Fayoum University

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Automated Detection of Human Mental Disorder

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Abstract

Mood swings, stress, depression, and anxiety these terms have become more common in present-day life. The persistence of these feelings in a person may lead to depression and anxiety. Unfortunately, most people's emotional/ behavioral changes go unnoticed, which leads to a late diagnosis of the situation. That leads to a person's likelihood of harmful behaviors' including alcohol abuse or even suicidal tendencies. Hence, it becomes essential to identify such emotional changes in an individual. In this work, a framework that uses some attributes, including observable facial behavior, has been developed to assess a person's mental health. The system uses a Haar-Cascade classifier to detect facial features and a VGG-16 algorithm to automatic predictions of anxiety, depression, or normal. The system has achieved a 96% of overall prediction accuracy. The proposed method was evaluated on a dataset (FER+ dataset), which was designed to detect depression and anxiety by training the dataset (FER+ 2013). and in the case of uploading the frontal face videos the model extracts the facial features from each frame, and analyses these facial features to detect signs of depression, anxiety, or normal in them. This system will be trained with frontal face images of some facial expressions. The presence of these features in the video frames will be analyzed to predict mental disease in the user suffer.

ACKNOWLEDGEMENT

We take this opportunity to express our profound gratitude and deepest regards to our devoted Supervisor Dr. Shereen Ahmed for her outstanding supervision and constant encouragement throughout the work of this Project. The blessing, help, and guidance given by her from time to time shall carry us a long way in the journey of life on which we are about to take the ship. We also take this opportunity to express our gratitude to the Board of the Faculty of Computers and Information for their support and efforts in providing us with all useful resources. Lastly, we thank the Almighty, our team (ourselves), our parents, and all the people who helped, supported, and encouraged us to finally and successfully finish the graduation project whether they were in the university or in the industry.

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Chapter 1

Introduction

1.1 Mental health

Mental health is a state of well-being in which a person understands his/her abilities, can cope with the everyday stresses of life, work productively and fruitfully, and contribute to his/her community. Both physical and mental health is the result of a complex interplay between many individual and environmental factors, including:

- family history of illness and disease/genetics
- lifestyle and health behaviors (e.g., smoking, exercise, substance use)
- exposure to trauma

When the demands on someone exceed their resources and coping abilities, their mental health will be negatively affected, including their emotional, psychological, and social well-being. It affects how they think, feel, and act. It also helps determine how they handle stress related to others. There are many different mental disorders with different presentations. There are effective treatments for mental disorders and ways to alleviate the suffering caused by them. It also includes depression, Mood swings, stress, anxiety, schizophrenia, and other psychoses. Unfortunately, health systems have not yet adequately responded to the burden of mental disorders. Consequently, the gap between the need for treatment and its provision is wide all over the world. In low- and middle-income countries, between 76% and 85% of people with mental disorders receive no treatment for their disorder. People with mental illness require social support and care to support healthcare services.

As we have mentioned in the previous paragraph, there are many different mental disorders, diseases, and illnesses. anxiety disorders, including panic disorder, depression, bipolar disorder, and personality disorders. post-traumatic, ..., etc. But in our paper, we will focus more on the popular disorders as follows:

1.1.1 Depression

Depression is a mental health disorder characterized by a depressed mood, low self-esteem, remorse, and a lack of enthusiasm or interest in doing things. About 300 million people worldwide suffer from depression. The main symptoms of depression from a clinical point of view are loss of memory, lack of concentration, an inability to make decisions, loss of interest in recreational activities and hobbies, overeating and weight gain or low appetite and weight loss, feelings of guilt, worthlessness, helplessness, restlessness, and irritation, as well as suicidal thoughts. These symptoms were found to have a significant effect on essential areas of an individual's life – such as education, employment, and social activities, and this provides a vital clue for forming a clinical diagnosis.

1.1.2Anxiety

Anxiety is a natural and beneficial emotion. When an individual experiences disproportionate amounts of Anxiety on a regular basis, however, it can become a medical problem. It is a set of mental illnesses marked by a high level of apprehension, anxiety, anticipation, and worry. According to the World Health Organization, almost two-thirds of patients with depression often suffer from comorbid anxiety disorders. The symptoms of Anxiety are irritability, nervousness, fatigue, insomnia, gastrointestinal problems, panic, a sense of impending danger, increased heart rate, sweating, rapid breathing, and difficulty in concentrating.

1.1.3 Communication Psychotherapy

Communication is an essential aspect of expressing feelings, ideas, desires, and needs to communicate a tool is needed. The primary tool in communication is language. It means that both communication and language cannot be separated. Therefore, it needs communication. It is known that in human communication, there are two essential aspects they are verbal communication and non-verbal communication.

1.1.4 Verbal communication

Verbal communication involves using words, speech, or auditory language to express emotions or thoughts or exchange information. The type of communication is formal and informal, and they communicate with precise information. They communicated in any written or oral format where words are used—anything in a written or oral format where words are used. Practical and constructive communication always results in contented people, increased productivity, smoother operations, and decreased errors. Practical and constructive communication always results in contented people, increased productivity, smoother operations, and decreased errors.

