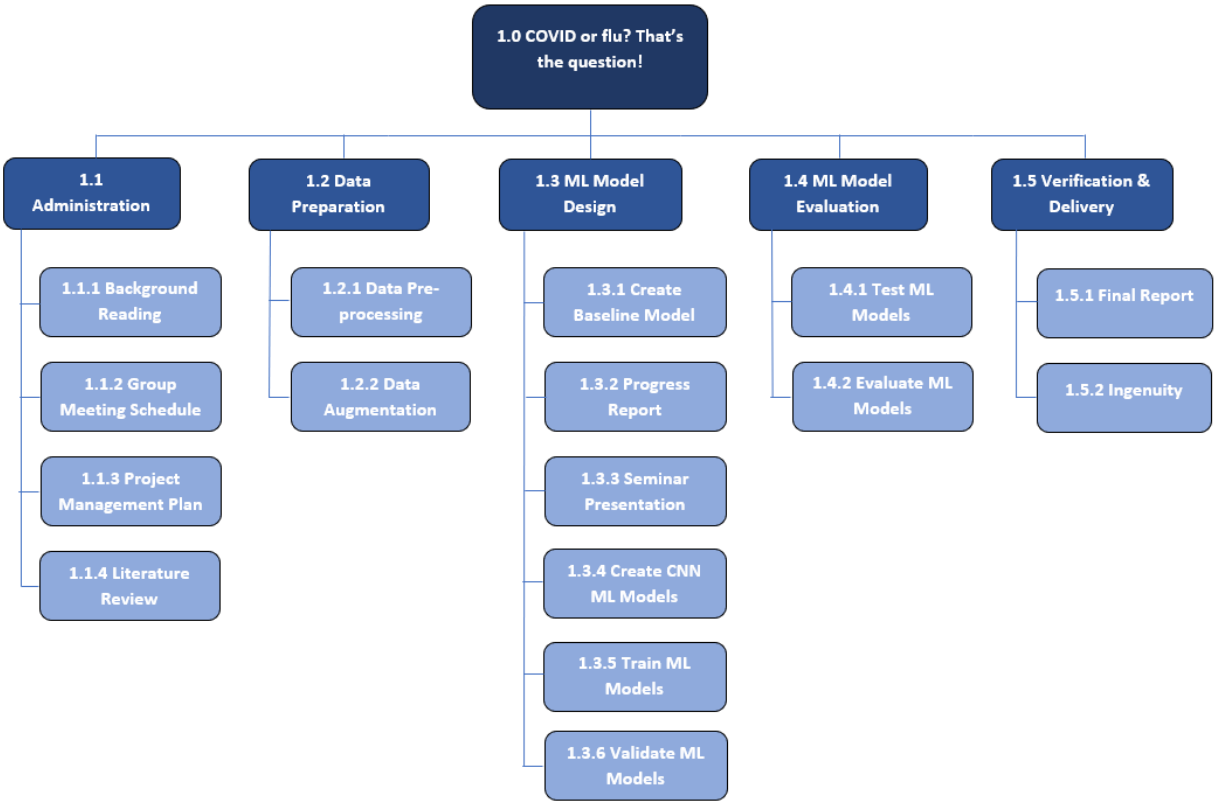

Figure 4: Work Breakdown Structure

The tasks in the WBS are placed in the order of its expected delivery time. Administration is the first phase of this project. Successful completion of this phase will establish and develop team cohesiveness, project understanding, and will provide a structure and foresight for the upcoming execution stages. The Data Preparation phase involves Pre-processing and Data Augmentation of the data. Pre-processing involves cleaning and mapping data from their raw format to a convenient form, such that it is suitable for analysis. In terms of ML standards, the dataset provided is very small, therefore, Data Augmentation is required and beneficial to enhance the performance of ML models by generating new and different examples to train datasets. The ML Model design phase constitutes of designing, implementing and validating ML models, and producing the deliverables, Progress report and Seminar Presentation. The ML Model Evaluation stage involves using newer data in the testing set to evaluate the performance of the ML models. For evaluating the performance of ML models, a series of evaluation metrics relevant and applicable to image classification problems will be utilised.

The final stage comprises of delivering the final required deliverables of the project, Final Report and Ingenuity Presentation and handing over all work done on the project, to transfer knowledge and operation.

10.3 Appendix 3: Likelihood-Consequence Risk Matrix

	Consequences				
Likelihood	Negligible	Minor	Moderate	Major	Severe
Almost certain	Medium	High	Very High	Very High	Very High
Likely	Medium	Medium	High	Very High	Very High
Possible	Low	Medium	High	High	Very High
Unlikely	Low	Low	Medium	Medium	High
Rare	Low	Low	Low	Medium	Medium

Figure 5: Likelihood-Consequence Risk Matrix