Middle East Technical University Northern Cyprus Campus
Computer Engineering Program

CNG491 Computer Engineering Design I

Iris Analyzer

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Final Report

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Chapter 1

Introduction

1.1 Problem Formulation

Given the widespread use of classical texture descriptors (texture features that are extracted from the iris) for iris recognition, including the Gabor phase-quadrant features , it is instructive to take a step back and answer the following question: how do we know that these image processing feature descriptors proposed in the literature are actually the best representations for the iris? Furthermore, can we achieve better performance (compared to the Gabor-based procedure) by designing a better feature representation scheme that can perhaps attain the upper bound on iris recognition accuracy with low computational complexity? Deep learning techniques are one of the best ways to solve the above problem as it increases the accuracy,by using improved feature extraction techniques, that is primarily data-driven.

1.2 Presentation of Background Problem

The first successful and commercially available iris recognition system was in 1993, and was suggested by Daugman[5]. In the system, the inner and outer boundaries are detected using an integro-differential operator. Afterwards, the iris region template is transferred into normalised form using Daugman's rubber sheet method. This is followed by using a 2D Gabor filter to extract the iris features and the hamming distance for decision making[6]. The limitation to this method is that it requires a high resolution camera to capture the iris image and its accuracy significantly decreases under non-ideal imaging conditions due to sensitivity of the iris localization stage.

After decades of comparative research, many iris recognition methods have been introduced to enhance the re-usability and reliability. In recent years, with the vigorous development of the annual ImageNet Large Scale Visual Recognition Challenge(ILSVRC)[8], deep learning networks, especially CNNs, have shown obvious improvement in the performance of computer vision tasks such as image classification, single object localization, and object detection[7].

Hence, we are going to use some of the newer techniques mentioned above(Deep learning CNN) to develop and create a model for our iris analyser system as they have better performance and accuracy.

1.3 Motivation

Iris Recognition is a biometric method of identifying people based on unique patterns within the ring-shaped region surrounding the pupil of the eye. Every iris is unique to an individual, making it an ideal form of biometric verification. One of the reasons Iris Recognition is such a sought after method of identifying individuals, especially in sectors such as law enforcement and border control, is that the iris is a very strong biometric, highly resistant to false matches as well as high search speed against large databases. Iris Recognition is an extremely reliable and strong method to accurately identify individuals [10].

Iris recognition can be used for verifying owner identity (biometric data) and demographic data of the identified person (soft biometric data). Verification(1-to-1 comparison) is the process where the bio-metrics information of an individual is compared with biometrics on the record [4], while identification(1-to-many comparison) is used to discover the origin of certain bio-metrics to prove or disprove the association of that information with a certain person/individual [4]. Research and studies have been done on gender prediction[1], age prediction[2], and biometric technology[3], using iris analysis with image processing and machine learning techniques.

In bio-metrics, iris data cannot be the same in two different individuals and cannot wear out as seen in some people's fingerprints, hence, iris recognition can be a secure way to identify and authenticate individuals. Our main motivation is to make iris recognition(in bio-metrics) a more widely used option, by improving the output accuracy using deep learning techniques like CNN's(Convolution Neural Networks) to extract features instead of the old-school image processing feature extraction ways. This makes the prediction process more accurate as the image is passed through a network of filters to extract different features over and over again.

The aim this semester is to work on the deep learning techniques used in the research papers, get the results and try to improve them by adding new techniques or by deleting ones used.

1.4 Aims and Objectives

The main aim of this project is to acquire identification and their demographic information by analyzing their eyes (iris). The objectives are:

1. Get eye data from a database.
2. Pre-processing where the eye image will be segmented using image processing techniques. This step will partition the eye image into image objects (iris and pupil) and this will be used to locate the objects and their boundaries(diameter and radius of pupil and iris). This will help us work on the image in the next stages.
3. Use deep learning to retrieve the identity data.

1.5 Stakeholders

1. System administrator : is responsible for updating and managing the iris analyser system.

2. Application users : every person that will use the iris analyser system to get an identity and demographic output i.e. students, teachers, workers as it can be useful for them in conducting research based around iris analysis.

Chapter 2

Literature Review

Iris analyser research has been done and discussed by many researchers. The process of retrieving data from the iris is difficult and has been improved over time, shifting from basic image processing techniques to complex deep learning techniques such as CNN. Below we discuss different ways to develop iris analyser system by researching different ways and choosing the best performing techniques.

In Tianming Zhao et al [7]. , they start by doing pre-processing on the iris image where they locate and segment the iris texture part from the original iris image through quality evaluation. The Region of Interest(ROI) is extracted, normalized and enhanced. In our model we are going to do pre-processing as discussed above.

They move on to convolution step where low level features are extracted from pixel intensities of the input images and form the primary features used for the primary capsule layer. Two strategies are used to construct the convolution part:

1. Applying transfer learning method: The entire network is divided into sub-networks with the vector part and a series of different networks is instantiated. This gets the outputs of different levels in the same network as the result of the convolution part to find the most suitable option of convolution structure for the entire network through experiments.

2. Building several several shallow convolution networks as the convolution part without pre-training.

The next step is the use of routing algorithm in the vector layer and is done in 2 stages:

1. Dynamic Routing in Capsule Network: provides non-linear mapping for two adjacent capsule layers. The dynamic routing algorithm uses the cosine similarity of two vectors to measure their agreement. However, this manner is not quite good at judging quite good agreement and very good agreement, which usually makes it difficult for the network to converge after training in the experiments.

2. Adjusted Dynamic Routing: Used to improve applicability of the capsule structure and make it easy for the network to converge when dealing with input images of large size.

The last step us the network architecture which consists of the convolution part, vector part, classification and reconstruction.

Finally,they simulate an environment with different illumination intensities, and train and test iris images with different pupil sizes (represent different light intensities) to show the recognition ability of the method when the environment is varied. Experiments show that a deep network with capsule architecture is feasible in iris recognition. In the test of the JluV3.1 iris dataset, InceptionV3-5blocksCDRDL achieves the highest accuracy of 99.37 percent. In the test of the JluV4 dataset, Iris-DenseCDRDL achieves the highest accuracy of 99.42 percent. In the test of the CASIA-V4 Lamp dataset, VGG16-4blocksCDRDL achieves the highest accuracy of 93.87 percent.

Kien Nguyen et al. [9], start by segmenting the eye image. Here, they localize the iris by extracting two circular contours pertaining to the inner and outer boundaries of the iris region. This is followed by normalization step which maps the iris to a region of fixed dimension. This helps to remove the effects caused by dilation and contraction of the pupil causing iris stretching.

The normalized iris image is fed into the CNN feature extraction module to extract features. They use 5 state-of-the-art and off-the-shelf CNNs(AlexNet, VGG, Google Inception, ResNet and DenseNet). We use ResNet and DenseNet as discussed above to extract the features.

Note that there are multiple layers in each CNN. Every layer models different levels of visual content in the image, with later layers encoding finer and more abstract information, and earlier layers retaining coarser information. One of the key reasons why CNNs work very well on computer vision tasks is that these deep networks with tens or hundreds of layers and millions of parameters are extremely good at capturing and encoding complex features of the images, leading to superior performance. To investigate the representation capability of each layer for the iris recognition task, we employ the output of each layer as a feature descriptor and report the corresponding recognition accuracy.

The extracted CNN feature is the fed to the Support Vector Machine (SVM) classification module for classification. The multi-class SVM for N classes is implemented as a one-against-all strategy, which is equivalent to combining N binary SVM classifiers, with every classifier discriminating a single class against all other classes. The test sample is assigned to the class with the largest margin.

CNNs are effective in encoding discriminative features for iris recognition. However according to Kien et al., deep learning offers the following problems and open questions:

1. Computational complexity: very high during training phase due to millions of parameters used in the network.

2. Domain adaptation and fine tuning: entails freezing early layers and only re-training a few selected later layers to adapt the representation capability of the CNNs to iris images. Fine tuning is expected to learn and encode iris-specific, as opposed to generic image features.

3. Few-shot learning: limited number of training images can be partially solved with few-shot learning, which allows the network to perform well after seeing very few samples from each class.

4. Architecture evolution: evolve off-the-shelf CNNs in order to generate powerful networks that are more suited for iris recognition.

5. Other architectures: Architectures like Deep Belief Network(DBN), Stacked Auto-Encoder(SAE) and Recurrent Neural Network(RNN) have their own advantages and can be used to extract features for iris images.

We employ the CNN method as discussed by Kien above, and lastly check the percentage accuracy the model gets, if the accuracy is not good enough(above 90 percent), we add more layers to the CNN and train the model more until we achieve the goal.

Chapter 3

Research Method

The project will be done in two parts: image processing part and deep learning part. Image processing techniques shall be used to segment the eye images. This will define the iris and pupil objects(pixel values) and their boundaries(radius and diameters) which will later be needed in deep learning process to work on specific objects i.e. the iris alone. The image processing part will be achieved using the following methods:

1. Images shall be acquired from the BioSecure Multimodal Database(BMDB). The BMDB is a database that contains eye images collected from a standard office environment using the LG Iris EOU3000 system. During acquisition, spectacles were not allowed, but contact lenses were allowed.

2. Pre-processing: The chosen eye image will be segmented using image processing segmentation algorithms. This process will localise the iris region and detect the sclera and pupil boundaries.

The deep learning part will use the method explained below:

1. The segmented eye images in the database shall be divided into training and testing sets.

   The training set: The actual dataset that we use to train the model (weights and biases in the case of a Neural Network). During each epoch, which represents an iteration in the model training cycle, our model will be trained over and over again on this same data in our training set, and it will continue to learn about the features of this data.

   Testing set: The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset. Once the model is built, the test dataset is used to get the accuracy of the hypothesis.

2. The system shall use deep learning algorithms to train the input images using the training set, and to predict the output based on the model using the testing set.