1.1.5 Non-Verbal communication

Nonverbal communication is the process of communicating messages through touch and space, and so on. It is often used to describe feelings and emotions. If a message received through a verbal system does not show the strength of the message, then the nonverbal signs are received as supporters. Nowadays, humans frequently use non-verbal communication rather than verbal communication in interacting with others. They become more comfortable using non-verbal communication to express their feelings and emotions to others. They spend more time with gadgets than spending time with people around them. This includes in a small family that they rarely communicate when they are together.

1.2 Problem Statement

This system can help the patient adjust to the new situation and continue the mental growth of his case. Furthermore, in recent years, machine learning-based intelligence, artificial intelligence, neural network, and other modern technologies used in diagnosis have been evolved to easily help the traditional clinical methods, which can be time-consuming and expensive, so using modern technologies help in making detection of the patient mental stability can help to improve the conditions that will reduce the time consumed and reduced the expensive.

1.3 Project Motivation

Generally, mental health does not have the attention needed nowadays in some countries. As some mental diseases need special treatment, the patients do not get it in the right way to affect their lives. As the coronavirus pandemic rapidly spreads across the world, it has caused a considerable degree of fear, concern, and anxiety among the entire population, especially in certain groups, such as the elderly, caregivers, and people with primary health conditions, many people are isolated, unable to interact with friends or family. Therefore, their mental health deteriorates. Disconnected from everything and may slip into depression or anxiety. So, a novel approach is proposed to detect the state of a person to track their wellbeing. Depression and anxiety are frequently undetected and are responsible for various morbidities, either directly or indirectly. While depression and anxiety are two distinct disorders, they often coexist. Recent studies have shown that machine learning and artificial intelligence can monitor a person’s mental health. The unconsciously transmitted behavioral symptoms expressed by head movements (pose), eye-gaze direction, and facial muscle movements (facial expressions) were used to model structures that could predict mental health conditions like depression and anxiety.

1.4 Problem Aim & Objectives

The system goals to accomplish within a timeline and with available resources are:

- Helping the patient detect if he has depression /anxiety/normal.
- Help in monitoring the patients' progress while diagnosing the test by focusing on the facial expressions, the more favored symptoms to show depression /anxiety tendency in clinical assessments.
- Decrease the expense and time consumed through the whole process of detection by classification the depression /anxiety using the facial expressions and uploading a video about the patient from his daily life and analyzing it.
- Besides the main reason adding to it COVID-19 pandemic made the people lose the intention to pay attention to the effect on people's mental health.

1.5 Project Requirements

The system needs special both software and hardware requirements:

♣ Hardware Requirements:

- Mobile or computer camera
- A computer with high “GPU” for model training.

♣ Software Requirements:

- Allow access to mobile logs for mobile.
- Allow access to the camera.

1.6 Project Limitations

The system has some limitations such as:

* Result Limitation
  - The accuracy of the measurement results system must high.
* Time frame Limitation
  - The project must be finished by the end of work on 26 June.
* Resource limitation
  - Hardware Resources:
    - o Mobile/computer camera
    - o A computer with high “GPU” for model training.

1.7 Project Expected Output

The expected output of the work outlined is to detect Depression, Anxiety, or normal during pandemics, can be beneficial for the the medical field where the doctor, patient, and patient family can know if the patient’s mental health is stable or not through our model.

1.8 project scope

The project will involve making a model which is user-friendly and interactive based on experience and user requirements. This Process would also include considering other related systems interactions such as a camera that is attached with pc, images, and video uploaded during the test that comes from a PC. Once the model is running, it would have the capability to real-time process the user that uses the model and detects their mental condition if they have anxiety, depression, or normal depending on the camera and computer logs.

1.9: Project Schedule:

- 1.9.1: Tasks

GANTT CHART

	Task Mode	Task Name	Duration	Start	Finish	Pre	Resource Names	Add New Co
1		**Graduation project**	**167 days**	**20/09/2021**	**20/07/2022**		**labtob core i7**	
2		Search	45 days	20/09/2021	07/12/2021		Google engine	
3		**Busniness Requirements**	**61 days**	**18/10/2021**	**31/01/2022**		**radwa,mohamed,mahmoud**	
4		tools installation	1 day	18/10/2021	18/10/2021		mahmoud,mohamed	
5		fields studing	60 days	19/10/2021	31/01/2022		ayat , saad , abdelrahman	
6		**system analysis**	**3 days**	**27/01/2022**	**01/02/2022**		**visual-paradiam-Lucidchar**	
7		DFD	1 day	27/01/2022	27/01/2022		mohamed ,mahmoud	
8		USE CASE	1 day	31/01/2022	31/01/2022		mohamed ,mahmoud	
9		USE CASE senario	1 day	01/02/2022	01/02/2022		mohamed ,mahmoud	
10		**Design**	**2 days**	**02/02/2022**	**03/02/2022**		**Lucidchar**	
11		Sequence Digram	1 day	02/02/2022	02/02/2022		mahmoud,mohamed	
12		Class Digram	1 day	03/02/2022	03/02/2022		mahmoud,mohamed	
13		**Dataset Model**	**1 day**	**06/02/2022**	**06/02/2022**		**mahmoud,saad,ayat**	
14		Mapping	1 day	06/02/2022	06/02/2022		radwa,mohamed,mahmoud	
15		**Programming**	**53 days**	**13/02/2022**	**19/05/2022**		**Pycharm**	
16		Model implementation	18 days	13/02/2022	13/03/2022		abdulrahman,saad,ayat	
17		**Back End Programming**	**37 days**	**14/03/2022**	**19/05/2022**		**Pycharm**	
18		Data set collection	20 days	14/03/2022	14/04/2022		saad,mahmoud,radwa	
19		Video processing	7 days	17/04/2022	26/04/2022		ayat,radwa	
20		System response	1 day	09/05/2022	09/05/2022		abdulrahman,saad	
21		Real Time Process	7 days	10/05/2022	19/05/2022		abdulrahman,saad	
22		**Testing**	**12 days**	**22/05/2022**	**09/06/2022**		**Pycharm**	
23		Model Testing	7 days	22/05/2022	31/05/2022		abdulrahman,saad	
24		Back End Testing	7 days	31/05/2022	09/06/2022		abdulrahman,saad,ayat	
25		Documentation	7 days	12/06/2022	21/06/2022		radwa,abdulrahman,ayat,mahmoud,mohamed,saad	
26		**Meetings**	**19 days**	**12/06/2022**	**20/07/2022**		**Google meet,abdulrahman**	
27		Exams	20 days	12/06/2022	19/07/2022			

