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Z CARE

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Chapter 1

Introduction

1.1 overview

Currently, more than 55 million people live with dementia worldwide "According to World Health Organization", and there are nearly 10 million new cases every year. Dementia results from a variety of diseases and injuries that primarily or secondarily affect the brain. Alzheimer's disease is the most common form of dementia and may contribute to 60-70% of cases. It is a brain disorder that slowly destroys memory and thinking skills and, eventually, the ability to carry out the simplest tasks. Typically, Alzheimer's symptoms mature after the age of sixty, affecting the patient's mental and physical condition. A person diagnosed with Alzheimer's could suffer from various syndromes including memory efficiency decreases, speaking difficulties, lack of attention, and a decline in the quality of lifestyle. More critically, the disease could develop to cause serious damage, and this could lead patients to start forgetting their family and friends. Currently, there is no available medication to fight and cure AD, hence the progression of this disease cannot be reversed. Thus, achieving an early diagnosis of AD can provide the patient with medication to slow the disease hence its symptoms of it. And for his family to be prepared for what the future is about.

1.2 Problem Definition

Alzheimer's disease makes you alive but not living and There is no medication for Alzheimer's disease, But healthcare providers have been successful in helping people maintain their mental function, control behavior, and slow the progress of the disease. Medicines are used to help people maintain mental function. And when symptoms start to appear we face another problem which is related to the caregiver. The caregiver needs to be with the patient all the time, give him medicine on time and make sure that the patient is fine, which is so stressful and with the daily routine, it becomes so hard.

1.3 Project Motivation

We believe that life is about helping others and giving back to our society! And we also believe in the power of technology and using it I,n this project could help patients to have more time. Being a human is about meeting new people, making new memories, and being with the ones that care about you and you care about them. Imagine that you can help someone and give him some more time with fewer symptoms of Alzheimer's by early diagnoses of the disease. You help a father to keep remembering his family, help a mother to remember to cook for her children and help a grandparent to remember the names of his grandchildren. Making it easier for caregivers to take care of their beloved ones.

1.4 Project Objectives

The main objectives of this project are to be accomplished within a timeline and with available resources are:
1. Diagnose Alzheimer's disease in its early stages which would give us the ability to
1-Slow the disease progression with medicine and exercises
2-Maintain mental function
2. Make it easier for caregivers to take care of the patient

1.5 Organization

We have structured the rest of this project as follows: Chapter(2) presents Related work including a brief history of some international Papers and their establishment, Chapter(3) presents the planning Phase is the fundamental process of understanding why a system should be built and also determining how the project team will go about building the system, Chapter(4) presents project analysis and reviews the Development methodology, the Agile Software Development Life Cycle also reviews the functional and non-functional requirements

Chapter 2

Literature Review

2.1 Overview

This chapter includes a brief history of some international Papers and their establishment, the technology involved in improving and facilitating the advising and enrollment processes, what problems happen and what they reach and their limitations, and references.
As discussed in the previous chapter, this project presents:

1. Used a deep learning-based approach to predict an early diagnosis of AD(Alzheimer's Disease).
2. Employed Traditional algorithms to distinguish AD.

2.2 A Deep learning-based approach to predict AD

DBNs(Deep Belief Networks with PET Images)employed a deep learning-based approach to distinguish AD from mild cognitive impairment using PET data. Their deep learning approach was based on DBNs (Deep Belief Netwok s) which serve as feature selection to identify key features from the regions of interest ROIs(A region of interest). The support vector machine model, which is a popular machine learning method for detecting AD with structural MRI data, was utilized to distinguish AD from mild cognitive impairment. [1].discovered that the proposed DBN-based method obtained good performances for differentiating subjects between AD and mild cognitive impairment (AUC = 0.908). In addition, the DBN model (accuracy = 0.866) excelled at PCA(Principal Components Analysis)(accuracy = 0.795) and anatomical automatic labeling (accuracy = 0.631). that only single-modal brain imaging data, namely PET images, was examined, and thereby other likely morphological changes from multimodal brain image data may be disregarded. Moreover, other deep learning algorithms such as CNNs, and other machine learning algorithms such as random forests were not utilized for comparison. Their study also did not always use AUC, a standard evaluation metric, for comparison. On the other hand, the main benefit of their study is that their approach was the first to apply the concept of DBNs to distinguish AD from mild cognitive impairment using PET data.[1].

Sparse-Response Deep Belief Networks with PET and MRI Images: utilized a deep learning-based approach to predict AD using PET and MRI images. Their deep learning approach was characterized by sparse-response DBNs ,which were used for extracting features from the images. Then, the extreme learning machine model was utilized to distinguish AD, mild cognitive impairment, and normal controls. In their study, support vector machines and CNNs were utilized for benchmarking. [2].indicated that the proposed approach (AUC = 0.87) outperformed the benchmarking models, such as A Convolutional Neural Network (CNN) (AUC = 0.77) and DBNs (AUC = 0.83) for distinguishing AD and normal controls (NC). In addition, the proposed approach (AUC = 0.79) exceeded CNNs (AUC = 0.60) and DBNs (AUC = 0.73) for distinguishing mild cognitive impairment and normal controls. Moreover, the proposed approach (AUC = 0.71) surpassed CNNs (AUC = 0.60) and DBNs (AUC = 0.68) for distinguishing AD and mild cognitive impairment. The main weakness is that other deep learning algorithms such as GANs (Generative Adversarial Networks), and other machine learning algorithms such as random forests were not utilized for comparison. On the other hand, the main strength of their study is that their approach was the first to leverage the concept of sparse-response DBNs to predict AD using multimodal brain image data such as PET and MRI images.[2].