Chapter 4

Requirements Specification

4.1 Functional System Requirements

1. The system shall use an authentication for the system administrator.

    1. The system shall display an authentication message to the administrator.

    2. The system shall give the administrator access to the database if the pin is correct.

    3. The system display an error message if the pin entered is correct.

    4. The system shall display a add confirmation message to the system administrator.

2. The system administrator shall be able to add eye images in the database.

    1. The system shall authenticate the system administrator.

    2. The system shall send the added images to the database.

    3. The system shall display an added image successfully message to the system administrator.

3. The system administrator shall be able to delete eye images in the database.

    1. The system shall authenticate the system administrator.

    2. The system shall discard the selected image from the database.

    3. The system shall display a deleted image successful message to the system administrator.

4. The system administrator shall be able to create a model to be used in deep learning section.

    1. The system shall authenticate the system administrator.

    2. The system administrator shall divide the eye images in the database into 2 parts: 50 percent training set and 50 percent testing set.

    3. The system shall save the 2 sets in the database.

4. The system shall use the training set for modelling and the testing set for prediction using deep leaning algorithms.

5. The user shall be able to choose eye images as inputs.

   1. The system shall display eye images as input to the screen.
   2. The system shall mark all the eyes images selected by the user as wanted input.
   3. The system shall move copies of the chosen eye inputs to the next stage (pre-processing stage).

6. The user shall be able to choose the expected output (identification and demographic output).

   1. The system shall read checkbox input of either or both identification and demographic data.
   2. The system shall display a confirmation message for the selected output.
   3. The system shall use the chosen input to process the data after the output confirmation from the user.

4.2 Non-Functional System Requirements

1. The system shall be available to users 24hrs a day so that users can access it at anytime in the day.

   1. The system shall check every 2hrs (system troubleshoot) that all parts are functioning properly.
   2. The system shall send a notification to the system administrator about any errors that occurred.

2. The system shall work on Windows, Linux and Mac operating system to work on all devices and be accessible to all users.

   1. The system shall run on all devices with Windows 7 and above, all Linux and Mac devices.
   2. The system shall display an error message if the device is incompatible.

3. The system interface input response time should not be more than 1 second to users for fast interaction process.

   1. The system shall shall detect keyed and clicked inputs at a response time of 50ms.

4.3 Domain Requirements

1. The eye images in the database should be negatives (black and white) so as to used in the pre-processing and prediction part.
2. The system administrator should seperate the training and testing datasets. This is to prevent the model seeing the test dataset and giving the exact results. (The model gives impartial results because it has not seen the test dataset)

4.4 Assumptions and Justifications

1. The eye images used are not captured in real time but are taken from a database. These is due to the following reasons:

   1. It needs special cameras and scanners.
   2. The eye is sensitive to flashes and they might be damaged.
   3. Ethic and privacy concerns, because users may not be sure of their safety of their images.

4.5 Structured Use Case Diagram

The system shall require authentication from the system administrator and give access to the system and Database. The System administrator shall choose training and testing sets from the images in the database. The sets will be used as a model to train the user inputs using deep learning algorithms and test them to get the output data.

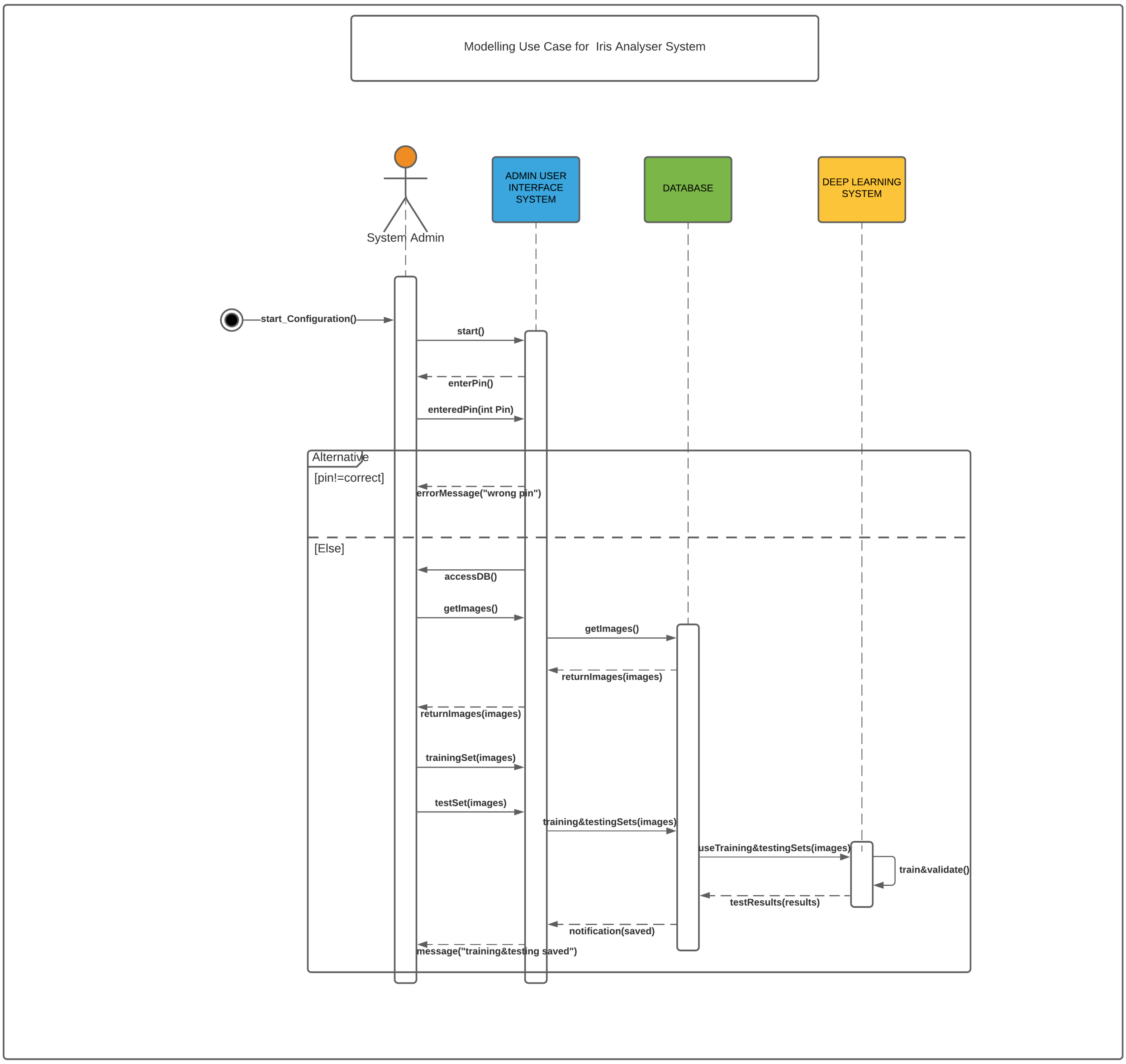


Figure 4.1: Modelling Image Use Case Sequence Diagram

The user shall choose an image and output option. The image shall be segmented first then passed through the Convolution Neural Network system for feature extraction. The features extracted shall be trained, validated and tested. The system through the test set shall give the output.

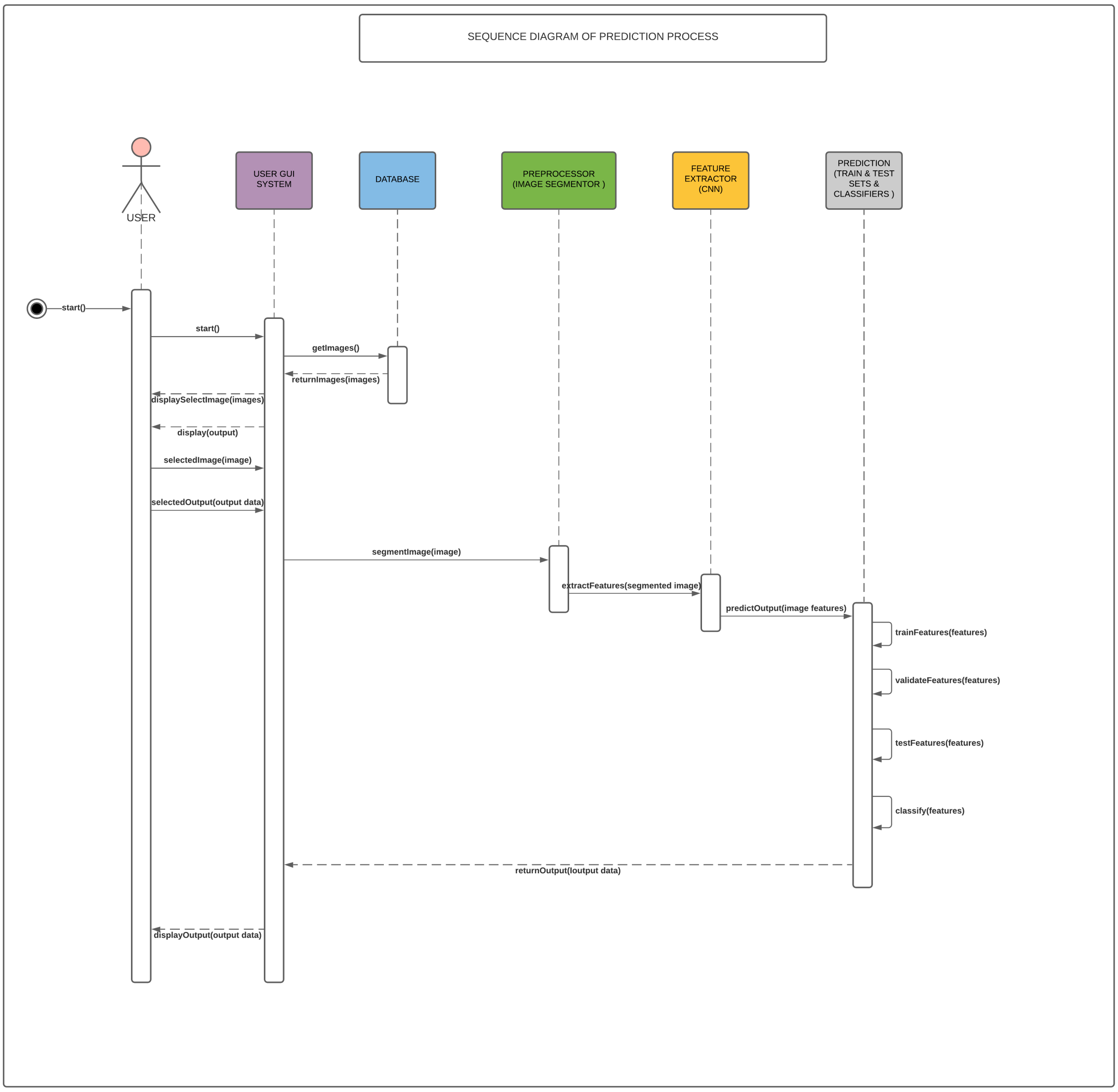


Figure 4.2: Prediction Image Use Case Sequence Diagram

4.6 Sequence Diagrams

The system shall require authentication from the system administrator and give access to the system and Database. The System administrator shall choose training and testing sets from the images in the database. The sets will be used as a model to train the user inputs using deep learning algorithms and test them to get the output data.