Figure 1.1 (project schedule with tasks & participants)

Chapter 2

Literature Review

This chapter discusses other similar current systems and reflects on how the issue is solved by these systems, providing their solutions, to these systems' overall challenges.

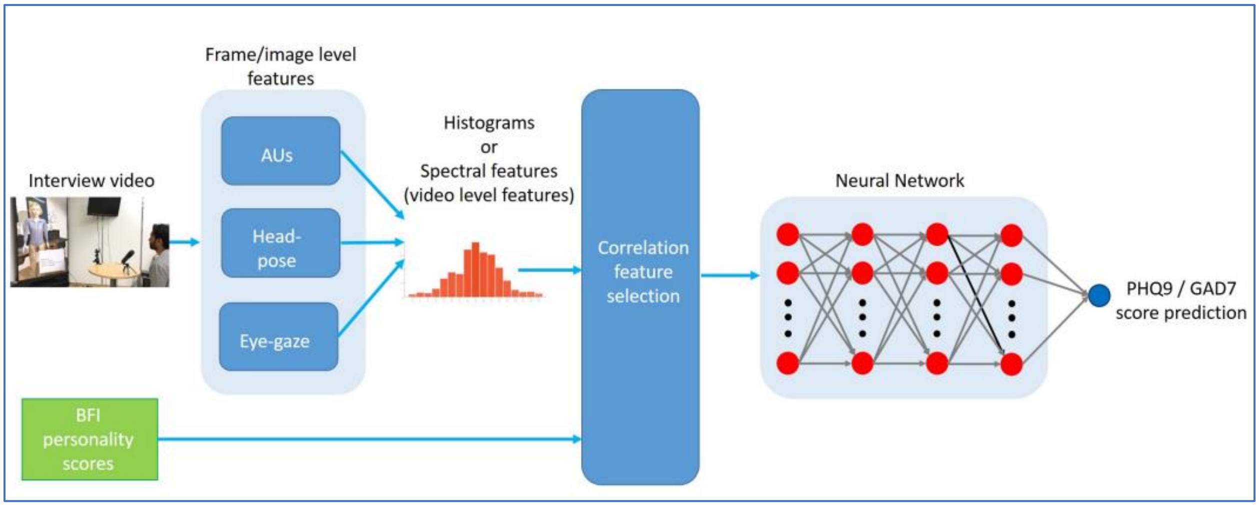
2.1 Existing Systems

As the coronavirus pandemic rapidly spreads worldwide, it has caused a considerable degree of fear, concern, and anxiety among the entire population. Many people are isolated and unable to interact with friends or family. Therefore, their mental health deteriorates. Some people use this time to improve themselves and find themselves learning and experimenting with new skills, while others are disconnected from everything and may slip into depression or anxiety. Furthermore, because of the pandemic, it made it hard for people to ask for phycologist and therapists. Nevertheless, the existing online system was not accurate with their results depending on some questions asked. Anyone can reply without any supervision from a certified phycologist.

Many papers had discussed this option and provided some ideas such as using facial expression, head movement, and eye expression with Gaze Tracking, which we think is the best one, so we conducted our system based on it.

2.1.1 Automatic prediction of depression and anxiety from behavior and personality attributes [1]

The Current vision-based approaches for automatic prediction of mental health conditions like depression and anxiety relied on models that used behavioral features (usually extracted from faces) only and did not take personality into account. However, there was a considerable amount of evidence that people with certain personality traits are more prone to depression and anxiety disorders. they proposed to use a combination of features consisting of observed facial behavior and self-reported personality scores. This combination of features was employed for training deep neural networks for predicting depression and anxiety scores. Learning models based on facial behavior could help predict mental health conditions like depression and anxiety and has the potential to be used as a valuable tool for the clinical diagnosis of such conditions. However, no prior work in affective computing models the relationship between personality and depression/anxiety disorders and exploits it to improve the prediction performance. In this paper, they explored the idea of using a combination of observed facial behavior and self-reported personality information to predict depression and anxiety disorders using deep neural networks (DNN). The facial behavior is encoded as a set of behavior primitives, to wit: facial Action Units (AUs), head-pose, and eye-gaze direction.