Multimodal deep learning models for early detection of Alzheimer's disease stage:
Pre-processing, the data analysis for EHR (electronic health record) data, the combination of the three data modalities, and the writing of the manuscript. Contributed to the pre-processing and analysis of the SNP (single-nucleotide polymorphism) data, and the writing of the manuscript. Contributed to the image processing pipeline and writing of the results of image processing. Contributed to the study design, result evaluation, and extensive relevant revision of the manuscript.[3].

Multimodal deep learning for Alzheimer's disease dementia assessment: implement a deep learning framework that accomplishes 2 diagnostic steps to identify persons with normal cognition (NC), mild cognitive impairment (MCI), Alzheimer's disease (AD) dementia, and dementia due to other etiologies non-AD dementias (nADD). We demonstrated that the framework compares favorably with the diagnostic performance of neurologists and neuroradiologists. To interpret the model, We also created three separate models: (i) MRI-only model,(ii) Non-imaging model,(iii)Fusion model, we conducted SHAP (Shapley Additive exPlanations) analysis on brain MRI and other features to reveal disease-specific patterns that correspond with expert-driven ratings and neuropathological findings.[4].

Multiclass diagnosis of stages of Alzheimer's disease using linear discriminant analysis scoring for multimodal data: In this study, we proposed a latent Dirichlet allocation (LDA) based scoring strategy approach for AD multiclass diagnosis in the presence of four modalities, i.e., Magnetic Resonance Imaging (MRI), fluorodeoxyglucose (FDG-PET), Cerebrospinal fluid (CSF), and genetic features. The LDA was used to calculate a score representing the pathological information from each modality, and the scores from different modalities ensured that the classifier could easily discriminate between different groups. LASSO and PCA were used to exclude irrelevant and interferential components before LDA, and a binary ELM-based tree decision classifier was built for multiclass classification. The experimental results indicated that the LDA scoring significantly improved the multiclass diagnosis. [5].
Benefiting from the information obtained from multiple modalities and the scoring strategy, we achieved a promising performance with an accuracy of 66.7 % .an F1-score of 64.9 percent for three-way diagnosis, and an accuracy of 57.3 % and an F1-score of 55.7 % for four-way diagnosis, which were significantly better than the original method. When compared to other studies, the proposed approach also showed a better performance. Although multimodal data help to improve the performance of AD diagnosis, the requirement of too many modalities would limit the practical usage of this approach. However, this study's more efficient multimodal fusion approach is still useful for further AD studies, such as AD longitudinal trajectory modeling.[5].

Multimodal neuroimaging data have been used to identify structural and molecular/functional biomarkers for AD. deep learning approaches have been applied to AD diagnostic classification using original neuroimaging data without any feature selection procedures. If the data is imbalanced, the chance of misdiagnosis increases and sensitivity decreases. Multimodal neuroimaging data such as MRI and PET have commonly been used in deep learning: MRI for brain structural atrophy, amyloid PET for brain amyloid-b accumulation, and FDG-PET for brain glucose metabolism. The performance in AD/CN classification and/or prediction of MCI to AD conversion yielded better results in PET data compared to MRI.[6].

Hybrid Machine Learning Approach Using Deep Learning for the Prediction of AD Using Genome Data: Most machine learning approaches developed for the prediction of disease progression are either single-task or single-modality models, which cannot be directly adopted to our setting involving multi-task learning with high-dimensional images. Moreover, most of those approaches are trained on a single dataset, which cannot be generalized to other cohorts we propose a novel multimodal multi-task deep learning model to predict AD progression by analyzing longitudinal clinical and neuroimaging data from multiple cohorts. Our proposed model integrates high-dimensional MRI features from a 3D convolutional neural network with other data modalities, including clinical and demographic information, to predict the future trajectory of patients. Our model employs an adversarial loss to alleviate the study-specific imaging bias, in particular the inter-study domain shifts. In addition, a Sharpness-Aware Minimization (SAM) optimization technique is applied to further improve model generalization. The proposed model is trained and tested on various datasets to evaluate and validate the results. Our results showed that 1) our model yields significant improvement over the baseline models, and 2) models using extracted neuroimaging features from 3D convolutional neural networks outperform the same models when applied to MRI-derived volumetric features.[7].

A Robust Deep Learning Model of AD Progression for Real-World Clinical Applications: Based on the age of the onset, there are two subtypes of the disease, they are: Early-onset AD (EOAD) and late-onset AD (LOAD). Approximately 5 percent of AD cases show EOAD the age-onset ranges from the '30s to early '60s. Compared with EOAD, LOAD is shown to occur later in life, from the late '60s onwards. The incidence of LOAD has a rate of 90%–95%. Genetic and environmental factors are both part of the LOAD which seems to show a more complex disorder. They have used hybrid machine learning algorithms for the classification of late-onset Alzheimer's disease. To the best of our knowledge, this work is the first of applying these models for Alzheimer's disease. Both models showed promising results, generally, Artificial neural networks (ANN) showed slightly improved accuracy than CNN. our model used two stages for feature selection. First, logistic regression is applied to select the most significant SNPs associated with the disease, Second Random Forest is applied to further reduce the number of SNPs. Thus, making the classification task computationally efficient.[8].

