Software Requirement Specification Document for Deep learning–based automated detection and classification of Alzheimer’s disease Using Neuroimaging Data

Salma Amr Abed, Mohamed Mourad, Mohamed Mohamed, Mostafa Ashraf
Supervised by: Dr. Walaa Hassan, Eng Youssef Talaat

May 15, 2023

Table 1: Document version history

Version	Date	Reason for Change
1.0	15-Nov-2022	SRS First version’s specifications are defined.

GitHub: https://github.com/salma-abed/Deep-learning-based-automated-detection-and-classification-of-Alzhe

Contents

Abstract

The main objective of this project is to develop an intelligent system that can recognize and categorize the four stages of AD (Alzheimer's Disease) utilizing cutting-edge image analysis methods and deep learning models, as well as to provide a full report on the model's diagnosis of the patient. This research will use MRI(Magnetic resonance imaging), which has been determined to be one of the most prevalent and common medical imaging methods, taking a non-invasive approach in the identification and classification of the AD stages. As such, we will utilize SHAP and a fuzzy-based expert system to fulfill the full potential for each diagnosis moreover, and we will choose the most efficient deep learning classifier to employ in the feature extraction phase.

1 Introduction

1.1 Purpose of this document

This paper's goal is to outline the criteria for "Deep learning–based automated detection and classification of Alzheimer's disease Using Neuroimaging Data." Doctors that need to identify Alzheimer's in their patients can utilize this document. It is also helpful for developers who plan to continue working on the project for system upkeep or additional development.

1.2 Scope of this document

This software requirements specification document seeks to outline the system's goals and walk through the system design. The paper's target audience includes prospective users of the software, including medical professionals and other field workers.

1.3 Business Context

According to The World Health Organization (WHO) [1] stated in 2012 that dementia became a public health priority. Alzheimer's Disease International and WHO reported in 2019 that over fifty million people worldwide are living with dementia; this number is projected to increase to one hundred fifty-two million by 2050, with an estimated dementia cost of about $818 billion. The project will benefit two groups in terms of business. It will help doctors identify individuals with Alzheimer's disease earlier and begin therapy, and it will assist patients to understand where they are in the disease's progression.

2 Similar Systems

2.1 Academic

2.1.1 EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE WITH DEEP LEARNING[2]

1. Pros: The tuning of early-stage diagnosis models because most studies currently conducted have indicated a performance bottleneck for diagnosis, mostly as a result of the inherent constraints of the selected learning models.

2. Cons: For the time when this was project proposed there were little to no prior experiments conducted using multileveled models on biomedical datasets while also having small datasets to extract high-level biomarkers.

3. Models Used: A neural network with several hidden layers serves as the encoding structure for the sparse auto-encoder. The original input vector is represented by neurons in the input layer. It is typically difficult to pinpoint the precise significance of each concealed layer, although each one may be thought of as a more elevated depiction of the layer before it. The output layer has the same dimensions as the input layer and is a sparse representation of the input layer.

4. Preprocessing: Their two main parts—stacked sparse auto-encoders and a softmax regression layer-showcase their learning structure. Deep representations of the original input are obtained by the auto-encoders. Instances are classified using the softmax regression layer by choosing the labels with the highest predicted probability. a mapping of ROIs on a 3D MRI image with masking from feature stability (83 ROIs). The differences between different ROIs may be easily seen. The characteristics recovered from the darker ROIs tend to benefit all the buried neurons equally, making them more sensitive to the course of AD and MCI than the lighter ROIs. For clearer distinctions, they applied a Gaussian filter to the picture. While not entirely inconsequential, the dark areas are said to convey less predictive data.

5. Data-set Used: They used MRI images of 311 subjects from the Alzheimer's disease Neuroimaging Initiative (ADNI) baseline cohort, including 65 AD subjects, 67 cMCI subjects, 102 ncMCI subjects, and 77 normal control subjects.

6. Accuracies /Results: Their method was conducted for the early diagnosis of AD and MCI based on deep learning. Compared to the conventional binary classification methods, such as SVM, their method conducts AD diagnosis as a multi-class classification task with overall accuracy and overall specificity of (47.42% and 83.75%).

7. Contribution: The method's first contribution is proving that a multi-layered parametric learning model can be applied to biomedical datasets with smaller sizes to extract high-level biomarkers.

2.1.2 Multi-modal deep learning models for early detection of Alzheimer's disease stage[3]

1. Pros: The fusion of multiple data modalities provides a holistic view of ad staging analysis by using deep learning to analyze MRI, genetic (single nucleotide polymorphisms (SNPs), and clinical tests.