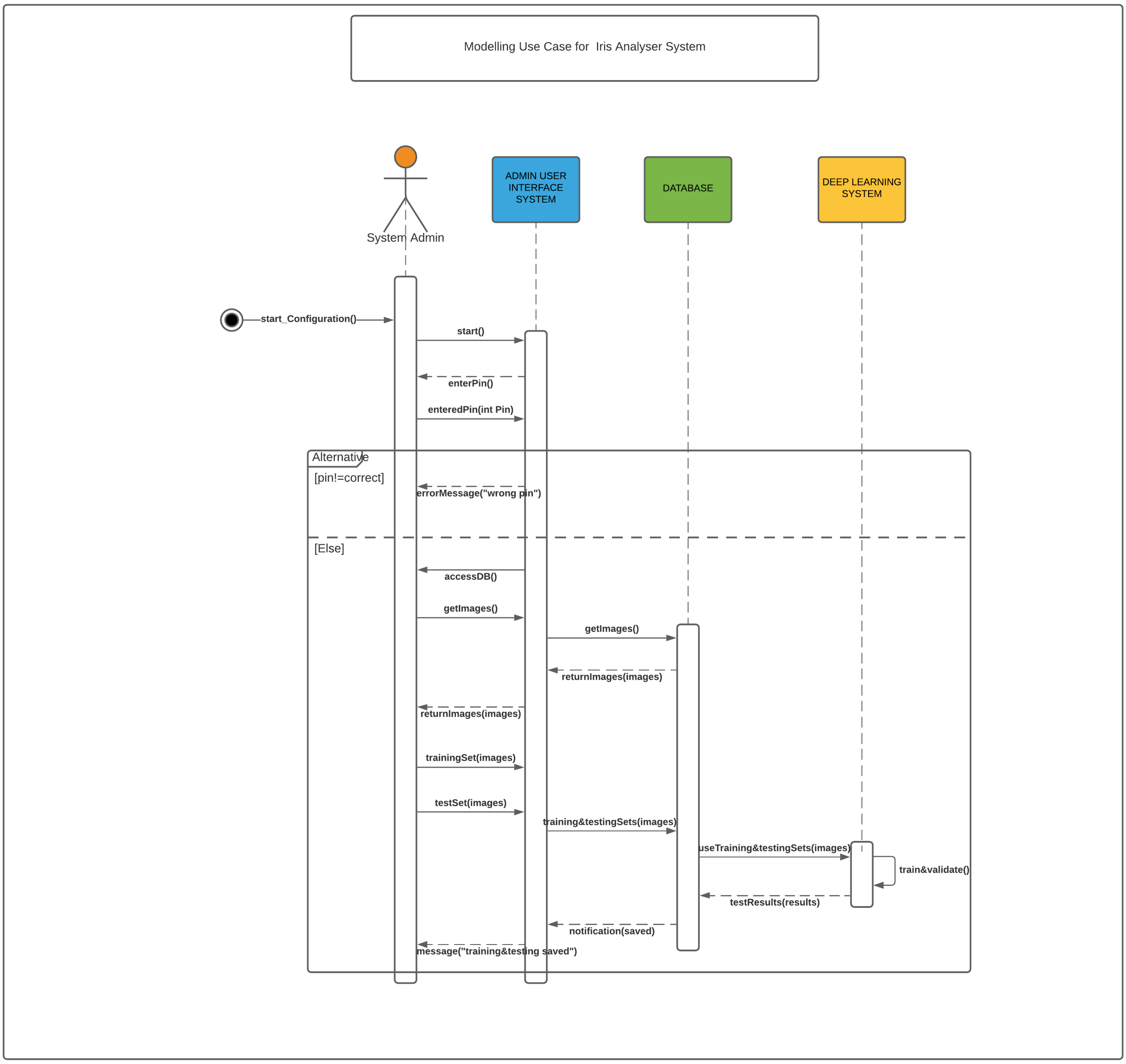


Figure 4.3: Modelling Image Use Case Sequence Diagram

The user shall choose an image and output option. The image shall be segmented first then passed through the Convolution Neural Network system for feature extraction. The features extracted shall be trained, validated and tested. The system through the test set shall give the output.

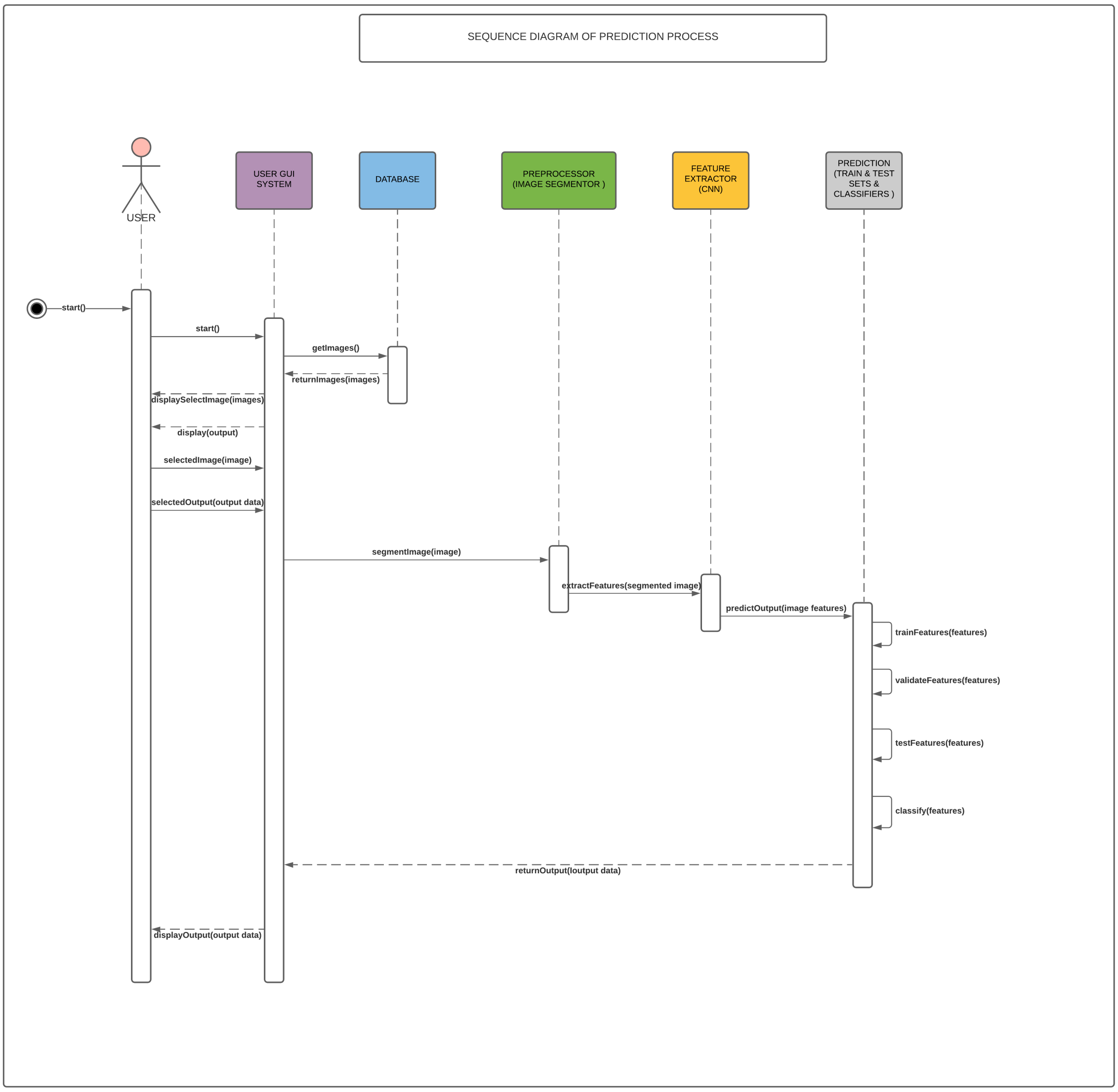


Figure 4.4: Prediction Image Use Case Sequence Diagram

4.7 Graphical User Interface

Below is an early iteration of how the graphical user interface of the Iris Analyser application will look like. The interface is in early stages of design and is subject to many changes during the next semester as the focus of this semester was on coding and modelling rather than the GUI itself.

Main Page GUI:

The user will be given an option either to open the system administrator section or User section.