Assisted Diagnosis of Alzheimer's Disease Based on Deep Learning and Multimodal Feature Fusion: Used 3D convolutional neural networks and autoencoders to capture AD biomarkers. Used a multiscale residual neural network to collect multiscale information on a series of image slices and to classify AD, mild cognitive impairment (MCI), and improved the VGG-16 network for constructing a classification model of AD, MCI, and NC. used stacked automatic encoders and functional connection matrices to classify migraine patients and normal people. proposed a dynamic time normalization distance matrix, Pearson correlation coefficient matrix, warping path distance matrix, and convolutional neural network to realize AD-assisted diagnosis. The method is used to preprocess MRI images including segmentation, generating specific template generation, flow fields generation, and normalization. The above preprocessing steps are all implemented using Statistical Parametric Mapping (SPM8) software. Medical image processing software Data Processing Analysis of Brain Imaging (DPABI) is used to preprocess fMRI images including the data removal of the first 10 time points, slice timing, realignment, normalization, smoothing, detrending, filtering, and extracting time series to calculate function link matrix. sMRI features extracted by the 3DShuffleNet network are fused with the Functional magnetic resonance imaging(fMRI) features extracted by the principal component analysis network(PCANet). Compared with a single modality, better classification

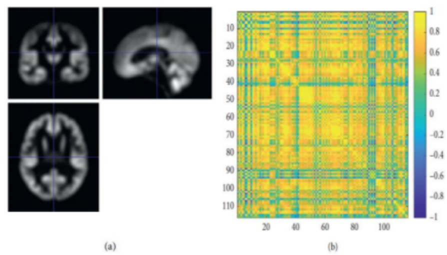

Figure 1: Preprocessing results of (a) sMRI data and (b) fMRI data.

Figure 2.1: Preprocessing results of (A) sMRI data and(B) fMRI data

results on multiple modalities are obtained.[9].

Diagnosis of AD disease (Classification problem), Distinguish between 4-stages of AD: • Huntington's disease (HD) • Normal • minor Alzheimer's disease (MAD) • AD A hybrid model of DBN CNN is better than traditional approaches. Datasets from Alzheimer's Disease Neuroimaging Initiative(ADNI) contain: • MRI magnetic reverberation imaging • EEG electroencephalography signal The methodology is:- Median Filtering for EEG preprocessing. - Gaussian filtering for MRI preprocessing. - Gray level co-occurrence matrix GLCM Feature Extraction.- Classifiers o Support Vector Machine SVM. o Multi-Layer Perceptron MLP. o Deep Belief Network DBN. o Conventional Neural Network CNN. [10].

2.3 A Traditional approaches to distinguish AD

Auto-Encoders with MRI Images: using MRI (Magnetic resonance imaging)data. An auto-encoder is an artificial neural network for encoding purposes, where the input layer serves the original MRI data, layers, and the previous multiple hidden layers provide nonlinear transformations from the output layer reconstructs MRI samples. In their study, various widely used machine learning methods, such as linear discriminant analysis, logistic regression, and support vector machines, were utilized for benchmarking.[1].reported that the proposed auto-encoder method (AUC = 0.916) surpassed various benchmarking models such as linear discriminant analysis (AUC = 0.710), and logistic Int. of 20 regression (AUC = 0.765), and support vector machines (AUC = 0.789) to predict an early stage of AD using MRI images. The main disadvantage of the study. is that only single-modal brain imaging data, namely MRI images, was examined, and thereby other likely morphological changes from multimodal brain image data may be disregarded. Moreover, other deep learning algorithms such as CNNs, and other machine learning algorithms such as random forests were not utilized for comparison. On the other hand, the main advantage of their study is that their approach was the first to exploit the concept of auto-encoders to predict an early diagnosis of AD using MRI data.[1].

AD is an irreversible, progressive brain disorder marked by a decline in cognitive functioning with no validated disease-modifying treatment. Much effort has been made to develop strategies for early detection, especially at pre-symptomatic stages, to slow or prevent disease progression. One weakness of deep learning is that it is difficult to modify potential bias in the network when the complexity is too great to guarantee transparency and reproducibility. Progress will be made in deep learning by overcoming these issues while presenting problem-specific solutions. form of learning that adapts to changes in data as it makes its own decision based on the environment, may also demonstrate applicability in the field of medicine. Machine learning generally requires four steps: feature extraction, feature selection, dimensionality reduction, and feature-based classification algorithm selection. Well-known pattern analysis methods, such as linear discriminant analysis (LDA), linear program boosting method (LPBM), logistic regression (LR), support vector machine (SVM), and support vector machine recursive feature elimination (SVM-RFE), have been used and hold promise for early detection of AD and the prediction of AD progression When deep learning is used together with traditional machine learning methods, i.e., SVM as a classifier, it is referred to as a "hybrid method". [6].

Hybrid deep learning approach for classifying Alzheimer's disease based on multimodal data: Distinguishing between the 4 stages of Normal, minor Alzheimer's disease(MAD), AD, and Huntington's disease(HD), the Hybrid model of DBN CNN are better than traditional approaches. [10].

