MTHE 493 Project Proposal

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1 Introduction and Background

Facial recognition by computers has applications in many fields in the world today such as criminal identification, security systems, and human-computer interaction. The fundamental idea regarding the functionality of this technology is by comparison of selected features of images of faces within a larger set. There are multiple methods through which this can be achieved from a mathematical and algorithmic basis.

The goal of facial recognition algorithms is to extract the relevant information of the human face and compare its encoded information with that of other faces in a set. The grayscale image of a face can be represented by an N by N real-valued matrix. This representation can be considered mathematically as a mapping $\boldsymbol{x} : \{1,2,\ldots,\mathrm{N}\}^2 \rightarrow \mathbb{R}$ [1]. This mapping can be plotted as a vector in a real vector space and then compared to other vector mappings in the same space for identification. However, making use of such a vector for facial recognition would be extremely difficult because of its large dimension. The vector must be simplified to a lower dimension. Here lies the main difference between facial recognition algorithms: the manner in which each method reduces dimensionality.

The first well-known method is through eigenfaces. The eigenfaces algorithm uses principal component analysis (PCA) to reduce dimensionality. The process identifies the most relevant variables in the vector under consideration and lowers the dimensionality by eliminating variables that are not relevant [2]. The second well-known method is through fisherfaces. This method first reduces the space using PCA and then applies Fisher's linear discriminant to identify and separate classes of information within the image for further analysis [3]. These two methods will be focused on for the scope of this project.

Both of these methods work in reducing the dimensionality of the images, however they both rely on the assumption that the faces cluster around a low-dimensional linear subspace [4]. The assumption that it is linear achieves good results but is nonetheless a simplification. In theory, better results can be achieved by formulating the facial recognition algorithm without the assumption that the submanifold is linear [1].

In this project, the focus will be on designing an algorithm for automated face recognition by formulating it as a problem of dimensionality reduction. The general submanifold of R^{N^2} will be explored first as a linear problem and then as a nonlinear problem. Validation of the designed algorithm will proceed this.

The goal is to integrate the improved facial recognition algorithm at Queen's University to eliminate the current identification method - the student card. This change will improve campus security, financial losses, and operational issues associated with the outdated method. Additionally, the overall efficiency of identifying students as needed will be increased due to the fast and non-contact process that the facial recognition algorithm uses.

2 Problem Description

As previously stated, facial recognition systems exist in a wide variety of applications. Certain implementations, such as facial recognition in cell phones, have received great consumer feedback due to user convenience and security [5]. However, as these recognition systems continue to improve and become more widely available, their societal implications also continue to grow. A brainstorming session was held to ideate potential areas of application. These applications were considered relative to the primary stakeholders involved. The results are summarized in a mind map in Figure 1.

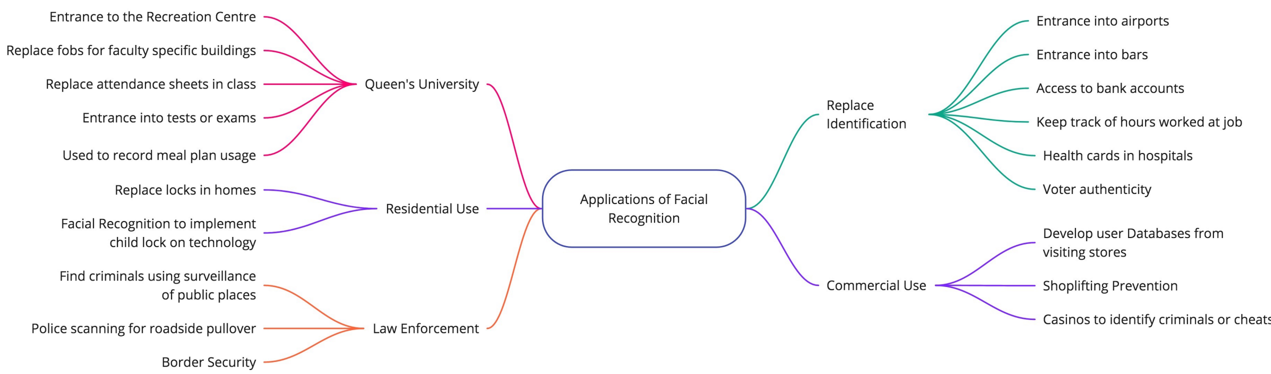

Figure 1: Mind map used to brainstorm potential application areas.