2.1.2 Reading simple and complex facial expressions in patients with major depressive disorder and anxiety disorders [2]

Most studies have focused on only a few emotions (such as Ekman's basic emotions), overlooking complex mental states that can appear more frequently in real life. Also, people can read not only feelings but also thoughts from facial expressions. The current study investigated the recognition accuracy of simple (affective mental states) and complex (complex mental states) emotions. Complex emotion reflects one's wishes and beliefs and always involves cognitive appraisal of the situation. Simple emotion only reflects affective states and does not necessarily involve cognitive appraisal.

For example, if a person is frustrated (complex emotion), they may think that something is not going as they desire. Then they would express this frustrated emotion with angry and sad facial expressions (simple emotions). Accordingly, an observer might recognize their complex mental state: the thoughts of frustration and the affective states of anger and sadness. In their study, they aimed to examine recognition accuracy for facial expressions in patients with major depressive disorder (MDD), anxiety disorders (AnD), and healthy controls (HC). They hypothesized that:

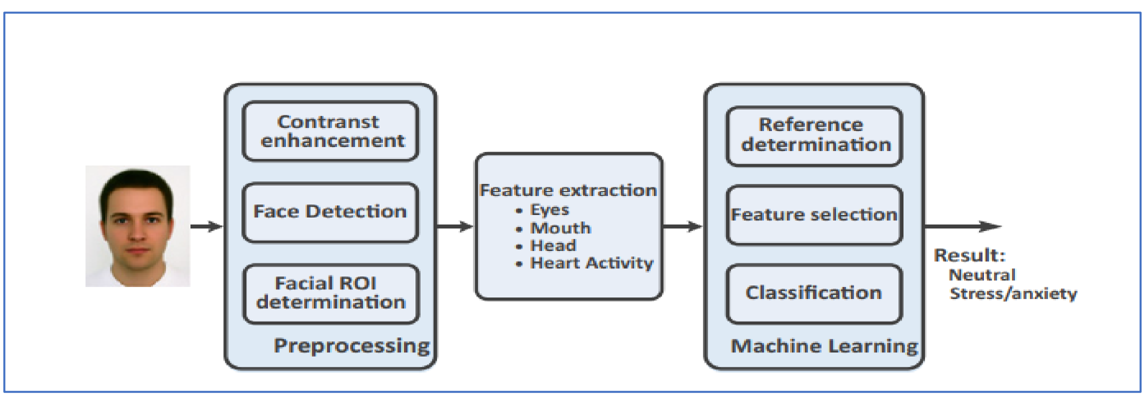
(i) patients with MDD and AnD would show lower recognition accuracy for complex emotions compared to HC;

(ii) patients with MDD would show more difficulties in recognizing pleasant emotions compared to unpleasant emotions, and

(iii) patients with MDD would display lower recognition accuracy compared to patients with AnD and HC. In order to check the reliability of the task, they compared their results from HC with previous studies that used the same task. The overall recognition accuracy of HC was 76% in the current study.

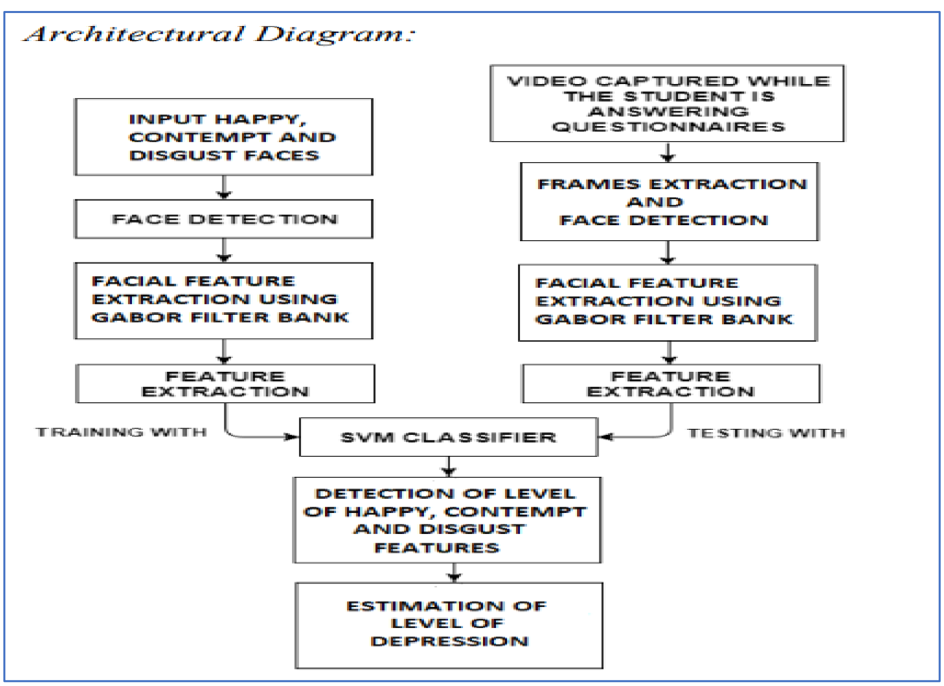
2.1.3 Stress and anxiety detection using facial cues from videos [3]