2.4 Summarizes the Presented Exhaustive

Table (2.1) summarizes the presented exhaustive survey of state-of-the-art studies related to AD(Alzheimer's Disease) approaches based on deep Learning.

Table 2.1: Summarizes the Presented Exhaustive

Author	Objectives	Model	Data Modality	Dataset	Performance Accuracy %
Ju et al.2017 [1]	predict an early diagnosis of AD	Autoencoders	MRI	ADNI	91
Shen et al.2019 [1]	distinguish AD From mild cognitive impairment	DBNs	PET	ADNI	86
Zhou,P.et al.2020 [2] May D. Wang.2021. [3].	To predict AD Distinguish between 3-stages of AD • Normal (CN) • MCI • AD	Sparse-response DBNs • CNN • Shallow Models	• PET • MRI • MRI • SNPs • HER	ADNI ADNI	87 78
Shangran Qiu.(2022) [4].	Differential diagnosis of Alzheimer's disease, differentiating between normal cognitive aging, NC, MCI, AD, and nADD, and other dementia etiologies	CNN	• MRI • Non-Imaging	ADNI • AIBL • NACC • NIFD • OASIS • PPMI • FHS • LBDSU	69.2
Weiming Lin.2021.[5]	propose a framework that can diagnose AD	Hybrid (CNN - RNN)	• MRI • FDG-PET • CSF • genetic features	ADNI	66.7
fnagi.2019.[6].	Early detection of AD - Prediction of AD progression	SAE - DBM - SVM	• MRI • PET • CSF	ADNI	91
jancen et al.2019.[7].	To predict the progression of Alzheimer's Disease 12 months from the first patient visit (baseline visit)	CNN architecture	Genetic data	ADNI	87
May D. Wang.2021. [3].	Distinguish between 3-stages of AD • Normal (CN) • MCI • AD	• CNN • Shallow Models	• MRI • SNPs • HER	ADNI	92
Yu Wang et al.2021.[8].	Making correct diagnoses of AD disease	ShulffleNet - PCANet	• sMRI • fMRI	ADNI	92

Chapter 3

Project Planning

3.1 Introduction

Project management is a process of planning and controlling the development of a system within a specified time frame with the right functionality, and define Project Focuses, Strategies, and Action Steps, and measuring progress and performance.

3.2 Project Plan

The planning Phase is the fundamental process of understanding why a system should be built and also determining how the project team will go about building the system

3.2.1 Gathering Requirements

The analysis of this information leads to the development of a concept for a new system

3.2.2 System Analysis

-functional and non-functional requirements
-DFD
-Use Case

3.2.3 System Design

-Sequence diagram
-Class diagram
-Activity diagram

3.2.4 Implementation

-ML model
-Back-end
-Mobile Application

3.2.5 Project Schedule Gantt Chart

A gantt chart is a horizontal bar chart used in project management to visually represent a project plan over time.
Gantt charts typically show the timeline and status