2. Cons: Non proven

3. Models Used: When employing DL, they disguise a certain modality as zeros when it is not accessible. The classification layer receives the intermediate characteristics from the three modalities. They evaluate many possibilities for the classification layer, including KNN, decision trees, random forests, and support vector machines. The best internal cross-validation (CV) accuracy uses deep models as the classification layer, followed by random

forests. Deep models that combine the three modalities perform better than DL for single modalities. Additionally, for both CV and external test sets, deep models outperform shallow models like feature-level and decision-level during combination.

4. Preprocessing: Shallow learners are used to performing feature-level combinations by directly concatenating the data modalities. The extraction of intermediate features using DL is followed by concatenation and passage through a classification layer in order to execute the intermediate-feature-level combinations. Voting on the single modalities is used to execute decision-level combination tasks also, They employ EHR data from 2004 patients with an average of 1680 normalized characteristics to categorize the patients into AD, MCI, and CN (three classes). They employ an auto-encoder with three layers, each having 200, 100, and 50 nodes. Adam is used to training the deep networks, and a maximum epoch count of 25 is used (DL network training must be repeated on the whole dataset in order to be sufficiently trained).

5. Data-set Used: They used a total of 2004 patients in this study, with all 2004 patients having clinical data, 503 patients having imaging data, and 808 patients having genetic data. For participants with multiple visits, they use the diagnosis from the patient's last visit., 220 patients have all three data modalities, 588 patients have SNP and EHR, 283 patients have imaging and EHR, and the remaining patients have only EHR data.

6. Accuracies /Results: "Combination of SNP and EHR modalities: deep model outperforms shallow models.Internal CV accuracy of 0.78±0 using deep models followed by random forests as the classification layer, Combination of imaging and EHR modalities: deep model outperforms shallow models. Internal CV accuracy of 0.79±0 using deep models followed by random forests and SVM as the classification layers, Combination of imaging and SNP modalities: shallow model outperforms deep models. We perform two-class classification using a combination of SNP and imaging intermediate features (CN vs. AD/MCI). Internal CV accuracy of 0.75±0.11, using feature-level combination models"

7. Contribution: they figured three things including that novel DL framework for multi-modality data fusion outperforms single-modality DL, Novel perturbation and clustering-based feature extraction assisting DL model interpretations are capable of AD stage prediction, Application of 3D convolutional neural network architecture for MRI image data benefits the AD analysis.

2.1.3 Detection of Alzheimer's Disease and Dementia States Based on Deep Learning from MRI Images: A Comprehensive Review[4]

1. Pros: the usage of Computer-aided detection systems (CADS) tools for detecting abnormal conditions in medical imaging processes and increasing diagnostic accuracy using advanced image processing and pattern recognition techniques.

2. Cons: the constraining nature of having high-resolution (super-resolution) photos probably function heavily limited their choice of datasets.

3. Models Used: "For the purpose of detecting AD, features from brain MR images are classified. In AD-related areas of structures, features should accurately represent the ventricular size, hippocampus shape, cortical thickness, and brain volume. MRI neuroimaging technology has being researched for use in such a system.Three categories of features drawn from existing MRI scans are established: Alzheimer's disease, moderate cognitive impairment (MCI), and normal control (NC) group. This article looks at the deep learning techniques for MRI-based dementia and Alzheimer's diagnosis. Important and well-liked deep learning models include Deep Neural Networks (DNN), Deep Belief Networks (DBNs), Restricted Boltzmann Machines (RBMs), Deep Auto-encoder (DA), Recurrent Neural Networks (RNN), Deep Boltzmann Machine (DBM), and Convolutional Neural Networks (CNN).which were used in combination with each other in a multimodel algorithm "

4. Preprocessing:Not provided

5. Data-set Used: Not provided

6. Accuracies /Results: Each of their models had varying accuracies consisting of: DNN=99.2%, CNN=99.9%, DA=91.95% and DBM=95.35 with each of them using a modality which is in the same order as above going by MRI, (MRI and Functional MRI), MRI and lastly PET and MRI.[5]

7. Contribution: Their method shortens the processing timing needed in low-resolution images using the super-resolution methodology, a high-resolution image is obtained from the low-resolution image, this study did not aim to compare methods with each other.

2.2 Business Applications

There is no similar system currently in the market.