Facial recognition technology has quickly outgrown much of the legislation controlling it, and governments are fighting to enact regulations on the indiscriminate use of the software [6]. The widespread use of facial recognition systems to identify members of the public is a highly controversial international topic. The Chinese Social Credit System is an example of facial recognition software that has invaded the privacy of millions of people [7]. This controversy resulted in the elimination of many potential applications as it is inadvisable to consider global identification or security - the social and economic considerations are too polarizing to be an appropriate implementation. Conversely, services on a local scale could be greatly improved by the implementation of facial recognition software at Queen's University.

There are three potential implementations which could immediately benefit Queen's University. Firstly, the attendance sheet in class is used as a form of identification. This system of recognition is easily bypassed if there is a person in the class willing to forge a signature for a colleague. Class attendance has a direct correlation to grades earned [8]. Secondly, entrance to the cafeteria is facilitated using a student card. A supervisor is then required to check each student card for authenticity. Implementing facial recognition at the entrance to the cafeteria would streamline the authorization process. Finally, entrance to the Athletics and Recreation centre requires only a functioning student card, not necessarily one matching the user of the card. Those with unauthorized possession of a student card can access the building resulting in a potential loss of income for the university.

Table 1 is the weighted decision matrix used to assess feasibility for the remaining application areas. Cost refers to the amount of money required to implement the system, student support refers to how well the project would be received by the student body, population impacted refers to the percentage of the student body that would be impacted by the change, and privacy refers to the amount of unwanted data that could be collected on a subjects everyday life.

Table 1: Decision Matrix.

		Options					
Criteria	Weight	Attendance Sheet		Cafeteria Entrance		Building Entrance	
		Score	Total	Score	Total	Score	Total
Cost	2	2	4	3	6	2	4
Student Support	3	1	3	3	9	4	12
Population Impacted	5	5	25	2	10	3	15
Privacy	5	5	25	2	10	3	15
	TOTAL:		57		35		46

Based on the results of Table 1, the most feasible application of facial recognition technology is replacing attendance sheets in class. This option would positively affect the most students on campus while collecting the least personal data about their daily schedule outside of class. Implementing a facial recognition system to track attendance would save instructors hours of mundane work, promote increased attendance in class, and attract attention to the university as an innovative solution to skipping class. A project of this scale would be an excellent pilot project for potentially larger facial recognition usage on campus in the future.

Every student admitted into the university is required to submit a piece of photo identification to the school. Hence, there is a database of photographs available to the university; an ideal training set for a facial recognition software!

3 Proposed Solution

3.1 Modelling

The model upon which this research is based was originally proposed in the 1991 paper *Eigenfaces for Recognition* [2]. This paper describes a method of facial recognition by projecting high-dimensional face images onto a much smaller subspace which spans the significant variations among the known face images. The projection operation characterizes a face by a weighted sum of the principal components of the known face images. This work was extended upon in 1997 in the paper *Eigenfaces vs. Fisherfaces* [3]. With this extension, a new method of projection based on Fisher's linear discriminant is utilized to achieve lower error rates particularly when images contain varying lighting conditions and facial expressions.