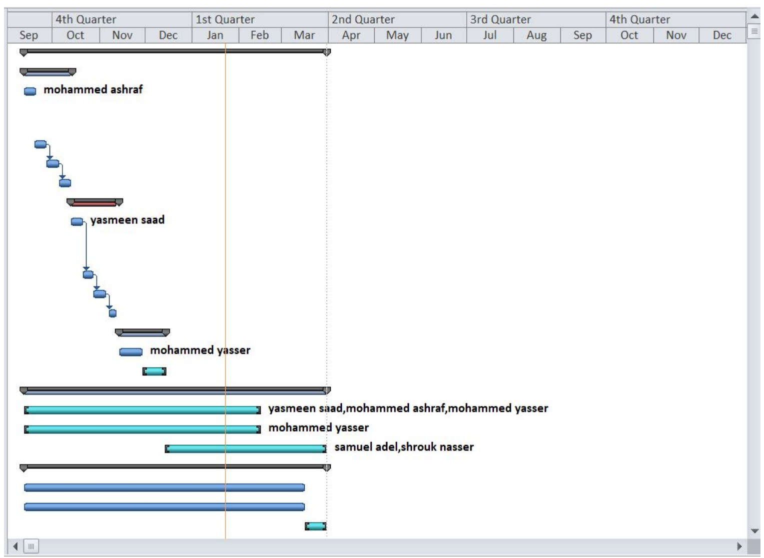

Figure 3.1: Gantt Chart

		Task Mode	Task Name	Duration	Start	Finish	Predecessors	Resource Names
1			**ZCARE mobile app**	**144 days**	**Mon 9/12/22**	**Thu 3/30/23**		
2			**Planning**	**24 days**	**Mon 9/12/22**	**Thu 10/13/22**		**mohammed ashraf**
3			Collect Advantages and Disadvantages From Related Work	6 days	Mon 9/12/22	Mon 9/19/22		mohammed ashraf
4			Check Data Availability	6 days	Mon 9/19/22	Mon 9/26/22		
5			Identify stakeholders	6 days	Tue 9/27/22	Tue 10/4/22	4	
6			Set & prioritize goals.	6 days	Wed 10/5/22	Wed 10/12/22	5	
7			**System Analysis**	**23 days**	**Thu 10/13/22**	**Sun 11/13/22**		**yasmeen saad**
8			Functional & non Functional Requirements	6 days	Thu 10/13/22	Thu 10/20/22		yasmeen saad
9			context diagram	5 days	Fri 10/21/22	Thu 10/27/22	8	
10			DFD level 0	6 days	Fri 10/28/22	Fri 11/4/22	9	
11			Use Case	5 days	Mon 11/7/22	Fri 11/11/22	10	
12			**System Design**	**23 days**	**Mon 11/14/22**	**Wed 12/14/22**		**mohammed yasser**
13			Sequence diagram	11 days	Mon 11/14/22	Mon 11/28/22		mohammed yasser
14			Activity Diagram	12 days	Tue 11/29/22	Wed 12/14/22		
15			**Implmention**	**144 days**	**Mon 9/12/22**	**Thu 3/30/23**		
16			ML Model	112 days	Mon 9/12/22	Tue 2/14/23		yasmeen saad,mohammed ashraf,mohammed yasser
17			backend	112 days	Mon 9/12/22	Tue 2/14/23		mohammed yasser
18			Mobile App	77 days	Wed 12/14/22	Thu 3/30/23		samuel adel,shrouk nasser
19			**testing**	**144 days**	**Mon 9/12/22**	**Thu 3/30/23**		**mohammed ashraf,mohammed yasser,samuel adel,shrouk nasser,yasmeen saad**
20			Component Testin	133 days	Mon 9/12/22	Wed 3/15/23		
21			System Testing	133 days	Mon 9/12/22	Wed 3/15/23		
22			Acceptance Testing	11 days	Thu 3/16/23	Thu 3/30/23		

Figure 3.2: Project Schedule

3.3 Feasibility Study

The feasibility study outlines and analyzes several alternatives or methods of achieving business success.

3.3.1 Focus

Helping Alzheimer's disease patient

3.3.2 Strategies

-Build a recommendation system that recommends activities to help Alzheimer's patients through Mobile Application.
-Create Business Model
-lunching Application

3.3.3 Action Steps

-team members are familiar with technology to create an app easy to use.
-team members will get educated more about Alzheimer's disease
-create Business Plan which includes Marketing, Financial plans.

3.3.4 KPIs

-Model Classify Patients Correctly.
-API works properly with Mobile APP.

3.3.5 MOS

-Application has been launched and a lot of patients use it

Chapter 4

Proposed System

4.1 Overview

This chapter reviews the Development methodology also reviews the functional and non-functional requirements. It also discusses System analysis through the life cycle and its requirements showing the USE-CASE Diagram which is a list of actions or events steps typically defining the interactions between a role (known in the Unified Modeling Language as an actor) and a system to achieve a goal, Activity diagram which is a graphical representation of workflows of stepwise activities and actions and process modeling.