They developed a framework for detecting and analyzing stress/anxiety emotional states through video-recorded facial cues. First, a thorough experimental protocol was established to induce systematic variability in affective states (neutral, relaxed, and stressed/anxious) through various external and internal stressors. The analysis was focused mainly on non-voluntary and semi-voluntary facial cues to estimate the emotion representation more objectively. A feature selection procedure was employed to select the most robust features, followed by classification schemes discriminating between stress/anxiety and neutral states concerning a relaxed state in each experimental phase. Study participants were seated in front of a computer monitor while a camera was placed at a distance of approximately 50 cm with its field of view (FOV) able to cover the participant's face adequately. The classification accuracy reached good levels as compared to the results of the few related studies available among other features, facial features achieving 75%–88% and 90.5% classification accuracy, respectively.



2.1.4 Extraction of Facial Features for Depression Detection among Students [4]

The psychological health of college students proves a vital role in their overall academic performance. Neglecting this can result in several problems such as anxiety, depression, etc. These problems need to be detected and controlled at the initial stages. It was better to identify the signs of depression at the initial stages of depression. This system mainly used different image processing techniques for face detection, feature extraction, and classification of these features as depressed or nondepressed. The system was trained with features of depression. Then videos of different students with frontal faces were captured using a web camera. Then the facial features of these faces were extracted for the prediction of depression. Based on the level of depression features the student was classified as depressed or non-depressed. using the SVM classifier dataset.

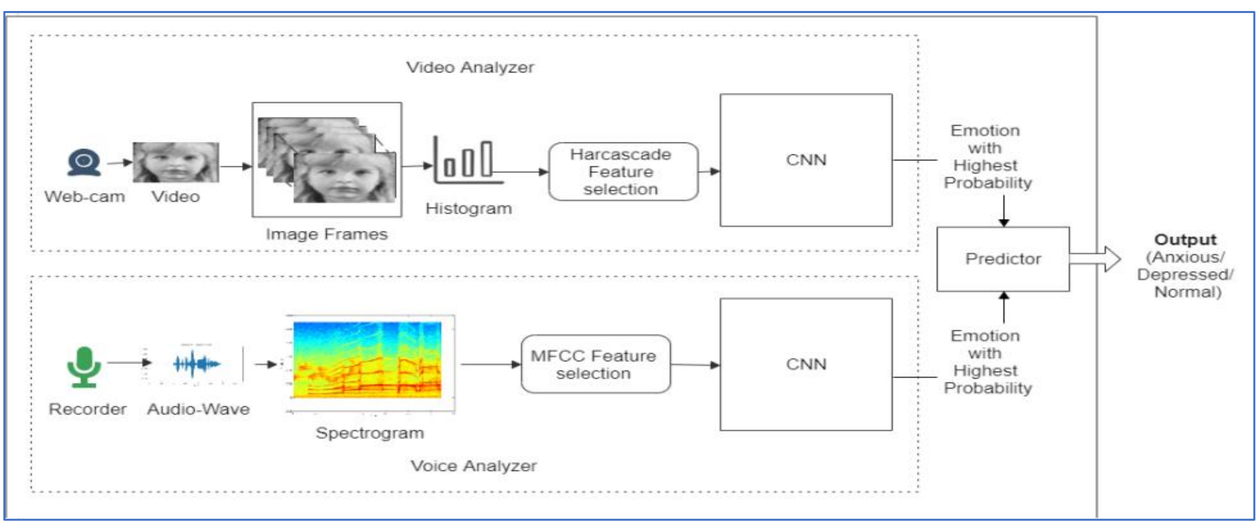


2.1.5 Facial Emotion Recognition: State of the Art Performance on FER2013 [5]

they used Facial emotion recognition (FER) as it is significant for human-computer interactions such as clinical practice and behavioral description. Accurate and robust FER by computer models remains challenging due to the heterogeneity of human faces and variations in images such as different facial poses and lighting. they convey basic emotions such as fear, happiness, disgust, etc. as it plays an important role in human-computer interactions and can be applied to digital advertisement, with advancements in computer vision, high emotion recognition accuracy had been achieved in images captured under controlled conditions and consistent environments, rendering this a solved problem. they aim to improve prediction accuracy on FER2013 using CNNs. they adopt the VGG network and construct various experiments to explore different optimization algorithms and learning rate schedules. they then construct several saliency maps to better understand the network's performance and decision-making process. In training on FER2013, they adhere to the official training, validation, and test sets as introduced by the ICML. FER2013 consists of 35888 images of 7 different emotions: anger, neutral, disgust, fear, happiness, sadness, and surprise. In their work, they achieved the highest single-network classification accuracy on the FER2013 dataset. To their best knowledge, their model achieves state-of-the-art single-network accuracy of 73.28 % on FER2013 without using extra training data.