Both of the aforementioned algorithms make use of methods of linear principal component analysis (LPCA). LPCA is a method of dimensionality reduction by removing dimensions which carry the least significance when reproducing the variance of the original data. The dimensions of least significance can be identified by constructing an orthonormal basis consisting of the eigenvectors of the covariance matrix representing the original image space. From this basis, we can quantify the magnitude of error in our reproduction of the variance by taking the sum of the eigenvalues corresponding to the rejected eigenvectors. Therefore, by reducing the high dimensional space by means of removing the eigenvectors with the smallest corresponding eigenvalues from our orthonormal basis, we may reproduce the variance of our original data with the lowest degree of error. The models proposed in *Eigenfaces* and *Eigenfaces vs. Fisherfaces* carry out this dimensionality reduction with the objective of extracting a linear subspace of the original image space. LPCA accomplishes this task.

The aim of this research is to eliminate the requirement that the principal components of a face image will cluster around a linear subspace of the image space. Instead, the proposed algorithm will result in the projection of the principal components to a lower dimensional sub-manifold of the original image space. To accomplish this, a method of non-linear principal component analysis must be employed to extract this sub-manifold while maintaining a low degree of error when reproducing the covariance of the original image space.

3.2 Design Process

In developing an algorithm to accomplish the task of automated facial recognition as described above, an iterative design process will be utilized. The initial design will closely resemble the algorithm proposed in the paper *Eigenfaces*. This design will remain restricted to projection of face images to a linear subspace of the original image space and projection will be accomplished by method of weighted sums of the principal components. The next iteration will draw from the algorithm proposed in the paper *Eigenfaces vs. Fisherfaces* in that it will still be constrained to a linear subspace; however, it will employ Fisher's linear discriminant for the purpose of projecting face images onto this subspace. The final design iteration will result in the algorithm proposed from this research. In this algorithm, the linear subspace assumption will be lifted and as a result some method of non-linear principal component analysis will be utilized. Additionally, it may be necessary to determine an alternative approach to projecting faces onto the identified sub-manifold which is more suited to the non-linear space than Fisher's linear discriminant.

3.3 Performance Objectives

The main advantage to the iterative design process described above is the ability to develop common test results which will act as a benchmark for the performance of the proposed algorithm. The primary performance objective of this initiative is to produce an algorithm which is capable of receiving a database of labelled face images and a single unidentified face image and matching that face to one of the known individuals in the original database with a reasonable degree of accuracy. As a further objective, the proposed algorithm will outperform the preexisting algorithms of *Eigenfaces* and *Eigenfaces vs. Fisherfaces* by relaxing the linear subspace assumption.

To measure the performance of the proposed algorithm the National Institute of Standards and Technology's (NIST) "The Good, the Bad and the Ugly" (GBU) data set will be provided to the algorithm. The GBU data set is a set of face images that consists of three distinct classes: the "good", the "bad", and the "ugly" representing a face image that is easy, challenging, or very challenging to identify [9]. For each individual in the data set there are six face images. The images are grouped into the respective image classes. An example can be seen below in Figure 2. This method of sampling allows us to evaluate the performance of the algorithm in an unbiased fashion and evaluate the specific advantages of the algorithm. For example, if the algorithm performs well given varying lighting conditions, or facial expressions.