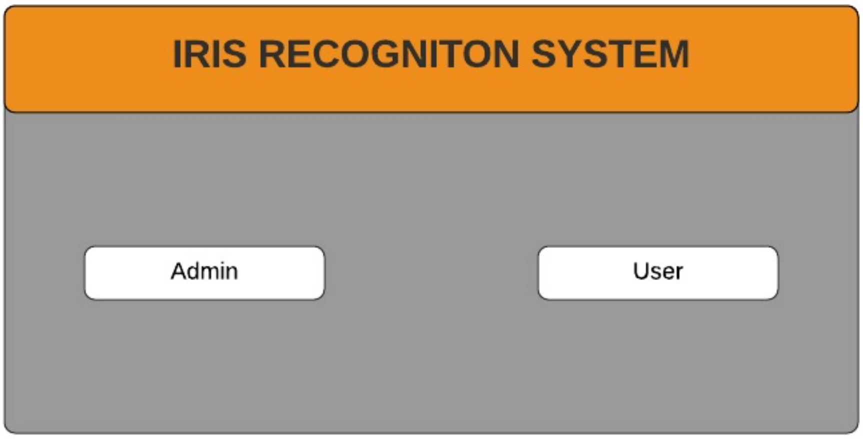


Figure 4.5: Graphical User Interface Main page view

User GUI:

The User Interface works as follows; After the appearance of the interface below, the user must first click on "Choose eye image" in order to choose an eye image of their choice from the Iris Analyzer eye image database. If the user presses any other option before doing so an appropriate error message will be prompted. The user shall choose either the identification or demographic output or both. After having chosen an eye image, output and confirming, the user must press the "Start Configuration" button and will be immediately presented with the identification and demographic result in the "Identification output" and "Demographic output" boxes respectively.

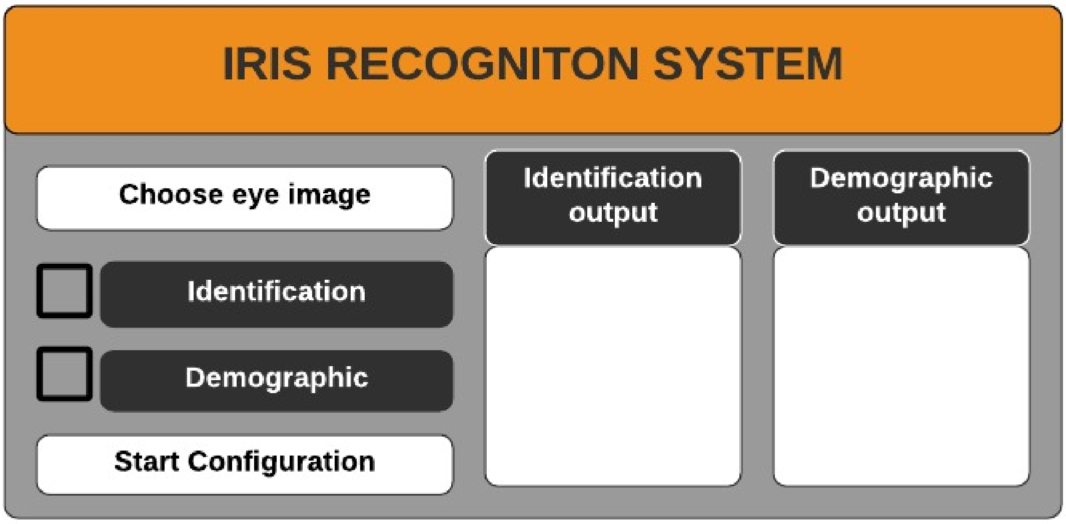


Figure 4.6: Graphical User Interface User view

System Administrator GUI:

The system administrator interface works as follows; After the appearance of the interface below, the system admin shall be prompted to enter a 4-digit pin. The system shall move on to the next interface if pin is correct and if its wrong display an error message. In the next interface the system admin can add and delete images from the database.

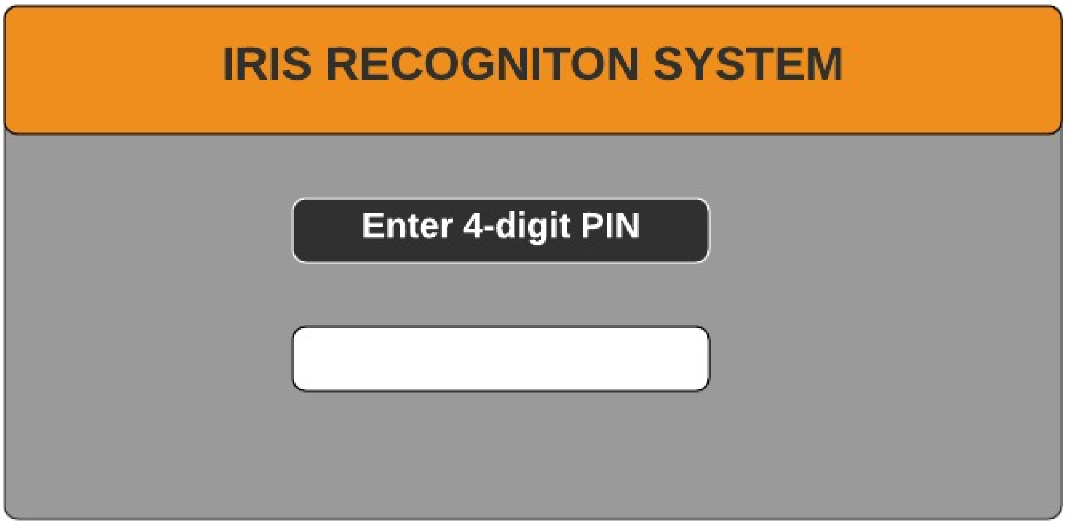


Figure 4.7: Graphical User Interface Authentication view

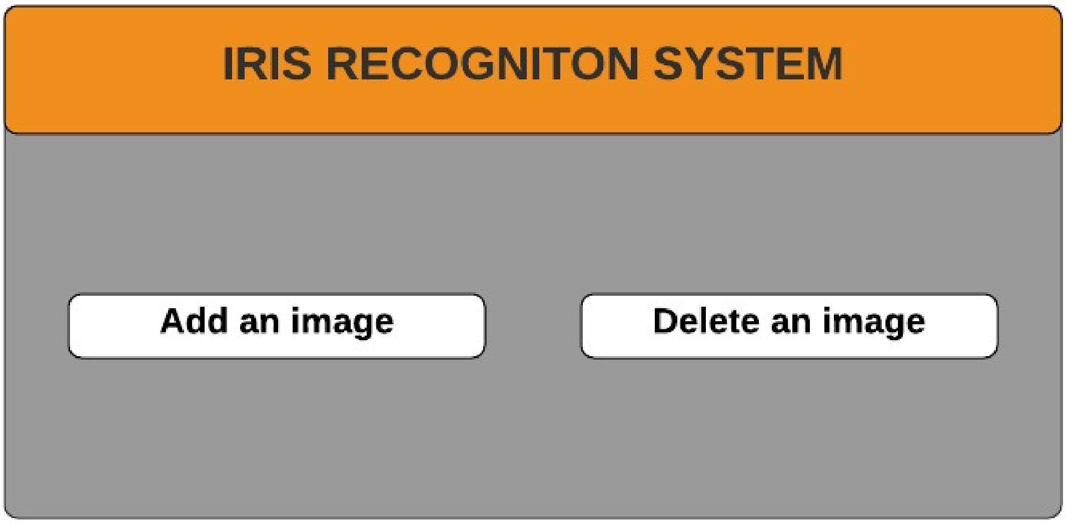


Figure 4.8: Graphical User Interface User database add/delete image view

Chapter 5

System Architecture and Models

5.1 Architectural Model

This is a pipe and filter architecture diagram since the flow of the diagram is very straight forward. We have a data-set in which some parts of it get segmented, to build the ımage processıng model. After that, the user can insert an image or set of images. These pictures will be first filtered and segmented by ımage processıng model, then passed to the prediction model which is developed by deep learning for the final result.

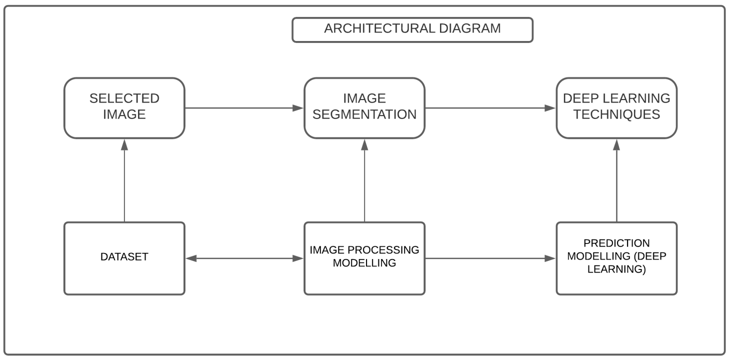


Figure 5.1: Architectural Model for the Iris Analyzer System

5.2 Process Model

Figure 5.2 shows the procedure to get the output from the inputted data. The user shall choose and image and the expected output wanted. The image shall be segmented and prediction done using deep learning methods to display the output.