3 System Description

3.1 Problem Statement

Alzheimer's disease has been a bane of an astronomical number of people's lives throughout the ages with no regard for the region [6] since it is a progressive neurological disorder that not only causes the brain to shrink(atrophy) and for a significant amount of brain cell to die or deteriorate but also Alzheimer's disease is one of the most causes of dementia which leads to a rapid and constant decline in a person thinking, social and behavioral skills as such this disease affects significantly the human's ability to function independently, however despite the severity and the extreme repercussions caused by such a disease most cases are discovered in the later stages of the disease since it can be mistaken for a person just losing their edge or just the fact they are getting older and thus having no way to discover such an aggravating disease in its earlier stages will cause a significant increase in its mortality rate.[7]

3.2 System Overview

The system overview will use MRI pictures from a data set divided into training and testing sets. The images will then go through various image preprocessing models to ensure the data fulfills the requirements for the suggested deep-learning model. The extracted features from the preprocessed output will then be subjected to various feature selection techniques, with the results being compared over time. This process will be repeated until the best results are obtained, at which point the CNN model, which has been sufficiently trained, is applied to the testing set to establish how well the model performs in practical use. Additionally, the model will produce a comprehensive report utilizing SHAP and fuzzy-based machine learning rules to justify each choice it made in its categorization and diagnosis of Alzheimer's patients.

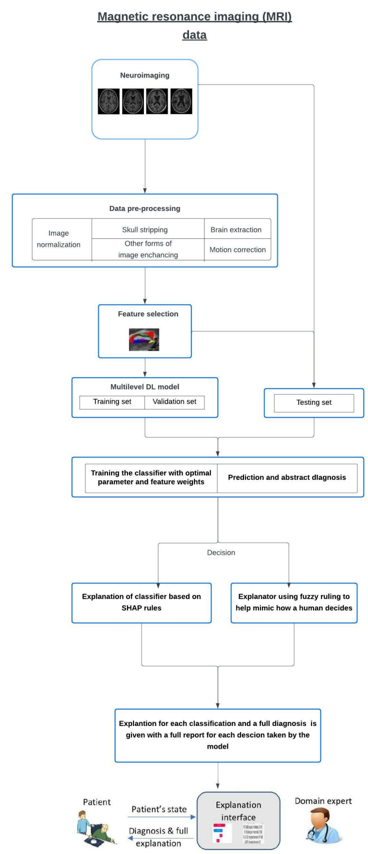


Figure 1: System Overview

3.3 System Scope

The proposed system uses a brain MRI image to detect and diagnose the four stages of Alzheimer's disease (Preclinical Alzheimer's, Mild cognitive impairment, Mild dementia, Moderate dementia, and Severe dementia). The classification system will detect the abnormality faster than a traditional diagnosis while also being able to detect Alzheimer's in its earlier stages. The system will:

- Classify whether the brain's MRI is healthy or demented.
- Classify the stage of the disease (Preclinical Alzheimer's, Mild cognitive impairment, Mild dementia, Moderate dementia, and Severe dementia).
- Generate a patient report.
- Generate a report with a full description of the reasoning behind each choice the model made.

3.4 System Context

The following context diagram, as depicted , describes the proposed system's classification process.An approved neurologist initially enters the essential data (mri scan) for the classification. A stage of AD (Preclinical Alzheimer's, Mild Cognitive Impairment, Mild Dementia, Moderate Dementia, and Severe Dementia) is determined by the trained model by evaluating the picture. The neurologist is then able to check the machine's results and add the patient's data into the database of the patient records. In the end, the patient can get their medical report by logging in using temporary credentials.

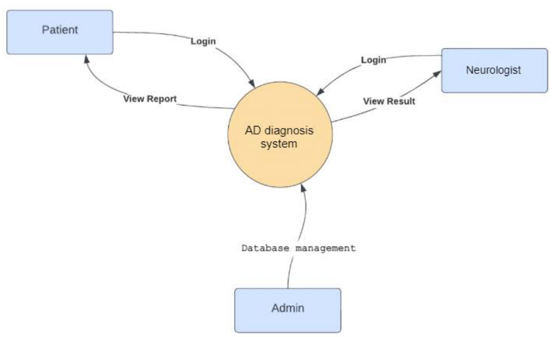


Figure 2: system context

3.5 Objectives

- Fully automated diagnosis and discrimination between the stages of the disease while also being able to declare the mentioned stages (Preclinical Alzheimer's, Mild cognitive impairment, Mild dementia, Moderate dementia, and Severe dementia) as shown in Figure 2.