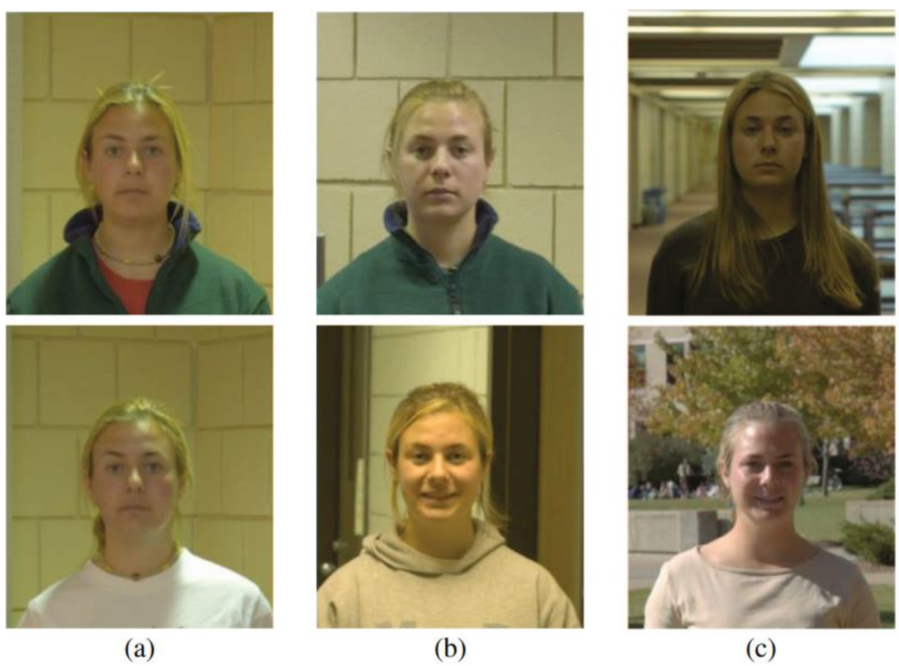

Figure 2: Face image pairs of the same person from the three respective image classes: (a) good, (b) challenging, and (c) very challenging.
Source: Adapted from [9]

The performance criteria that the algorithm will be assessed on is the verification rate and the false acceptance rate [9]. The verification rate is simply the number of faces which the algorithm correctly identifies in the given data set. The false acceptance rate is defined as the rate at which the algorithm claims to have matched the face to an individual and the claimed match is not pictured. This criteria assessed on the GBU data set is commonly used to evaluate modern facial recognition algorithms. This standard will allow for an unbiased comparison of our developed algorithm to those of the *Eigenfaces* and *Eigenfaces vs. Fisherfaces* publications as well as modern algorithms which implement alternative approaches to facial recognition.

4 Triple Bottom Line

The implementation of facial recognition software at Queen's University would impact a number of stakeholders. The first stakeholder is the university, which has a responsibility to ensure the privacy of all students. The second stakeholder is the students who will primarily be concerned with privacy. The third stakeholder, instructors and professors, will benefit from higher efficiency and reliability for recording attendance. The final stakeholder is the Canadian Government who will be pushed to introduce new legislation by the introduction of facial recognition at a Canadian institution. Such legislation could affect the application of the software. As a recent example, San Francisco has banned the use of facial recognition [7]. However, no such actions have taken place in Canadian cities.

The triple bottom line analysis is outlined below in Table 2.

Table 2: Triple Bottom Line Analysis

Stakeholder	**Economic**	**Social**	**Environmental**
Queen's University	The estimated cost of a low resolution camera with memory is $30. The university would need to purchase a camera for every classroom where attendance is taken (approx. 200). The implementation would cost the university approx. $6000. It is possible that more professors will want to include mandatory attendance as a part of their classes. Queen's would have to purchase additional cameras to meet the demand.	The university will face scrutiny from students and the public over privacy concerns. The implementation would be a first among Canadian universities. Other universities could consider a similar implementation based on the results at Queen's.	The university will be responsible for the waste that thrown out cameras create. It is likely that the cameras will not be recycled properly.