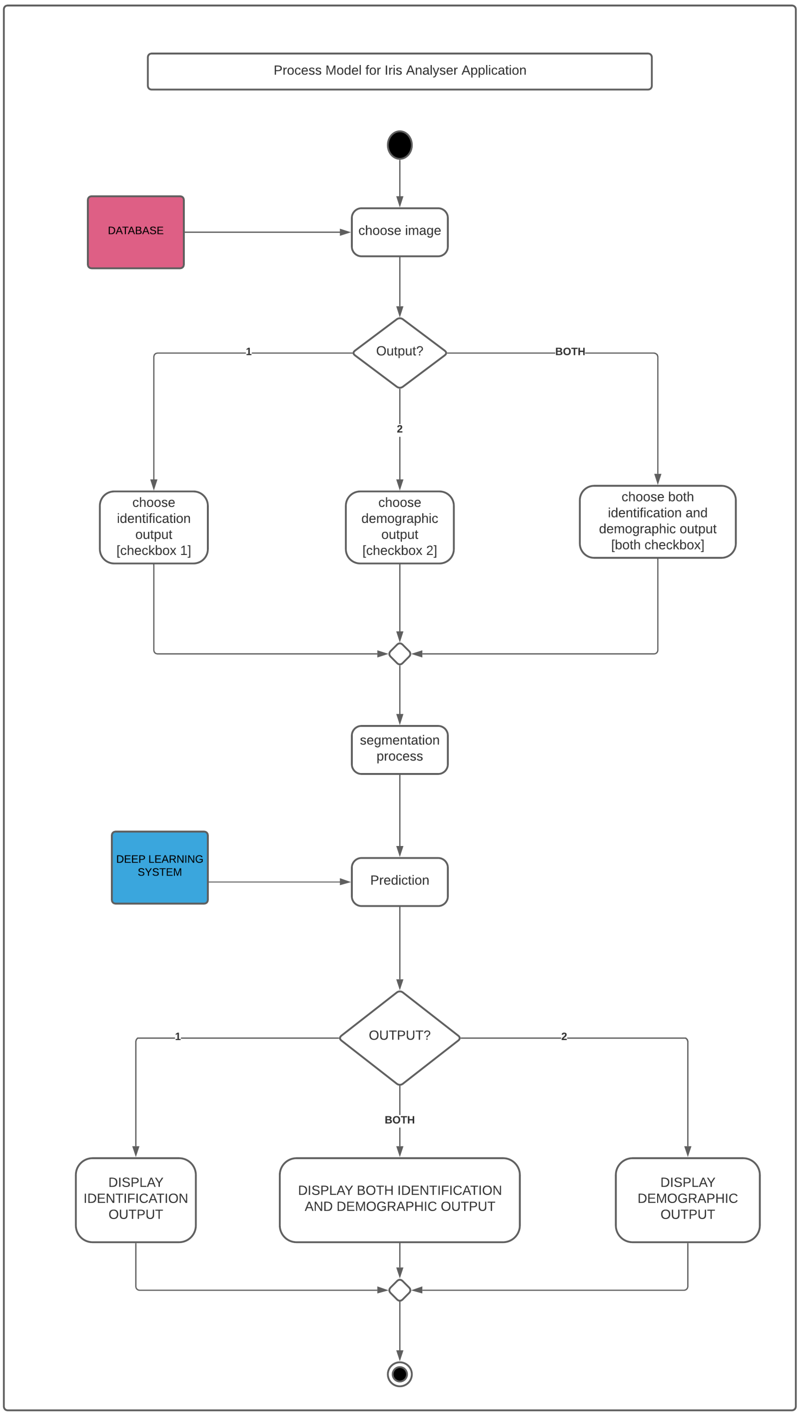


Figure 5.2: Process Model

An image is taken through the first step which is segmentation process. The segmented image is then passed through the Convolution Neural Network system which extract the features. The features are then trained using the training set and validated. This validation process helps give information that may assist us with adjusting our hyper-parameters. The trained data is then tested and if the accuracy threshold is above 85percent we accept the output otherwise it is trained again to improve the accuracy.

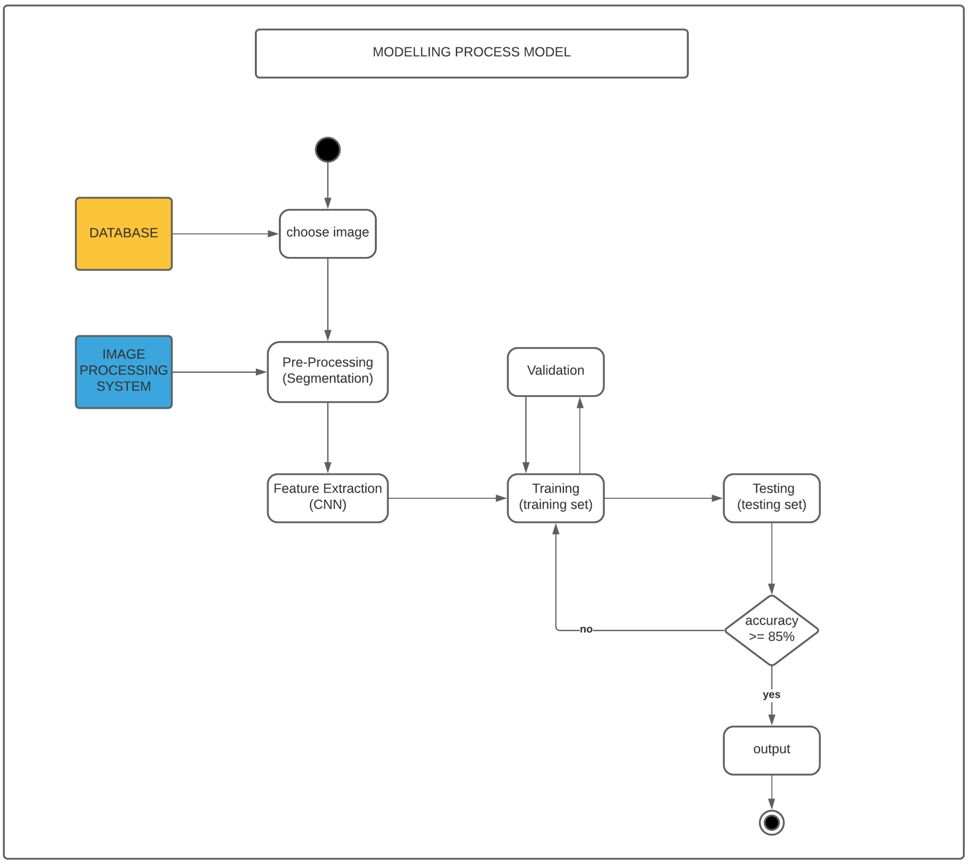


Figure 5.3: Modelling Process Model for the Iris Analyzer System

5.3 Data Flow Models

Figure 5.4 represents the data flow model which shows the abstract form of each process and how it is decomposed further into the deeper level.

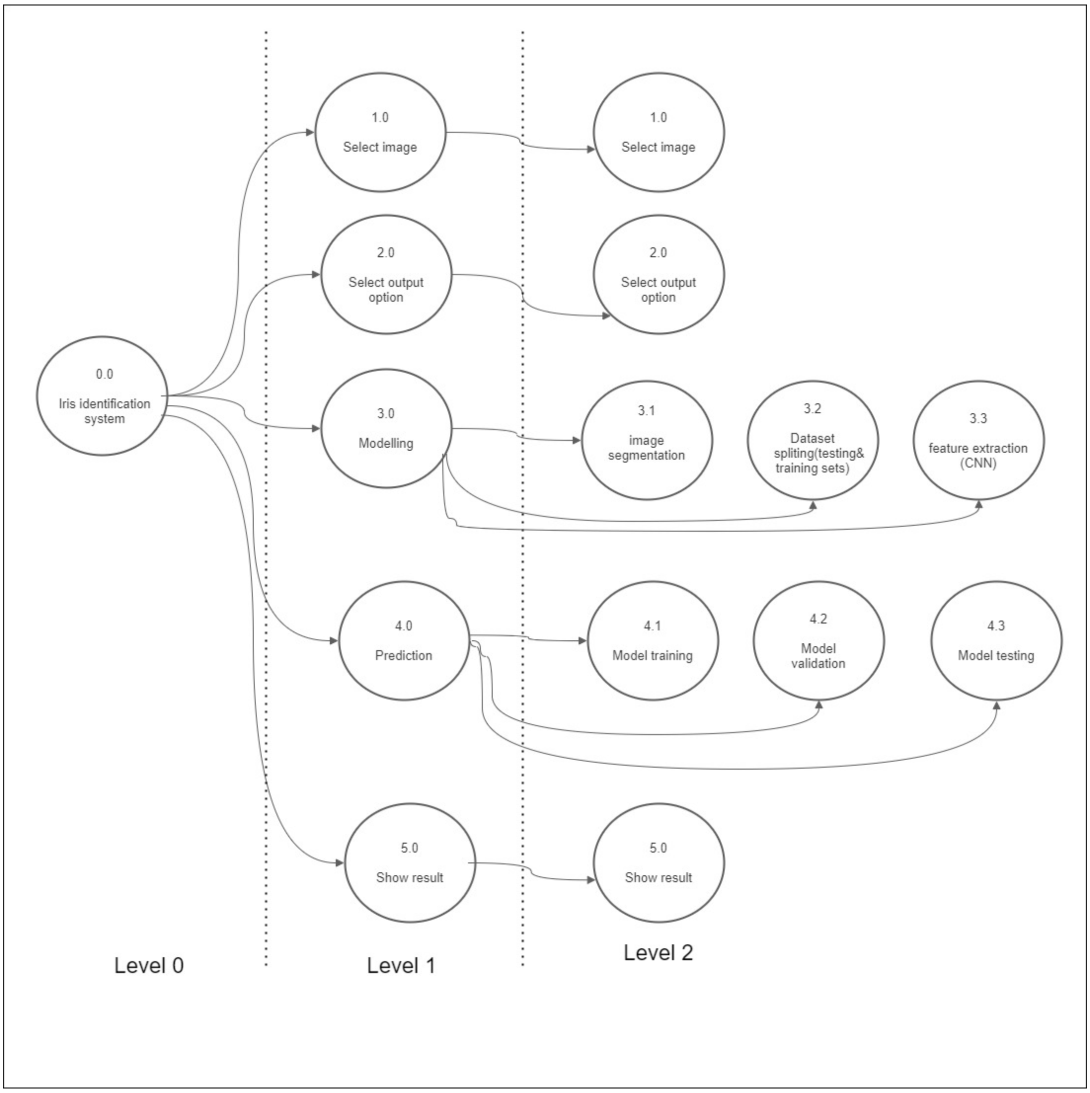


Figure 5.4: Data Flow Process Decomposition (Level 0,1 and 2)

Level 0 of the data flow diagram (context diagram) shows the flow of data between the main system and the external systems and actors which are the Users, System Administrator and Database in figure 5.5.