2.1.6 AUTOMATIC PREDICTION OF DEPRESSION AND ANXIETY [9]

the majority of people's emotional/behavioral changes go unnoticed, which leads to a late diagnosis of the situation. In their work, a framework that used a combination of attributes, including observable facial behavior by Haar-Cascade classifier, modulations in the voice, and self-reported personality ratings by Mel Frequency Cepstral Coefficient, has been developed to assess a person's mental health. Their system also detects the gender of the person. They have achieved a 70% of overall prediction accuracy. the automatic prediction of anxiety, depression, or both can be achieved in their system by machine learning, and artificial intelligence as they were known as can be used to monitor a person's mental health, two sequence descriptors are generated as a result. The first measures the behavior primitive's sequence-level statistics, while the second transforms the problem into a Convolutional Neural Network problem based on a spectral representation of the multichannel behavior signals.



2.2: Overall Problems of Existing Systems

These are not a good method to achieve our goal (measuring a person's mental health) because of many problems such as:

* These systems use limited facial expressions which decreases their accuracy

* Dataset collected and evaluated exclusively under different conditions which decrease their accuracy.

2.3: Overall Solution Approach

Our System is a real-time system using software and hardware developments for processing based on machine learning and neural network techniques, using laptops cameras' real-time videos and prerecorded video as input to our system we can segment those videos to measure a person's diagnosis.

Chapter 3

System Analysis

This chapter represents System USE-CASE Scenario and 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, Sequence Diagram shows, as parallel vertical lines (lifelines), different processes or objects that live simultaneously, and, as horizontal arrows, the messages exchanged between them, in the order in which they occur, System Sequence Diagram which is a sequence diagram that shows, for a particular scenario of a use-case, the events that external actors generate, their order, and possible inter-system events, Class Diagram which is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects, Context Diagram which presents the sub-systems of our system and its data flow processing, and system architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system. It is organized into: 3.1 System Architecture, 3.2 Data Flow Diagrams, 3.3 UML Use case Diagram, 3.4 UML Sequence, and System Sequence Diagrams, 3.5 UML Class Diagram, and finally 3.6 System Requirements.

3.1 Traditional Diagrams

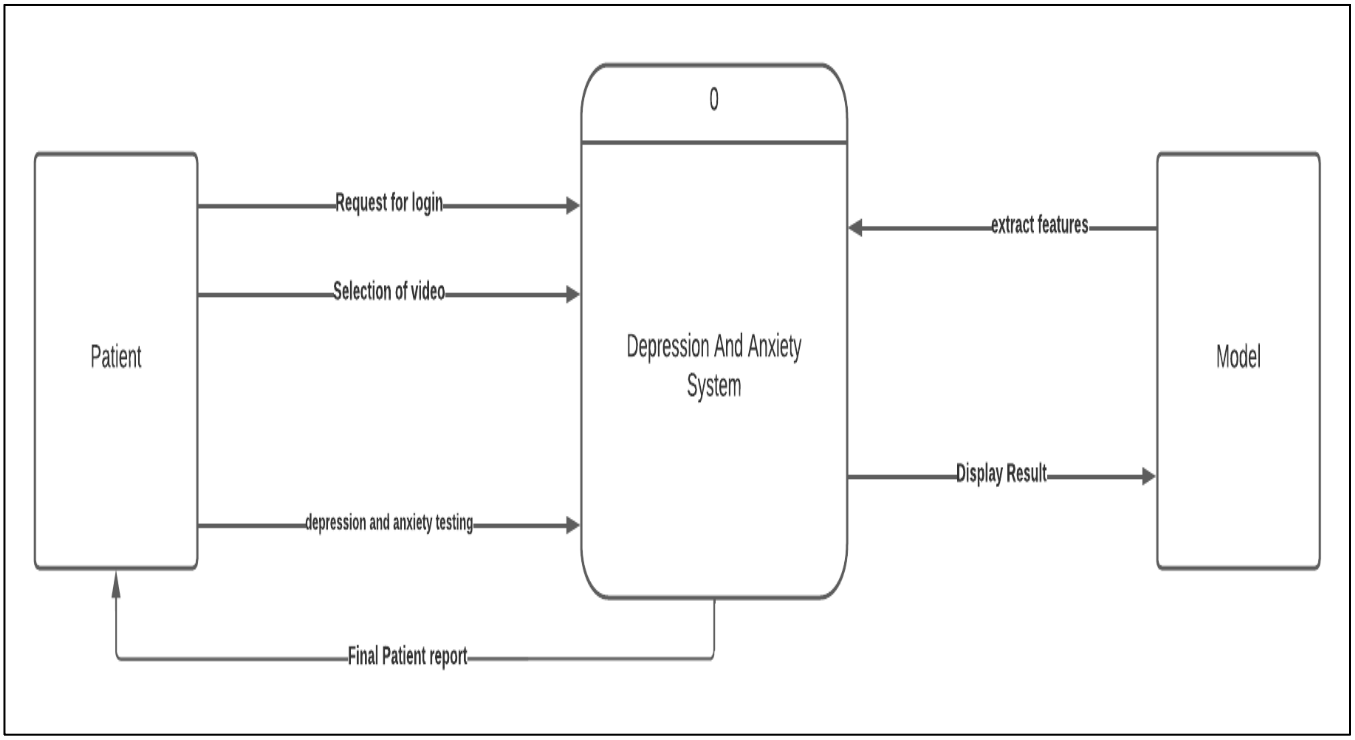


Figure 3.1(system Context Diagram)