Students	Funding for the implementation of the facial recognition system will come out of funding from other areas. The removal of funding from other areas could affect student life.	Attending lectures contributes to the academic success of students. Class attendance has a substantial correlation (>0.5) to student grades [8]. It is proven that most facial recognition systems misidentify people of colour 5 to 10 times more often than white people [10]. Some students will consider the collection of their facial data a violation of privacy. It is shown that 50% of citizens are unfavourable of facial recognition software in retail stores [11].	The increased attendance of students will increase the number of students travelling from off campus. Students driving to campus will have a negative affect on the environment.
Professors and Instructors	Recording attendance is a time-consuming practice for instructors. The facial recognition system would eliminate a weekly 20-minute process, which accumulates to 4 hours over a semester. For instructors on an hourly wage, the university would be able to save approx. $180 per instructor per year.	Some professors incorporate student attendance into student's grades. In classes with attendance sheets students are able to forge their friends' signatures. Facial recognition is a reliable way to take an accurate attendance.	Attendance sheets will not have to be distributed in class. Reducing paper waste is beneficial to the environment.
Canadian Government	The implementation of legislation in regard to facial recognition will be costly and time-consuming for the government. The process of passing and enacting a bill usually takes months and sometimes years [12].	Facial recognition is currently unregulated in Canada. The Canadian Government is already facing pressure to develop regulations that protect citizens privacy. The implementation of facial recognition at a Canadian university would put more pressure on the government to implement legislation. As the government introduces legislation, the system will need to be updated to abide by new rules.	

Alumni and Donors	Donors who do not agree with the implementation of facial recognition at the university will be less likely to donate to the school.	The controversy caused by the implementation of facial recognition could negatively affect the reputation of the school and thus the alumni.	

5 Project Timeline

A concise project timeline is presented in this section. The timeline includes all phases of the project, deliverable items for the course, weekly group meetings, and lectures with Professor Mansouri that have taken place or will take place over the duration of the project. This is summarized graphically on the following page through the use of a Gantt Chart.