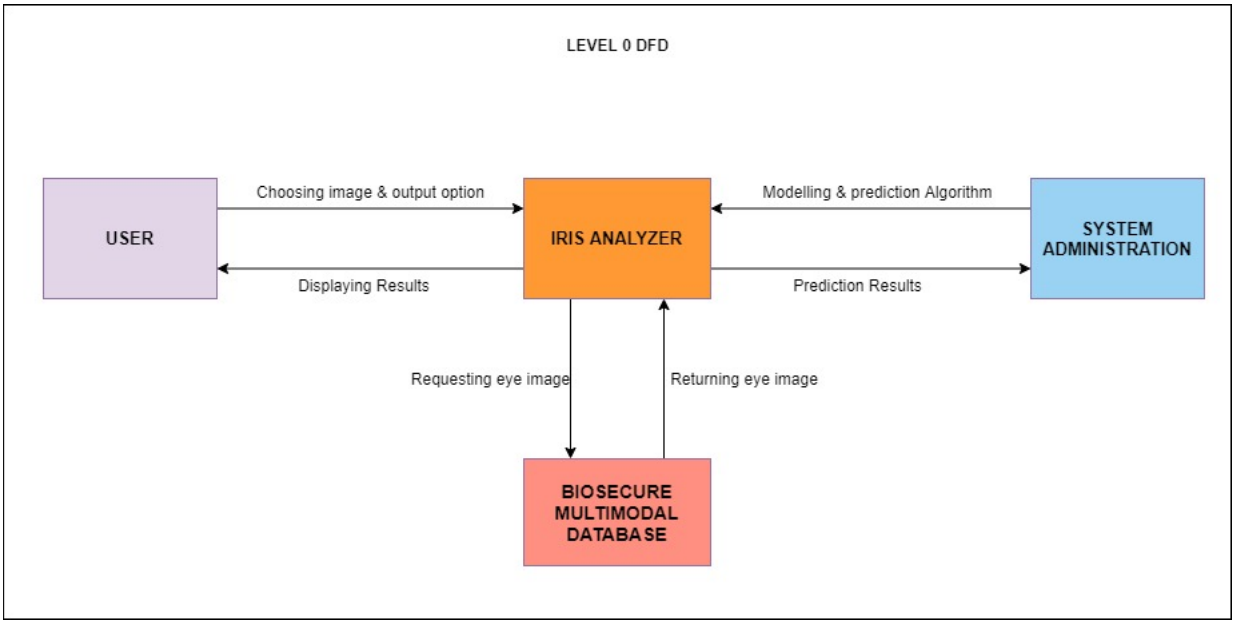


Figure 5.5: Level 1 Data Flow Diagram

The first level of the data flow model shows the base format of the processes without revealing the inner sub-levels. It also shows their relationship with the external system.

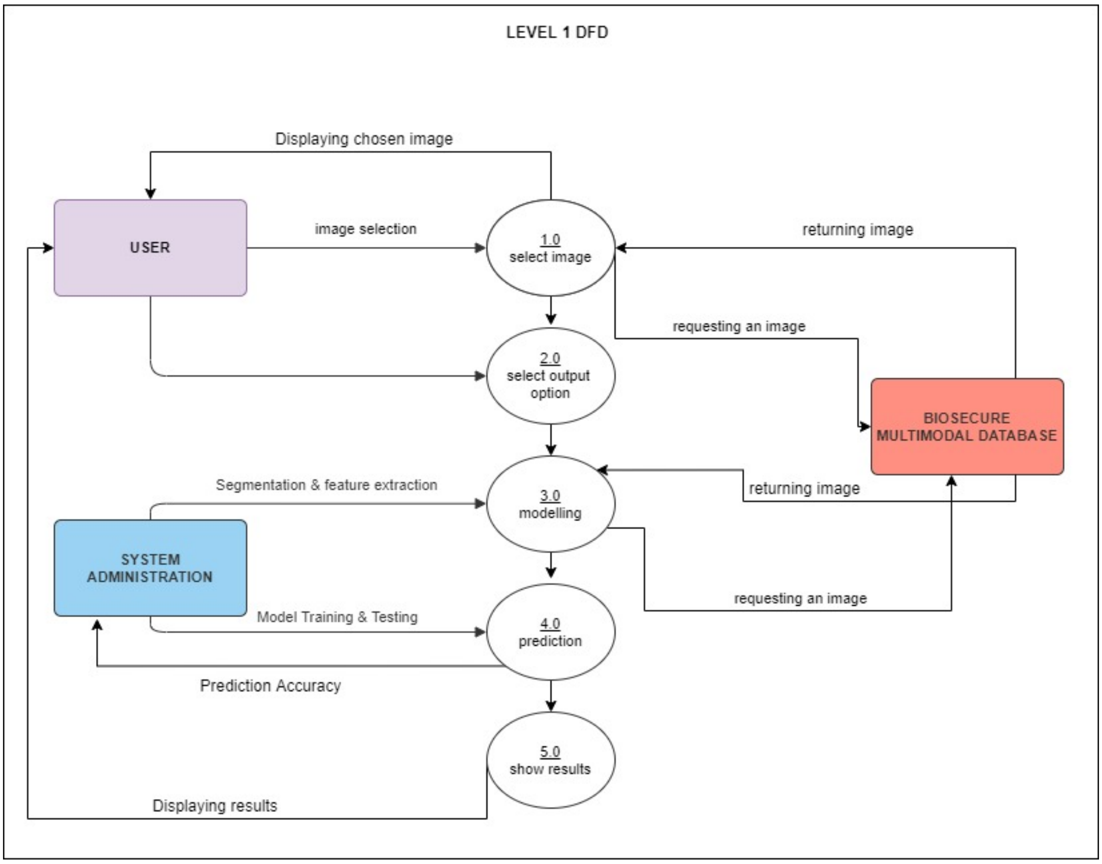


Figure 5.6: Level 1 Data Flow Diagram

Figure 5.7 is the inner level of the data flow diagram and it shows the inner workings of the processes in detail, step by step. As well as their relationship with the external system.

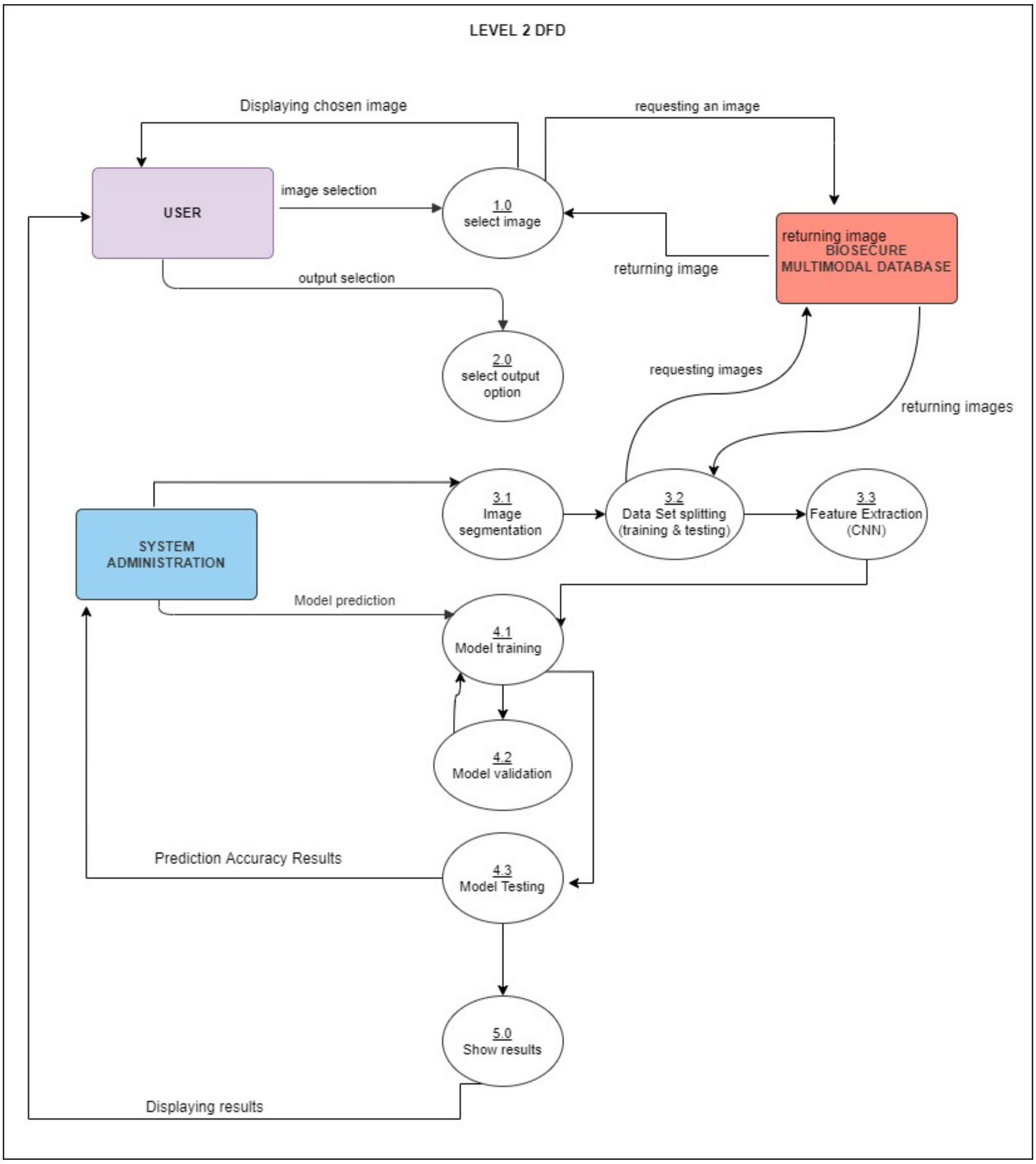


Figure 5.7: Level 2 Data Flow Diagram

5.4 Class Diagram

The class diagram is a representation of the system and its classes as well as its variables and methods. The relationship between each class or object is also shown.