4.2 proposed framework

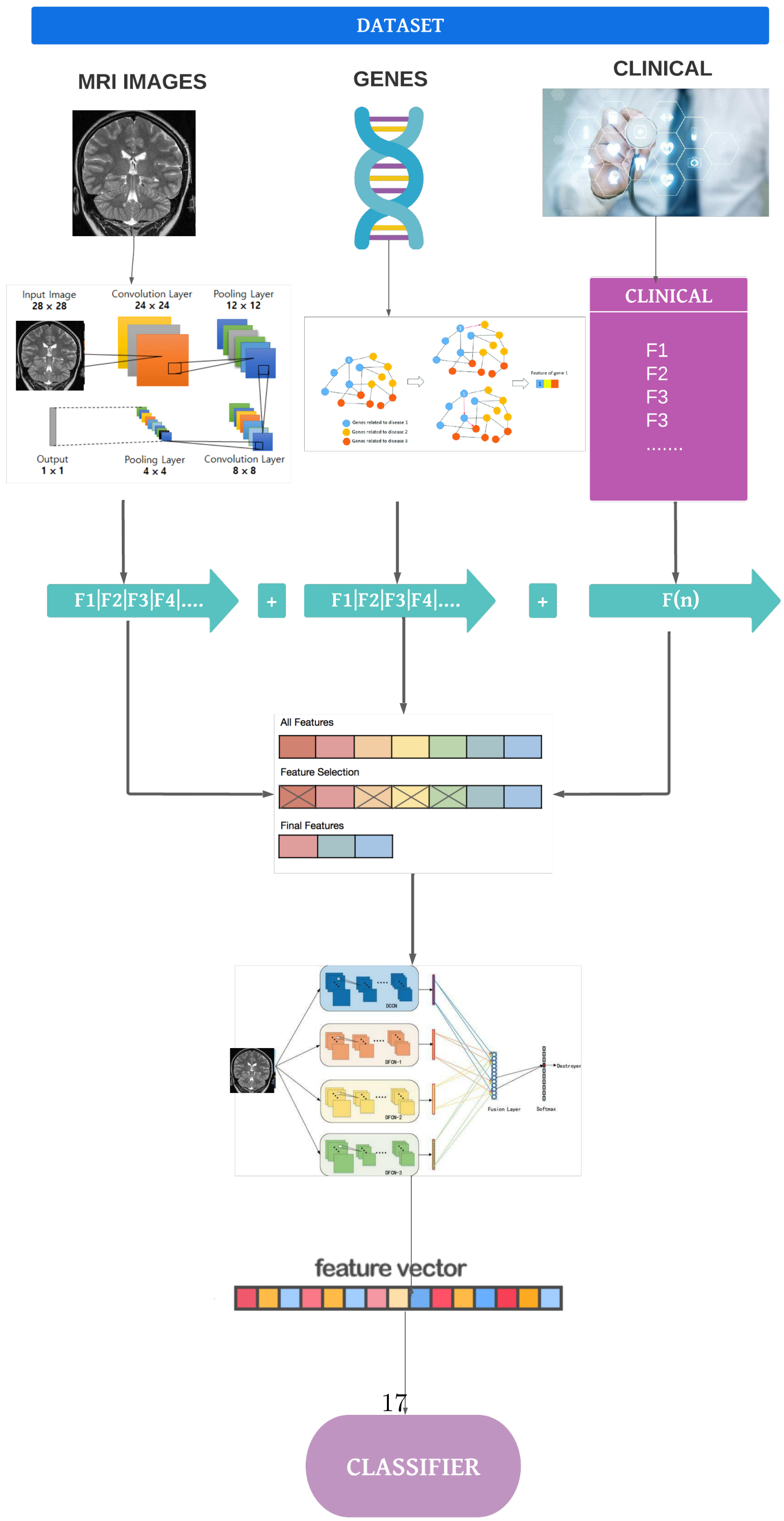

Figure 4.1: framework

4.3 System Analysis

4.3.1 Requirements Specification

Functional requirements are features that allow the system to function as it was intended. Put another way, if the functional requirements are not met, the system will not work. Functional requirements are product features and focus on user requirements.

Use Case Diagram

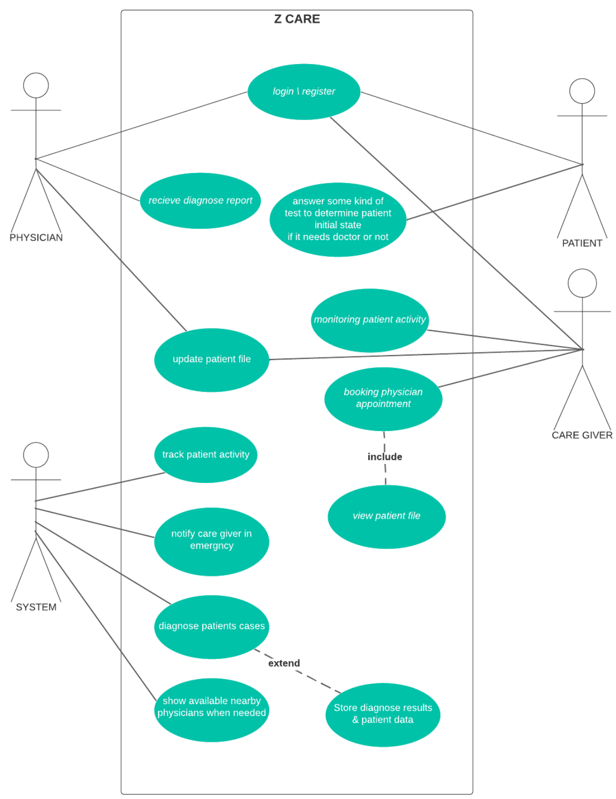

Figure 4.2: use case diagram

- it represents system functionality from the user's perspective
- describes who will use the system and in what ways the user expects to interact with the system.
- represents the interactions between use cases and actors.

- represents the interactions between system, external systems, and users.

4.3.2 Non Functional Requirements

Non-functional requirement (NFR) is a requirement that specifies criteria that can be used to judge the operation of a system, rather than specific behavior. They are contrasted with functional requirements that define specific behavior or functions.

- Usability: The Mobile Application cart should be easily usable by the Patient.
- Accessibility: the caregiver will receive the Call
- Performance: The main function must have specific real-time to be executed for each operation to not delay the whole system
- Security: The patient must be sure that all his details will be secured in the App options.

4.3.3 Context Diagram

The Context Diagram shows the system under consideration as a single high-level process and then shows the relationship that the system has with other external entities.