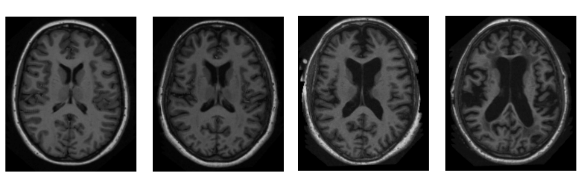


Figure 3: Sample

- Providing a fully comprehensive explanation of each feature given out in the result using fuzzy and shap Machine learning rules.
- Optimizing the automatic selection of the many features provided.
- Increasing the performance and efficiency of our model compared to previous research works.

3.6 User Characteristics

System Admin

- Will be required to keep a username and password secured for the login.
- Must be capable of managing the database by using provided UI.
- Should be familiar with the project's fundamental design.
- Will have full authority to create new accounts.

Neurologist

- Will be required to keep a username and password secured for the login.
- Should have sufficient knowledge with the functionality of the tools used.
- Should be familiar with the project's fundamental design.

Patient

- Will be required to keep a username and password secured for the login.
- Should have the required data when entering it into the system.
- Should be familiar with the project's fundamental design.

4 Functional Requirements

4.1 System Functions

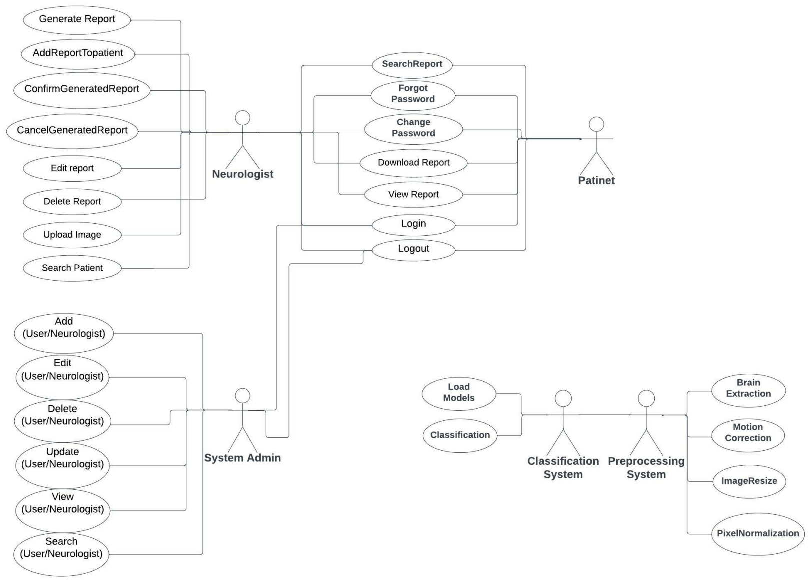


Figure 4: Use Case Diagram

System Admin

- System Admin shall be able to log in
- System Admin shall be able to logout
- System Admin shall be able to Add(User/Neurologist)
- System Admin shall be able to Edit (User/Neurologist) information
- System Admin shall be able to Delete (User/Neurologist) account
- System Admin shall be able to Update (User/Neurologist) account
- System Admin shall be able to view (User/Neurologist) account
- System Admin shall be able to search for (User/Neurologist)

Neurologist

- Neurologist shall be able to log in
- Neurologist shall be able to logout
- Neurologist shall be able to view the patient’s reports

- Neurologist shall be able to download the patient's reports
- Neurologist shall be able to search for the patient's reports
- Neurologist shall be able to change his password
- Neurologist shall be able to reset his password
- Neurologist shall be able to generate a report
- Neurologist shall be able to edit a report
- Neurologist shall be able to delete a report
- Neurologist shall be able to search for a specific patient's report using the date as a reference.
- Neurologist shall be able to add a report to the patient's account
- Neurologist shall be able to confirm the generated report before saving it into the patient's account
- Neurologist shall be able to cancel the generated report before saving it into the patient's account
- Neurologist shall be able to upload the patient's image (Brain scan)

Patient

- Patient shall be able to log in
- Patient shall be able to logout
- Patient shall be able to search for a patient's report
- Patient shall be able to download a patient's report
- Patient shall be able to view a patient's report
- Patient shall be able to change his password
- Patient shall be able to reset his password

Classification System

- Classifier shall load the trained models
- Classifier shall check the severity of the diseases

Preprocessing System

- The image shall pass by brain extraction
- The image shall pass by motion correction
- The image shall be resized
- The image pixels shall be normalized