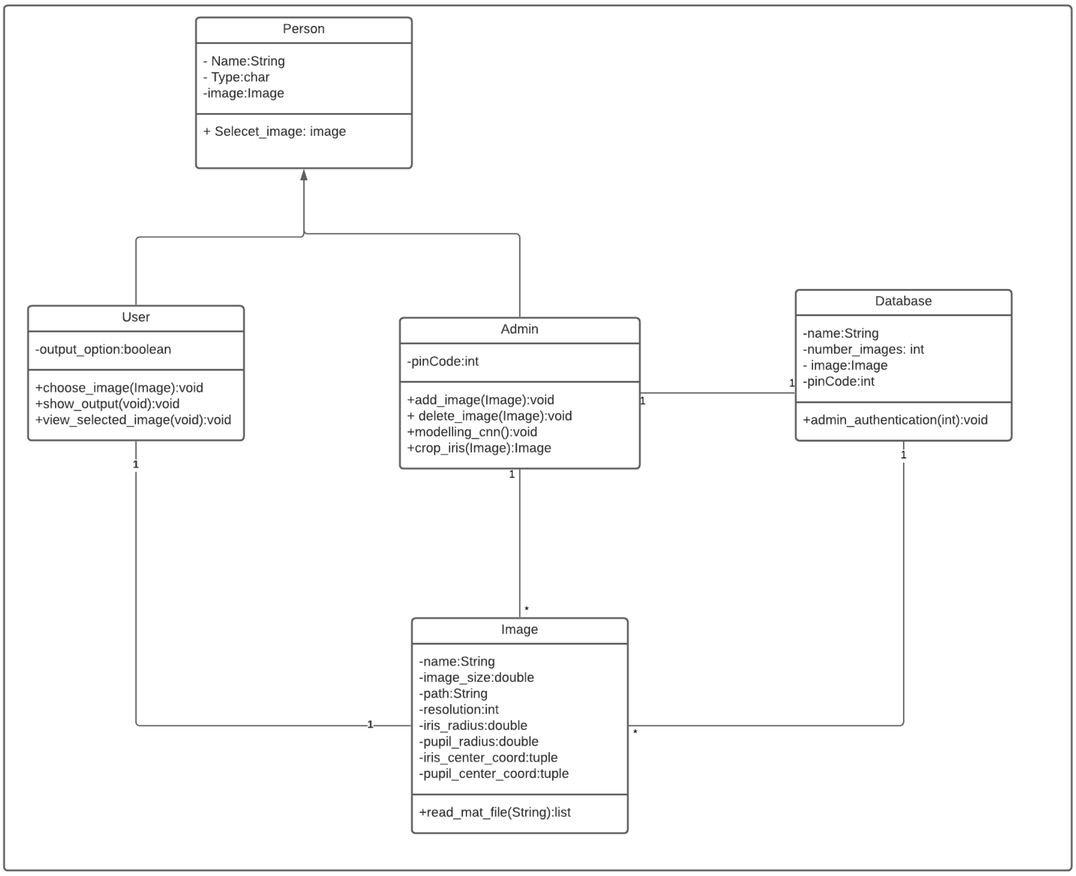


Figure 5.8: Class Diagram

5.5 Data Structures and Types

The Data Structures used are:

1. Dictionaries used to store users and their respective images.
2. Lists, e.g. training and testing lists, values of the keys in the dictionary.

The Data types used are:

1. Strings, as the images names and paths, and as keys in the dictionary.
2. Doubles, as the iris/pupil radius and center coordinates.

5.6 System Algorithms

The algorithms used are:

1. Cropping algorithm to extract the iris segment from the image.
2. CNN algorithm for feature extraction.

Chapter 6

Project Management

6.1 Software Estimations

6.1.1 Input

- **Inputs** : User image insertion-L, log-in form-M, Add images form(admin)-L, Delete images(admin)-L, View selection history(admin)-M, Edit processing model(admin)-H, edit images(admin)-H.

- **Outputs**: Showing the resulted image-H, predicted results-H

- **Inquiries**: User image insertion-L, admin image insertion-L, admin image deletion-L, Admin history display-M, admin modeling process modification-H, admin image modification-H, Password authentication-M.

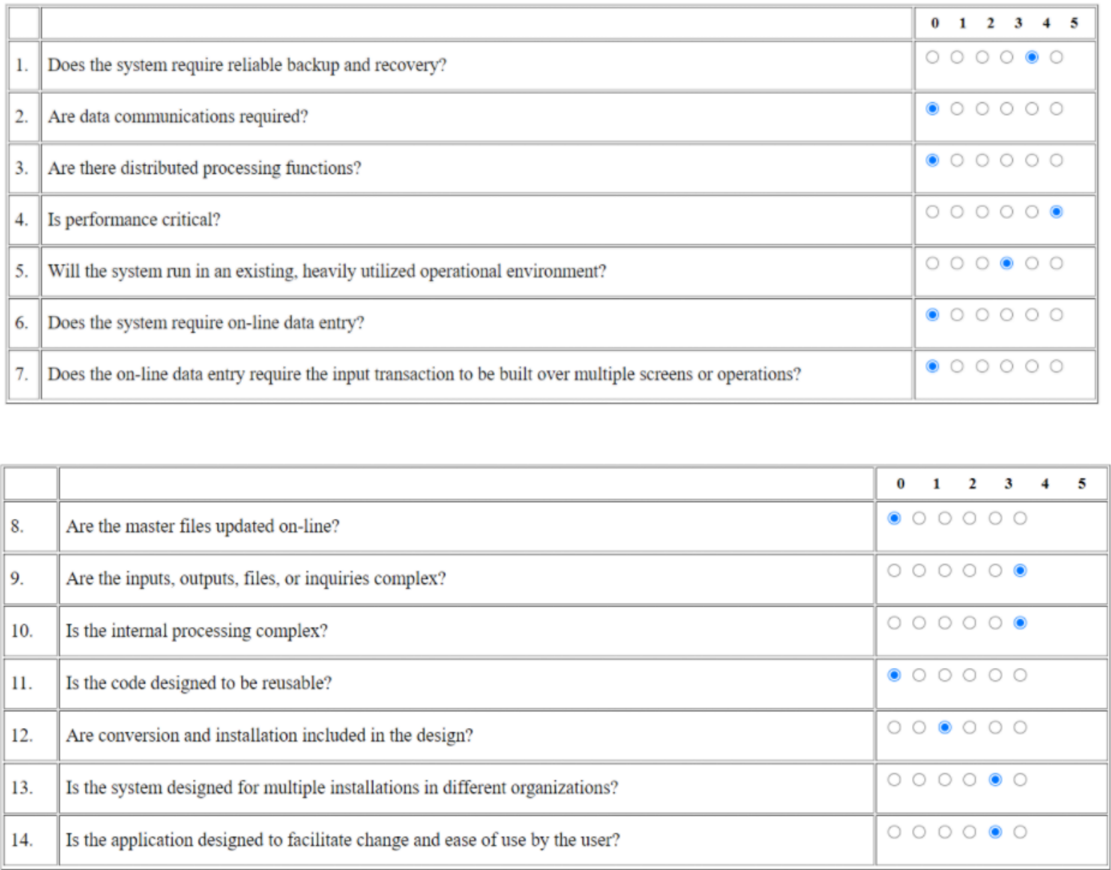
- **Logical internal files**: IRIS Images dataset-M, Coordinates file-M

Figure 6.1 shows the Estimation inputs based on their weight and complexity level.

	Simple	Average	Complex
Number of User Inputs	3	2	2
Number of User Outputs			2
Number of User Inquiries	3	2	2
Number of Files		2	
Number of External Interfaces			

Figure 6.1: Estimation Input

6.1.2 Complexity Adjustment Table



		0	1	2	3	4	5
1.	Does the system require reliable backup and recovery?	○	○	○	○	●	○
2.	Are data communications required?	●	○	○	○	○	○
3.	Are there distributed processing functions?	●	○	○	○	○	○
4.	Is performance critical?	○	○	○	○	○	●
5.	Will the system run in an existing, heavily utilized operational environment?	○	○	○	●	○	○
6.	Does the system require on-line data entry?	●	○	○	○	○	○
7.	Does the on-line data entry require the input transaction to be built over multiple screens or operations?	●	○	○	○	○	○
8.	Are the master files updated on-line?	●	○	○	○	○	○
9.	Are the inputs, outputs, files, or inquiries complex?	○	○	○	○	○	●
10.	Is the internal processing complex?	○	○	○	○	○	●
11.	Is the code designed to be reusable?	●	○	○	○	○	○
12.	Are conversion and installation included in the design?	○	○	●	○	○	○
13.	Is the system designed for multiple installations in different organizations?	○	○	○	○	●	○
14.	Is the application designed to facilitate change and ease of use by the user?	○	○	○	○	●	○

Figure 6.2: Estimation Complexity Adjustment Table

Result	
Project Function Points	89.6999999

6.1.3 Line of Code

To calculate the number of code lines we chose Python as the language to use and had a unit size of 29 which we multiplied by ATFP. This is the average unit size for both.

Python 100%

Loc = 29 * 89.7 = 2601.3

6.1.4 Estimate the Efforts

Constructive Cost Model COCOM0 Basic

Development mode: organic.

a=2.4, b=1.05, c=0.38

Number of thousand delivered source instructions = (KDSI) = ATFP* Python Language unit size/1000 = 2601.3 /1000=2.6013

Effort in staff months =effort in man-moths=MM=a*KDSIb = 2.4*($2.6013^{1.05}$) = 6.54

The development time=TDEV=2.5*MM^c = 2.5($6.54^{0.38}$) = 5.2 = $6 months$

Jones's first -order effort estimation methods

We are building a shrink-wrap kind of software in an average organization.

Rough schedule estimation = ATFP^{exp} = $90^{0.042}$ = 6.61 = $7 months$.