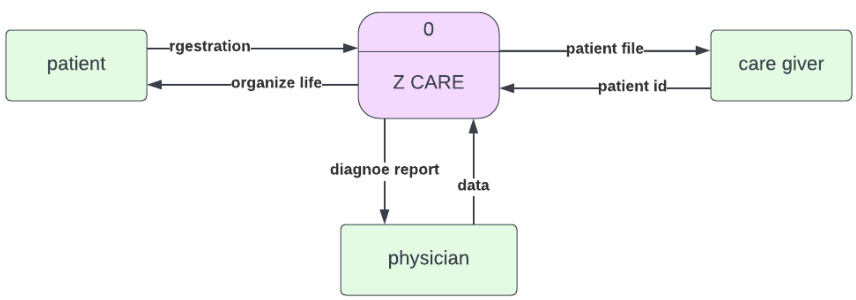

Figure 4.3: Context Diagram

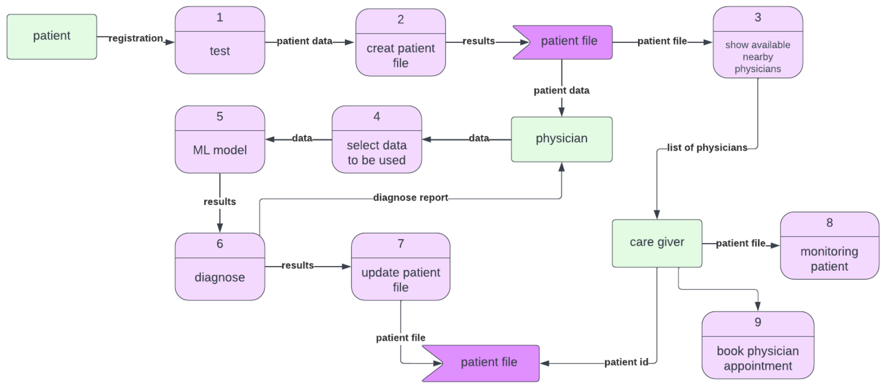

Figure 4.4: DFD level 0

4.3.4 Use Case Scenario

A use case Scenario represents the sequence of events along with other information that relates to this use case. A typical use case specification template includes the following information:

- Description
- Pre- and Post- interaction condition
- Basic interaction path
- Alternative pat

Use case name	Patient Registration	
Actor(s)	Patient	
Description	the Registration steps for a Patient to our Application.	
Typical of Events	Actor action	System Response
	1. a form appears to the patient-user, to fill in his information.	2. confirms with a message.
Alternative	3. shows a massage error, in case something happened.	
Precondition	Link to the Caregiver	
Postcondition	Take Test	

Table 4.2: Patient Registration Use Case Scenario.

Patient use cases

Use case name	Link to Caregiver	
Actor(s)	Patient	
Description	steps for link to Caregiver.	
Typical of Events	Actor action	System Response
	1. enter caregiver username	2. search about caregiver username
Alternative	3. link to the caregiver, in case the username is found. otherwise shows a message error.	
Precondition	No Precondition	
Postcondition	Registration	

Table 4.1: Patient Link to Caregiver Case Scenario.

Use case name	Patient Take initial Test	
Actor(s)	Patient	
Description	steps of take test	
Typical of Events	Actor action	System Response
	1. answer some initial questions	2. determine is the patient need to the doctor or not
Alternative	3. in case the patient needs to the doctor, alarm his caregiver. otherwise suggest strategy to maintain his life	
Precondition	Registration use case	
Postcondition	System Create Patient File.	

Table 4.3: Patient Take Test Use Case Scenario.

Use case name	Patient Login	
Actor(s)	Patient	
Description	how patient open the Application	
Typical of Events	Actor action	System Response
	1. use Face ID or Finger ID from mobile.	2. determine the identity.
Alternative	3. in case the identity doesn't determine, show a help message.	
Precondition	Mobile has FaceID or FingerID	
Postcondition	No Postcondition	

Table 4.4: Patient Login Use Case Scenario.

Use case name	Caregiver Login	
Actor(s)	Caregiver	
Description	how caregiver open the Application	
Typical of Events	Actor action	System Response
	1. use Face ID, Finger ID from mobile or Password.	2. determine the identity.
Alternative	3. in case the identity doesn't determine, show an error message.	
Precondition	No Preconditions.	
Postcondition	No Postcondition	

Table 4.6: Caregiver Login Use Case Scenario.

Caregiver use cases

Use case name	Caregiver Registration	
Actor(s)	Caregiver	
Description	the Registration steps for a Caregiver to our Application.	
Typical of Events	Actor action	System Response
	1. a form appears to the caregiver-user, to fill in his information.	2. confirms with a message.
Alternative	3. shows a massage error, in case something happened.	
Precondition	No Precondition	
Postcondition	create Caregiver file	

Table 4.5: Caregiver Registration Use Case Scenario.

Use case name	Track Patient	
Actor(s)	Caregiver	
Description	steps of get patient information	
Typical of Events	Actor action	System Response
	1. Enter Patient username	2. search about the username
Alternative	3. in case the username is not found shows a message error.	
Precondition	Login to the system	
Postcondition	Retrieve the patient file	

Table 4.7: Caregiver tracks Patient Use Case Scenario.

Use case name	Choose Doctor	
Actor(s)	Caregiver	
Description	steps to choose doctor.	
Typical of Events	Actor action	System Response
	2. choose the desired Doctor.	1. list the available Doctors in the system.
Alternative	3. take an appointment and send confirm message.	
Precondition	Log in	
Postcondition	No Postcondition	

Table 4.8: Caregiver Choose Doctor Case Scenario.

Use case name	Physician Login	
Actor(s)	Physician	
Description	how Physician open the Application	
Typical of Events	Actor action	System Response
	1. uses Face ID, Finger ID from mobile or Password.	2. determines the identity.
Alternative	3. in case the identity doesn't determine, show an error message.	
Precondition	No Preconditions.	
Postcondition	No Postcondition	

Table 4.10: Physician Login Use Case Scenario.

Physician

Use case name	Physician Registration	
Actor(s)	Physician	
Description	the Registration steps for a Physician to our Application.	
Typical of Events	Actor action	System Response
	1. a form appears to the physician-user, to fill in his information.	2. confirms with a message.
Alternative	3. shows a massage error, in case something happened.	
Precondition	No Precondition	
Postcondition	No Postcondition	

Table 4.9: Physician Registration Use Case Scenario.