4.2 Detailed Functional Specification

Table 2: Classification

Code	FR01
Name	Classification
Priority	High
Critical	None
Description	Images will be classified according to their type whether Cognitively normal (CN), Mild Cognitively impairment (MCI), Late Cognitively impairment (LMCI) or Alzheimer disease (AD).
Input	Image
Output	The severity level of the disease
Pre-condition	None
Post-condition	None
Dependency	FR02 and FR03
Risk	None

Table 3: Training/Testing model

Code	FR02
Name	TrainingTestingModel
Priority	High
Critical	Very critical, as the system cannot operate without a training model
Description	The model is trained with the training data and then tested for accuracy with the testing data with a split ratio of 80% training and 20% testing
Input	Image
Output	The trained model
Pre-condition	None
Post-condition	None
Dependency	FR01
Risk	None

Table 4: Brain extraction

Code	FR03
Name	BrainExtraction
Priority	Medium
Critical	Critical, as the absence of this preprocessing method will result in lower testing accuracy
Description	Brain extraction is used on the scans to remove non-brain tissues such as neck tissue and skull tissue
Input	Image
Output	Image where non-brain tissues as neck tissue and skull tissue are removed
Pre-condition	There must be an image inserted
Post-condition	None
Dependency	None
Risk	None

Table 5: View patient report

Code	FR04
Name	ViewReport
Priority	High
Critical	Critical as it allows the Neurologist to check the patient's medical history before giving the proper diagnosis.
Description	This function is responsible for selecting patients' medical records by date, which contains their personal information and their medical history.
Input	None
Output	Patient's medical record
Pre-condition	Neurologist must be logged in and the patient must exist in the medical records database.
Post-condition	The medical record of the patient will be displayed
Dependency	FR06
Risk	The only risk that could take place is unauthorized access to the patient's records, so by using a strong and secured encryption algorithm the probability of unauthorized access will decrease.

Table 6: Add patient

Code	FR05
Name	Addpatient
Priority	High
Critical	Critical as the patient must be added to the system in order to be able to view, download, add, search or delete his report/reports
Description	This function is responsible for adding the patient to the system
Input	The Patient name, phone number and email address
Output	The Patient is added to the database
Pre-condition	The System Admin must be authorized to add Neurologists to the database.
Post-condition	The Neurologist is added to the system
Dependency	FR06
Risk	The only risk that could take place is unauthorized access to the Neurologist database, so by using a strong and secured encryption algorithm the probability of unauthorized access will decrease.

Table 7: Login

Code	FR06
Name	Login
Priority	High
Critical	None
Description	The system Login
Input	The user email address and password
Output	Boolean output, true if all parameters are correct and false if there is any invalid parameter
Pre-condition	The user's account must be added to the system by the admin first
Post-condition	None
Dependency	None
Risk	The only risk that could take place is unauthenticated access to the user's account, so by using a strong password consisting of upper and lower case letters so the probability of unauthorized access will decrease.

5 Design Constraints

5.1 Standards Compliance

To push the data across the internet via the play store or app store, the mobile application needs a server. Therefore, a smartphone should be used as a mobile device to access the internet. And also a web application will be used. The data needs to be pushed to the database.

5.2 Hardware Limitations

The suggested system has no hardware limitations. We gradually moved data and services to the cloud, which is motivated in part by cost and convenience savings. Since there is no requirement for user hardware, a cloud server handles all computations, which improves dependability and availability.

5.3 Other Constraints as appropriate

Good internet access to use the system.

6 Non-functional Requirements

6.1 Usability:

The system must be user-friendly, which enables smooth usage.

6.2 performance:

To protect user privacy, all passwords must be hashed as a part of the system's security. The system must also prevent the addition of invalid data types and the deletion of crucial data without verifying alerts. Also, authorization is an important process where each type of user has permission for accessing certain data and resources.

6.3 Maintainability:

It should be easy to update the system. MVC model will be used in this system to help in updating it and prevent any difficulty.[8]

6.4 Portability:

The system will be uploaded online and can be used from any device according to its operating system by connecting the device to the internet.

6.5 Availability:

The system shall be available all time 24/7.

6.6 Scalability:

The system shall work well during the growth of data without affecting its performance.

7 Data Design

7.1 ADNI Data-set

- The ADNI dataset consists of the following [9]
  1. Cross-sectional collection of 1288 subjects aged between 65 to 70
  2. For each subject T1-weighting was used for the MRI Scans
  3. Each image is of format (Dicom)
- To avoid inconsistencies, ADNI researchers collect a variety of data from study participants throughout their involvement in the study of Alzheimer's disease.