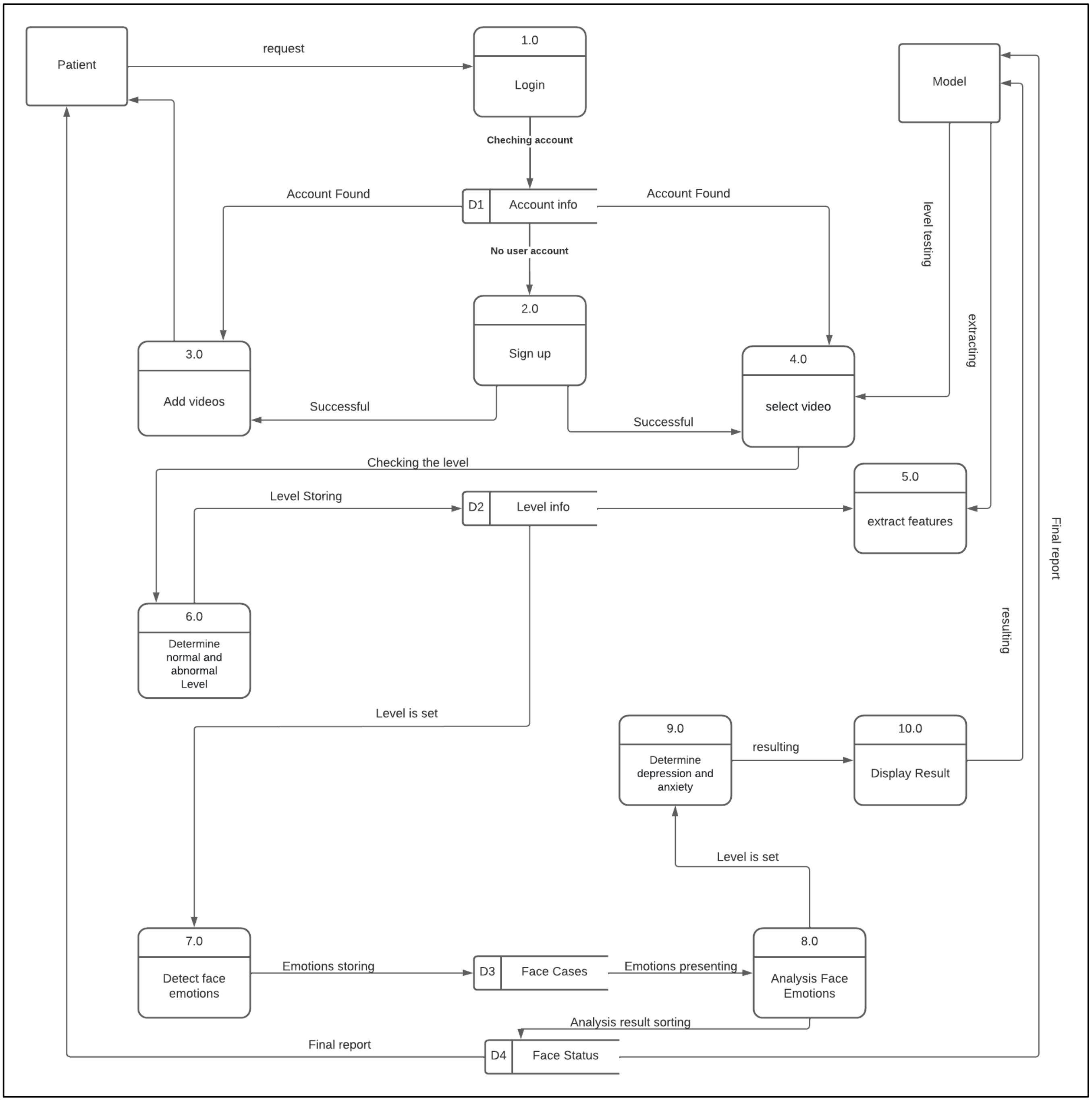


Figure 3.2 (system DFD Level 0)

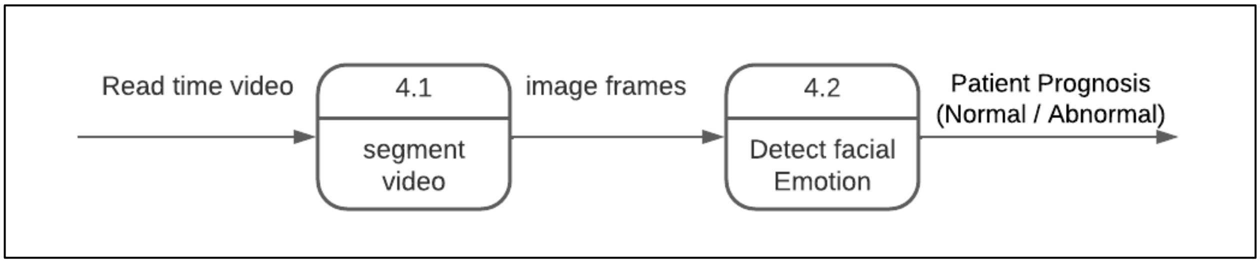


Figure 3.3 (system DFD Level 1)