Use case name	Patient Search	
Actor(s)	Physician	
Description	steps search about patient.	
Typical of Events	Actor action	System Response
	1. Enter a patient username.	2. in case the username is not found shows a message error.
Alternative		
Precondition	Physician logs in.	
Postcondition	Retrieve the patient file	

Table 4.11: Physician searches patient Case Scenario.

Use case name	Patient Diagnosis	
Actor(s)	Physician	
Description	steps to use ML model.	
Typical of Events	Actor action	System Response
	1. Enter model parameters.	2. display results.
Alternative		
Precondition	1. doctor logs in. 2. patient in the system (patient search use case).	
Postcondition	add results to Database	

Table 4.12: Physician diagnoses patient Case Scenario.

4.4 System Design

Systems design is the process of defining elements of a system like modules, architecture, components and their interfaces, and data for a system based on the specified requirements

4.4.1 Activity Diagram

An activity diagram gives a graphical representation of how data move around an information system based on data flows.

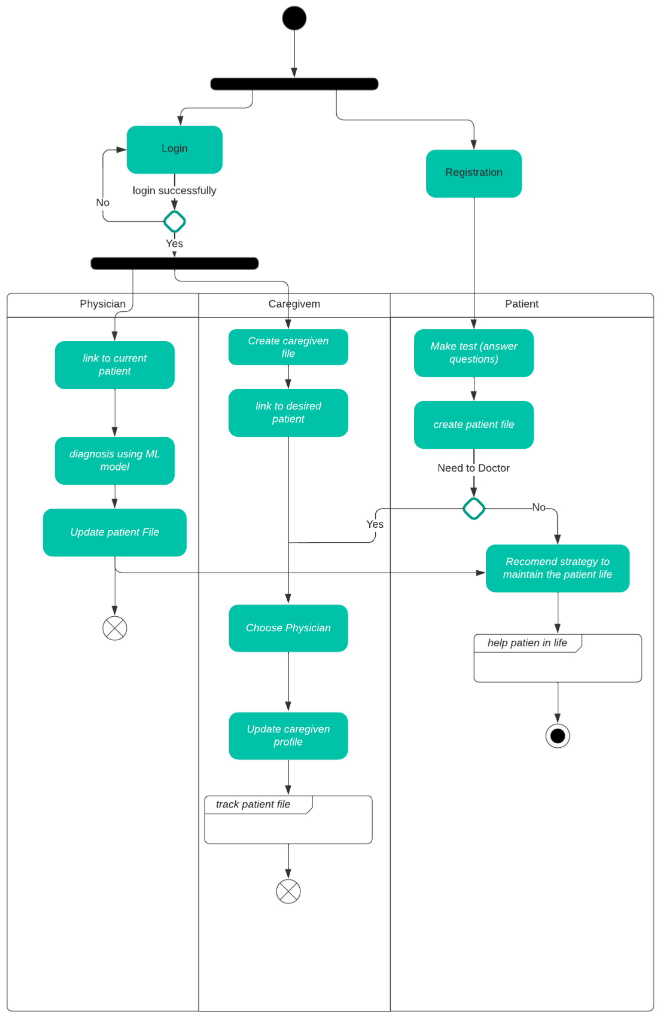

Figure 4.5: Activity diagram

4.4.2 Sequence Diagram

An sequence diagram gives is used to show the interactive behavior of a system

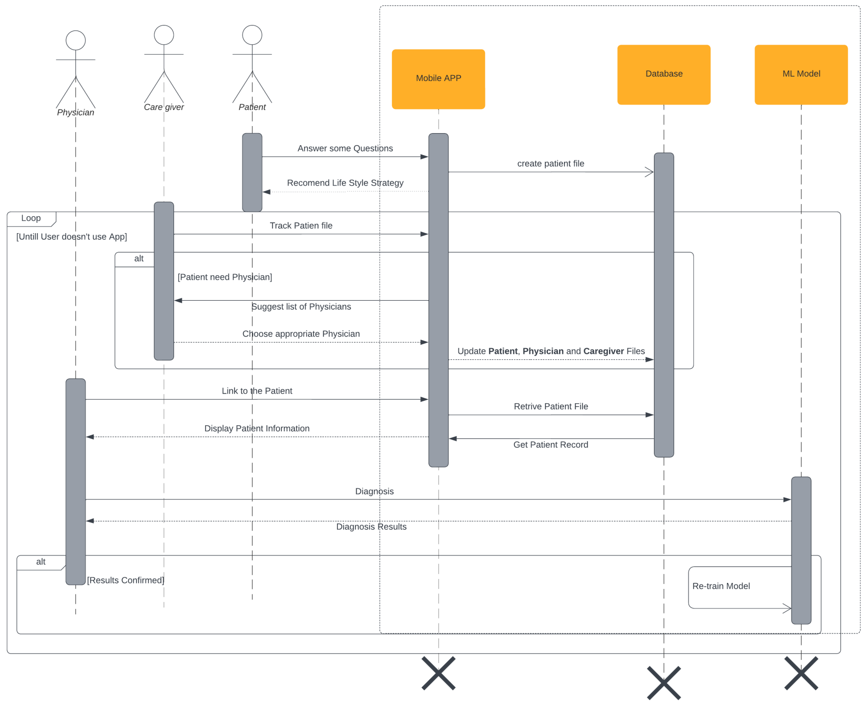

Figure 4.6: Sequence diagram

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