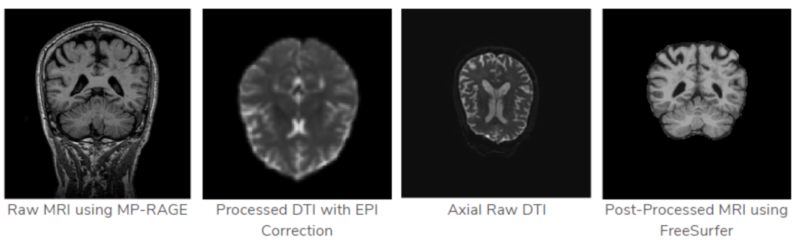
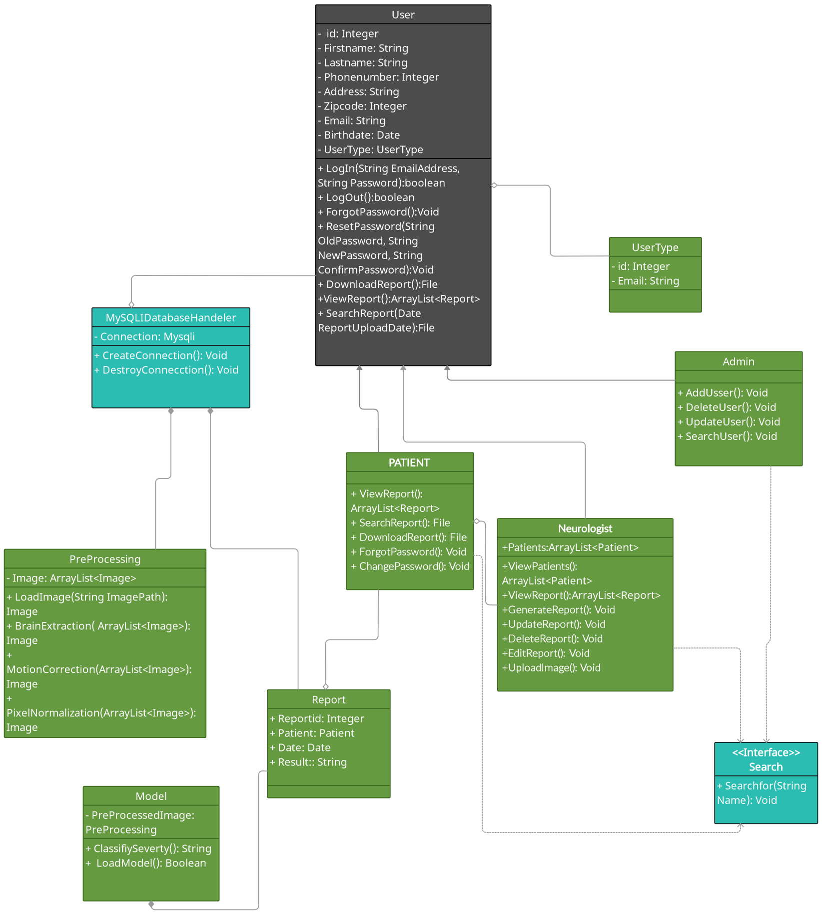


Figure 5: Types of images the data set provide

7.2 Oasis Data-set

- Data-set consists of a cross-sectional collection of 416 subjects aged 18 to 96.
- For each subject,3 or 4 individual T1-weighted
- MRI scans obtained in single scan sessions are included.
- The subjects are all right-handed and include both men and women.
- 100 of the included subjects over the age of 60 have been clinically diagnosed with very mild to moderate Alzheimer's disease (AD).
- Additionally, a reliability data set is included containing 20 non-demented subjects imaged on a subsequent visit within 90 days of their initial session.[10]

8 Preliminary Object-Oriented Domain Analysis



9 Operational Scenarios

9.1 Scenario 1: (Admin)

The admin will log in and gain access to the system in order to add, delete, or change a user's information. In addition, the admin will be able to see a list of users, either patients or neurologists, and search for a particular user by name in the list.

9.2 Scenario 2: (Neurologist)

The admin will add the doctor to the system. Then the doctor will be given credentials to log in and access the system. The doctor will log in. He will write all the information of the patient (like name, age, gender, phone no., etc. . .). The doctor will upload the MRI scans of the patient to be able to classify the Alzheimer's stage of the patient. He will make a report for each patient and add the patient's information and his Alzheimer's stage and the medicines he takes to his report. The doctor can update the report or add it to the report after each session with the patient.