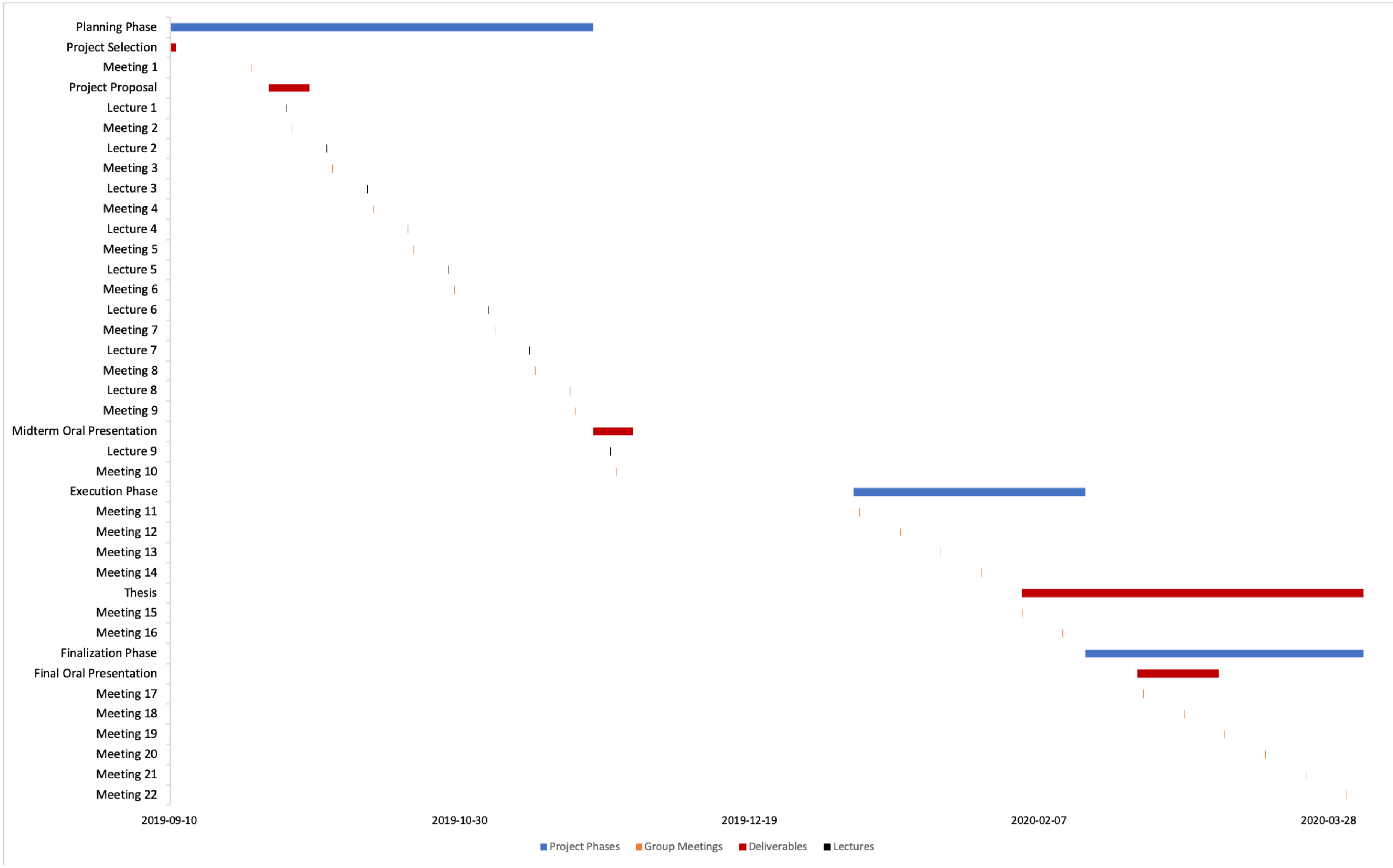

Figure 3: A Gantt Chart summarizing the expected timeline of the Thesis Project

All items in the Gantt chart have a width to scale with the amount of hours it is estimated will be necessary to complete them. In addition, for any deliverables the start date takes into account the amount of time that will be needed for planning, preparation and execution.

Along with the Gantt Chart, a tabular summary of the project timeline is also provided. This table includes start date, duration, and description (where applicable) for all items in the Gantt Chart. This table can be seen below:

Table 3: Project Timeline Summary Table

Date	**Type**	**Name**	**Description**	**Duration**
2019-09-10	Project Phase	Planning Phase	This phase includes project selection, group formation, as well as research and planning for the final thesis project.	10 Weeks
2019-09-10	Deliverable	Project Selection	All MTHE493 students filled out a form to select their preferred thesis projects. Groups were formed based on these results.	1 Day
2019-09-24	Group Meeting	Meeting 1	The team took time to discuss expectations and actionable items for the thesis project as a whole, and began delegating tasks for the upcoming Project Proposal deliverable	1 Hour
2019-09-27	Deliverable	Project Proposal	The team began work on the Project Proposal document one week before the submission deadline. This included summarizing the previous research and compiling it into a LaTex document on Overleaf.	1 Week
2019-09-30	Lecture	Lecture 1	In the first lecture, Professor Mansouri discussed probability theory in higher dimensions with a focus on principal component analysis. The purpose of this was to provide a foundation before researching the *Eigenfaces* publication.	1 Hour
2019-10-01	Group Meeting	Meeting 2	The team discussed progress on the Project Proposal deliverable and began planning how the document would be edited and submitted.	1 Hour
2019-10-07	Lecture	Lecture 2	N/A	1 Hour
2019-10-08	Group Meeting	Meeting 3	N/A	1 Hour
2019-10-14	Lecture	Lecture 3	N/A	1 Hour
2019-10-15	Group Meeting	Meeting 4	N/A	1 Hour
2019-10-21	Lecture	Lecture 4	N/A	1 Hour
2019-10-22	Group Meeting	Meeting 5	N/A	1 Hour
2019-10-28	Lecture	Lecture 5	N/A	1 Hour
2019-10-29	Group Meeting	Meeting 6	N/A	1 Hour
2019-11-04	Lecture	Lecture 6	N/A	1 Hour
2019-11-05	Group Meeting	Meeting 7	N/A	1 Hour
2019-11-11	Lecture	Lecture 7	N/A	1 Hour
2019-11-12	Group Meeting	Meeting 8	N/A	1 Hour
2019-11-18	Lecture	Lecture 8	N/A	1 Hour
2019-11-19	Group Meeting	Meeting 9	N/A	1 Hour