Schedule rule of thumb

Efficient Schedule (Shrink-Wrap)

Schedule(Months)= 5.9   6 months

Effort(Man-month) = 8

Table 8-9. Efficient Schedules

	Systems Products		Business Products		Shrink-Wrap Products	
System Size (lines of code)	Schedule (months)	Effort (man-months)	Schedule (months)	Effort (man-months)	Schedule (months)	Effort (man-months)
10,000	8	24	4.9	5	5.9	8
15,000	10	38	5.8	8	7	12
20,000	11	54	7	11	8	18
25,000	12	70	7	14	9	23
30,000	13	97	8	20	9	32
35,000	14	120	8	24	10	39
40,000	15	140	9	30	10	49
45,000	16	170	9	34	11	57
50,000	16	190	10	40	11	67
60,000	18	240	10	49	12	83
70,000	19	290	11	61	13	100
80,000	20	345	12	71	14	120
90,000	21	400	12	82	15	140
100,000	22	450	13	93	15	160
120,000	23	560	14	115	16	195
140,000	25	670	15	140	17	235
160,000	26	709	15	160	18	280
180,000	28	910	16	190	19	320

Figure 6.3: Estimation Efficient Schedules

6.2 Project Milestones, Tasks and Allocation

Having caught up to the end of the semester, we have completed the tasks and milestones we had set for ourselves throughout the semester. Moreover, we are still planning to continually make improvements to our code and model in order to make it more extendable as well as making the model more accurate and precise.

Table 6.1 shows all tasks scheduled to be completed by the end of the academic semester (January 2021) as well as the duration of each task. The dependencies show which tasks depend on other tasks to be completed before they can be started. The group members responsible for the corresponding tasks are also mentioned and allocated. The colors indicate different sprint duration's (Blue = Sprint 1, Purple = Sprint 2, Green = Sprint 3).

Table 6.1: Tasks for the semester

Task #	Task	Duration (weeks)	Dependencies	Resonsible By
T1	Research (Image Proc Techniques) + Literature Review	2		All
T2	Research (Deep learning Basics) + Literature Review	2		All
T3	Write a Project Report (1)	2	T1,T2 (M1)	All
T4	Research (Deep Learning Algorithms)	2		All
T5	Research (Image Segmentation Techniques)	2		Aref, Sameh
T6	Research (Convolutional Neural Networks)	2		Baraa, Evans
T7	Segmentation of Iris region from Eye Images	1	T5 (M2)	Aref, Sameh
T8	Crop and Prepare Segmented Images	1	T7	Baraa, Evans
T9	Divide Images into Training and Test set	1	T8	Baraa, Evans
T10	Write a Project Report (2)	2	T4,T5,T6 (M2)	All
T11	Convolutional Neural Network (Code)	1	T6	Baraa, Evans
T12	Train Deep Learning Model	1	T7,T8,T11(M3)	All
T13	Gather Outcome (Accuracy) Information	1	T12	Baraa, Evans
T14	Analyze Deep Learning Model Results	1	T13	Aref , Sameh
T15	Compare Deep Learning Outcome vs Traditional Methods	1	T13 (M5)	Aref, Sameh
T16	Write a Project Report (3/Final)	2		All

Table 6.2 shows the milestones occurring throughout the academic semester. Milestones represent any significant goal or activity in the project cycle.

Table 6.2: Milestones for the semester

Milestone #	Milestone
M1	Project Fundamentals Understood
M2	Sufficient Fundamental Research for Deep Learning Model
M3	Images are Segmented and Ready (Finalized Format)
M4	Deep Learning Model Complete
M5	Results (Output) Analysis Ready

6.3 Gantt Chart

Figure 6.4 shows the visual representation of tasks that are scheduled throughout a time period (one semester's length). The tasks mentioned in table 6.1 are shown on the left of the chart and the corresponding scheduled dates are followed. The progress of each task and completion status of each milestone is shown with a percentage. All the tasks have reached their full completion percentage as the semester period has come to an end and the tasks have been fulfilled. Each milestone from table 6.2 is indicated with an orange diamond and each color corresponds to a different sprint duration (Blue = Sprint 1,Purple = Sprint 2, Green = Sprint 3).

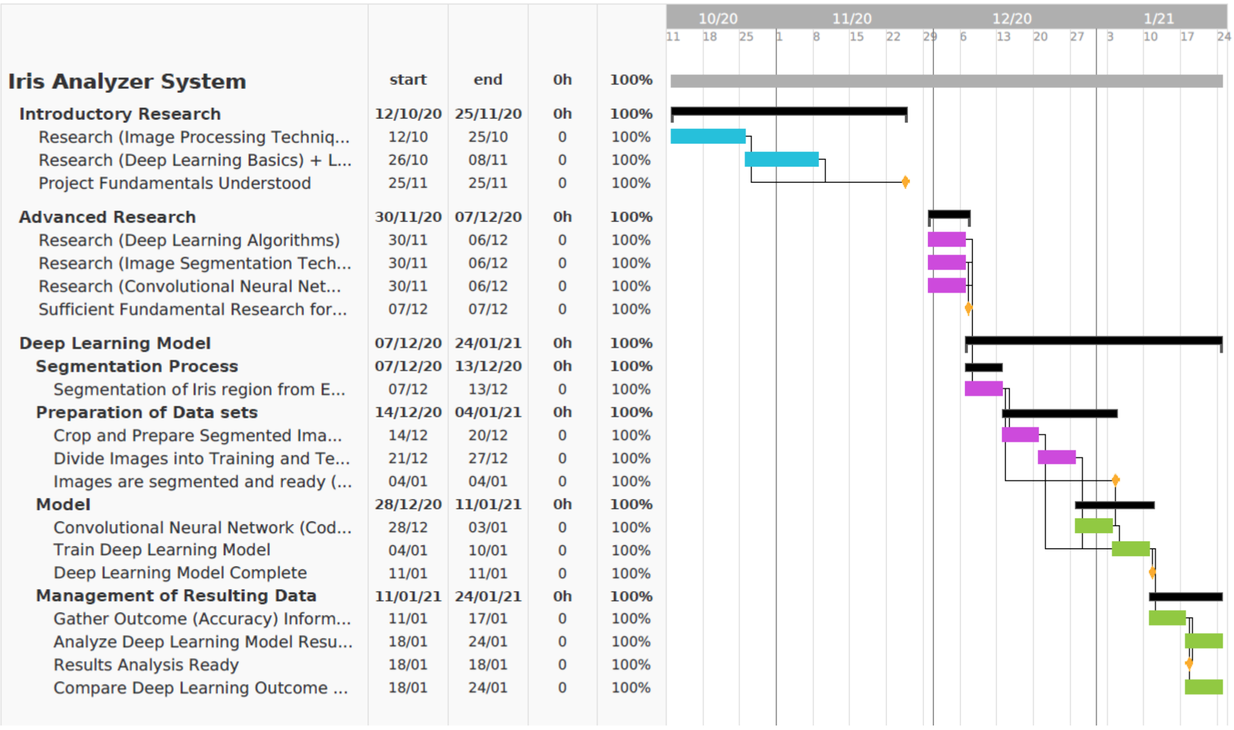


Figure 6.4: Gantt Chart

Chapter 7

Conclusion

7.1 Project Evaluation

This project targets scientists and researchers who work in fields related to image processing and machine learning. The goal was to optimize the current Iris analyzer, by embedding CNN algorithm into it. As a result to the new hybrid model, the accuracy of Iris analyzer increases significantly. However, image segmentation is still a hurdle in the way of improving the model applicability. Nevertheless, the outcomes of the model are promising and incentive to move forward in the process of development.

7.2 Retrospective

At the start of the project, it was difficult to look at the work flow and tasks, although it looked like we were on track, there were very few and limited tasks to complete as well as the fact that most of the tasks revolved around individual research by each group member rather than strongly defined tasks which made our visual progress charts such as the sprint charts obsolete. This caused us to encounter our first problem which was communication; although we met with our supervisor early on, the weekly meetings left many topics and questions regarding the project itself unanswered and unclear as we did not have a strong basis to work upon. This also resulted in miscommunication regarding a major aspect of the project as a whole: whether we were doing an application or research-based project.

However, during the second sprint which occurred after the 7th week of the project development process, we learned to become more collaborative and work better together as a team. The first step was to make ourselves more experienced with the Trello Board and learn to use it in a correct manner. This immediately had a positive impact on the shape of the group, as we started to become more expressive in our opinions. On the other hand, we did not have to change everything, for example, our method of communication from start to present is done through Google Meets as we found it to be the easiest, fastest and most clear way of staying in touch within the group and with the supervisor as well. We also kept in touch with our supervisor more often through Messenger which was initially only used to set up and approve meeting dates and timings, however, on week 7 and on-wards we started to share more ideas and ask more questions through the Messenger medium as well where we were able to receive almost immediate answers.

Following the end of the second sprint and entering the final phase of our project for this semester, the first major change that occurred was less communication with our supervisor. This was not the result of poor communication or bad planning, we had just reached the stage where we were more aware of the work we had to complete and it revolved around group work on the coding and implementation of the deep learning model. We were able to keep the momentum going until the end of the 14th and last week of the semester and successfully create a model which would provide results as well as accuracy levels. In summary;

What went wrong throughout the semester:

- Misunderstanding about the nature of the project (Research-based).
- Work done at the start and towards the end of the sprint more often, instead of being spread throughout the duration (caused fatigue).
- We were not able to complete the preparation of the data sets (training and test sets) in the specified time period we set for ourselves (Completed it past schedule).
- Some tasks took longer than expected, mostly due to the 2nd sprint being much shorter (sprint 1 was 7 weeks, sprint 2 was only 4 weeks)

What was improved throughout the semester:

- Improved expressiveness during meetings and chats.
- Better use of communication software such as Trello, Messenger.
- Incorporate supervisor more strongly in development process.
- Sprint 3 was as short as sprint 2 but task completion was well-optimized.

What can still be improved (next semester):

- Manage time more efficiently in order to complete more demanding tasks on time whilst still doing research on the side.
- Look even further ahead in order to plan better and more accordingly.
- Ensure each member is up to date with critical events.
- Organize work folders more efficiently using Google Drive/DropBox.

7.3 Future Work

In the future, we are planning to do the following:

1. Using the CNN and the model developed to predict other data sets such as gender and demographic (geographical location).
2. Improving the prediction accuracy of our model(identification data).
3. We are looking forward to develop the GUI for our iris recognition system.

Chapter 8

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