9.3 Scenario 3: (Patient)

The admin responsible for the patient will register him into the system. Then the patient will be able to log in and access the system to view the history of his reports. The patient will also be able to download the report in PDF format, and then the patient's information will be related to the whole system and all the doctors that use the system.

10 Project Plan

Task	Start date	End date
Research paper	19 Nov	22 Nov
Searching on covid 19 affects on Alzheimer's	22 Nov	30 Nov
Working on more models for better accuracies	29 Nov	15 Dec
Finish three preprocessing methods	29 Nov	15 Dec
Working on SRS	30 Nov	6 Dec
SRS Presentation	10 Dec	13 Dec
working on SDD	23 Dec	15 Jan
Implementing shap and fuzzy logic	9 Jan	23 Jan
Integration of code	19 Dec	27 Dec

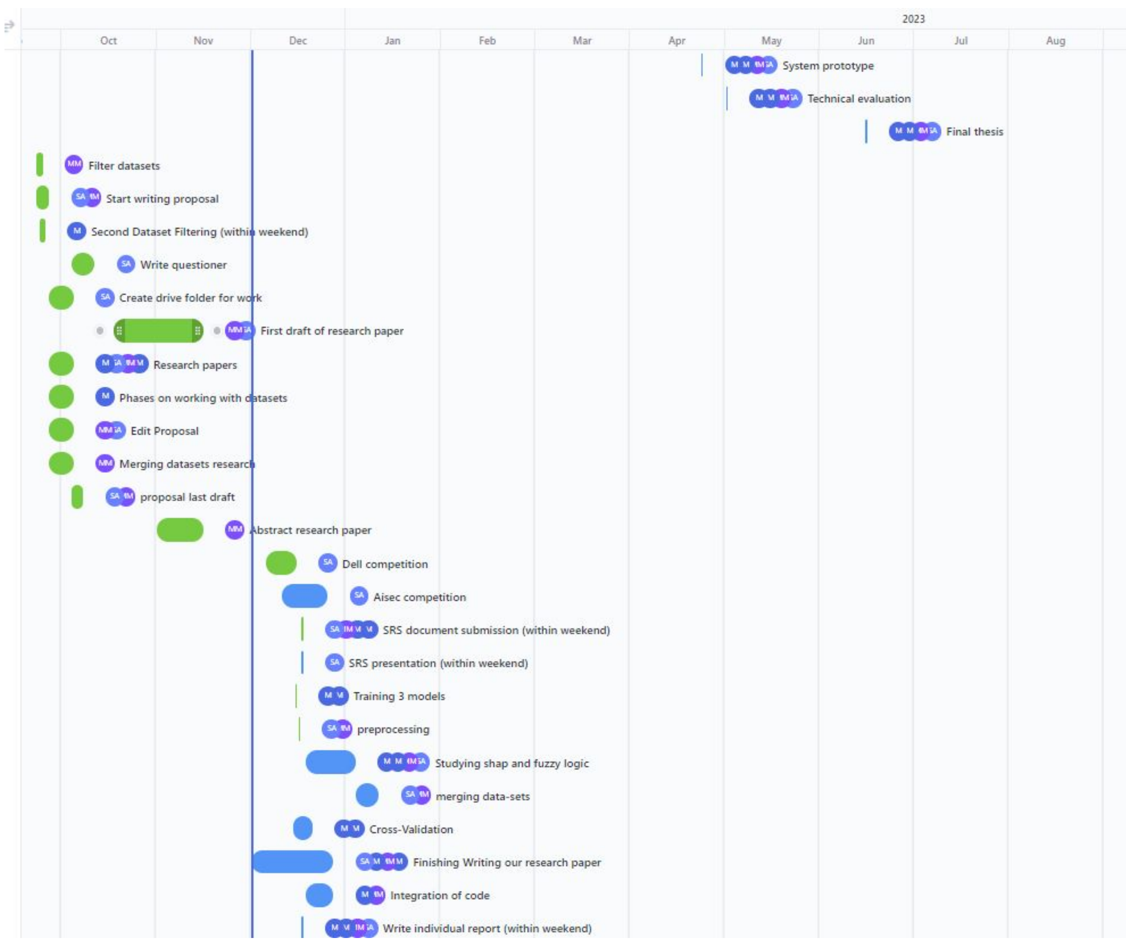


Figure 6: Time plan

11 Appendices

11.1 Definitions, Acronyms, Abbreviations

ROI	Region of Interest
MRI	Magnetic resonance imaging
MVC	Model–view–controller
GPU	Graphics Processing Unit
CNN	Convolutional Neural Network
AD	Alzheimer's Disease