2019-11-22	Deliverable	Midterm Oral Presentation	The team will provide a ten to fifteen minute progress report discussing the thesis topic, methodology, and progress to date. The audience will be the Mathematics and Engineering class and faculty supervisors.	1 Week
2019-11-25	Lecture	Lecture 9	N/A	1 Hour
2019-11-26	Group Meeting	Meeting 10	N/A	1 Hour
2020-01-06	Project Phase	Execution Phase	In this phase, the team will begin implementing the research collected in the Planning Phase. This includes designing and implementing an original algorithm for facial recognition.	6 Weeks
2020-01-07	Group Meeting	Meeting 11	N/A	1 Hour
2020-01-14	Group Meeting	Meeting 12	N/A	1 Hour
2020-01-21	Group Meeting	Meeting 13	N/A	1 Hour
2020-01-28	Group Meeting	Meeting 14	N/A	1 Hour
2020-02-04	Group Meeting	Meeting 15	N/A	1 Hour
2020-02-04	Project Phase	Thesis	The writing of the thesis will begin in Week 18, with drafts shown to supervisors along the way for guidance. The final draft will be submitted at the end of Week 24.	8 Weeks
2020-02-11	Group Meeting	Meeting 16	N/A	1 Hour
2020-02-15	Project Phase	Finalization Phase	In this phase, the results from the application will be documented and compiled in the thesis. The thesis will also be presented to an audience.	1 Hour
2020-02-24	Deliverable	Final Oral Presentation	Work on the thesis will be completely wrapped up by this point. A 20 to 30 minute oral presentation will be given to the class to summarize the thesis.	1 Hour
2020-02-25	Group Meeting	Meeting 17	N/A	1 Hour
2020-03-03	Group Meeting	Meeting 18	N/A	1 Hour
2020-03-10	Group Meeting	Meeting 19	N/A	1 Hour
2020-03-17	Group Meeting	Meeting 20	N/A	1 Hour
2020-03-24	Group Meeting	Meeting 21	N/A	1 Hour
2020-03-31	Group Meeting	Meeting 22	N/A	1 Hour

This summary will be useful as a high-level plan for the progression of the thesis project over the year. While certain items will likely change over the course of the project, this will still serve as a useful guideline during the planning, execution, and finalization of the project.

6 Team Members and Load Distribution

Going forward with the project, work will be spread equally among the five group members. To ensure this, work will be divided into five different specializations with each group member taking ownership of a specific one. Each member has been given a role pertaining to their specialization, which is summarized in the table below, along with the tasks they will be expected to complete over the course of the project.

Table 4: Work Distribution Summary Table

Team Member	**Role**	**Expected Tasks**
Gabriel Bettio	Research Specialist	Finding new research publications, delegating research to team members, summarizing research items for the rest of the team
Noah Ifergan	Team Lead	Task delegation, planning meetings, maintaining communication between the group and outside sources
Jake Stubbs	Algorithm Design Specialist	Researching existing facial recognition algorithms, developing several original facial recognition algorithms, comparing algorithms to choose an optimal one
Joey Tepperman	Algorithm Development Specialist	Creating a software application that uses the algorithm, testing the implementation for accuracy, optimizing for accuracy and efficiency
Isabella Wright	Data Aggregation Specialist	Finding existing image data sets, creating new image data sets, optimizing aggregated data set for accuracy

From the table above it is clear that each group member will play an equal role in the execution of this project. In addition to the unique tasks that each member will have, each member will also be responsible for a variety of shared responsibilities. These include contributing content to deliverables, editing and formatting deliverables, and staying up to date with research for the project. Ultimately, while required tasks will likely change over the course of the project, this combination of unique and shared responsibilities should lead to a successful team and project.

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