11.2 Supportive Documents

Would you use an application that helps you detect Alzheimer's disease using MRIs images or blood tests

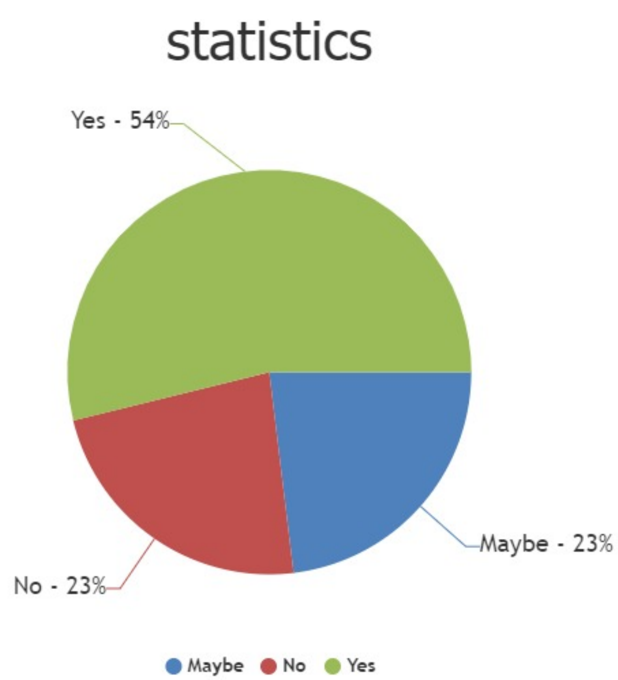


Figure 7: Statistics

References

[1] Hany I Hassanin, Heba M Tawfik, Stelios Zygouris, et al. "Setting up a cognitive training service for Egyptian older adults". In: *Journal of Alzheimer's Disease* 79.4 (2021), pp. 1673–1682.

[2] Siqi Liu, Sidong Liu, Weidong Cai, et al. "Early diagnosis of Alzheimer's disease with deep learning". In: *2014 IEEE 11th international symposium on biomedical imaging (ISBI)*. IEEE. 2014, pp. 1015–1018.

[3] Janani Venugopalan, Li Tong, Hamid Reza Hassanzadeh, et al. "Multimodal deep learning models for early detection of Alzheimer's disease stage". In: *Scientific reports* 11.1 (2021), pp. 1–13.

[4] Emre Altinkaya, Kemal Polat, and Burhan Barakli. "Detection of Alzheimer's disease and dementia states based on deep learning from MRI images: a comprehensive review". In: *Journal of the Institute of Electronics and Computer* 1.1 (2020), pp. 39–53.

[5] Asim Afaq, Francesco Fraioli, Harbir Sidhu, et al. "Comparison of PET/MRI with PET/CT in the evaluation of disease status in lymphoma". In: *Clinical nuclear medicine* 42.1 (2017), e1.

[6] Yan-Jiang Wang, Hua-Dong Zhou, and Xin-Fu Zhou. "Clearance of amyloid-beta in Alzheimer's disease: progress, problems and perspectives". In: *Drug discovery today* 11.19-20 (2006), pp. 931–938.

[7] Heiko Braak and Kelly Del Tredici. "Where, when, and in what form does sporadic Alzheimer's disease begin?" In: *Current opinion in neurology* 25.6 (2012), pp. 708–714.

[8] John Deacon. "Model-view-controller (mvc) architecture". In: *Online][Citado em: 10 de março de 2006.] http://www. jdl. co. uk/briefings/MVC. pdf* 28 (2009).

[9] Paul S Aisen, Ronald C Petersen, Michael C Donohue, et al. "Clinical Core of the Alzheimer's Disease Neuroimaging Initiative: progress and plans". In: *Alzheimer's & Dementia* 6.3 (2010), pp. 239–246.

[10] Muhammad Adeel Azam, Khan Bahadar Khan, Muhammad Aqeel, et al. "Analysis of the MIDAS and OASIS biomedical databases for the application of multimodal image processing". In: *International Conference on Intelligent Technologies and Applications*. Springer. 2020, pp. 581–592.