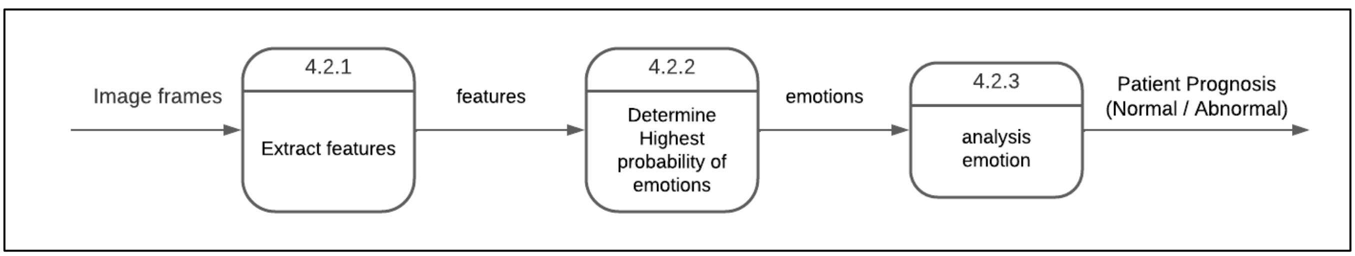


Figure 3.4 (system DFD Level 2)

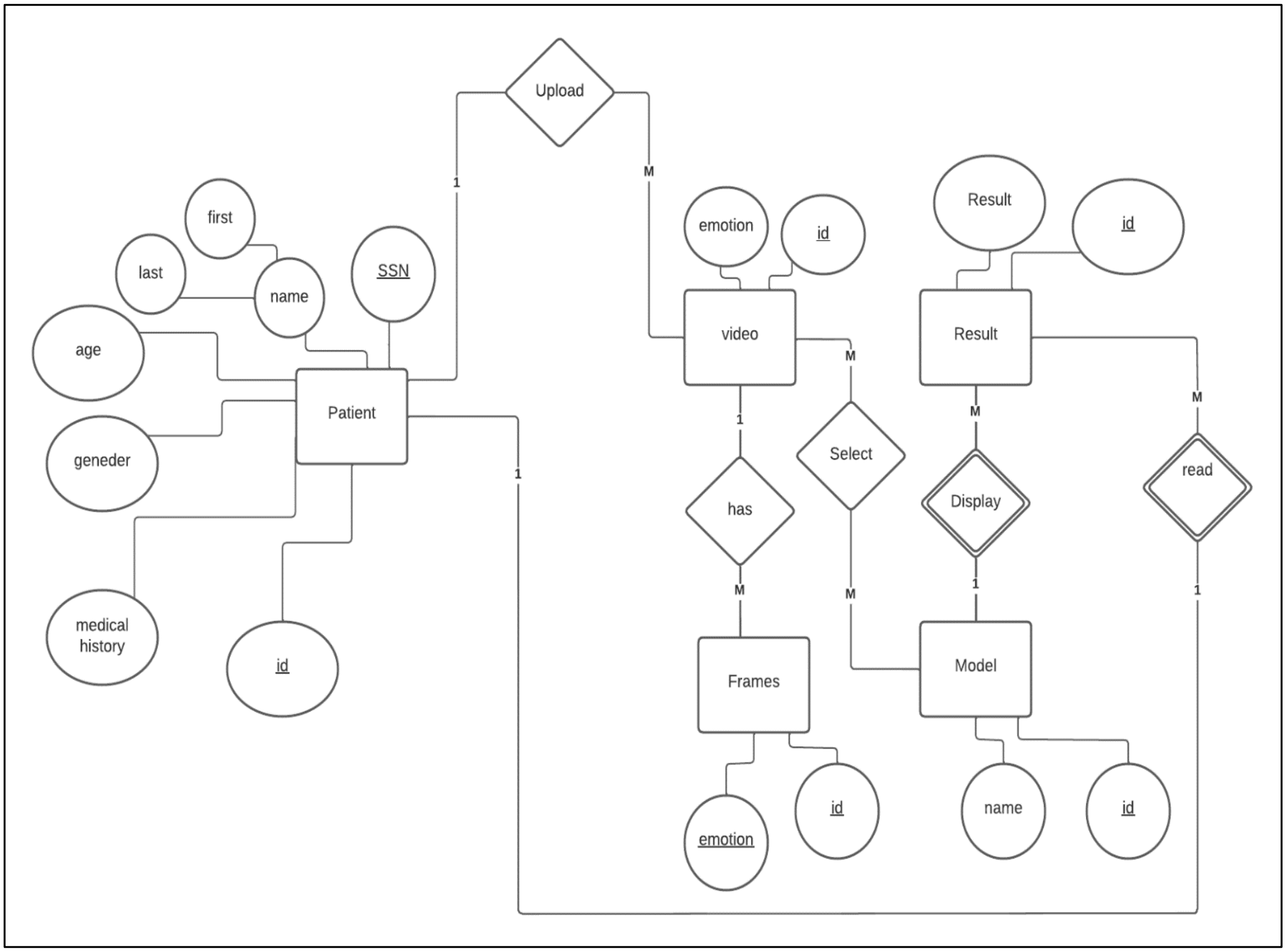


Figure 3.5 (system Database model (ERD))

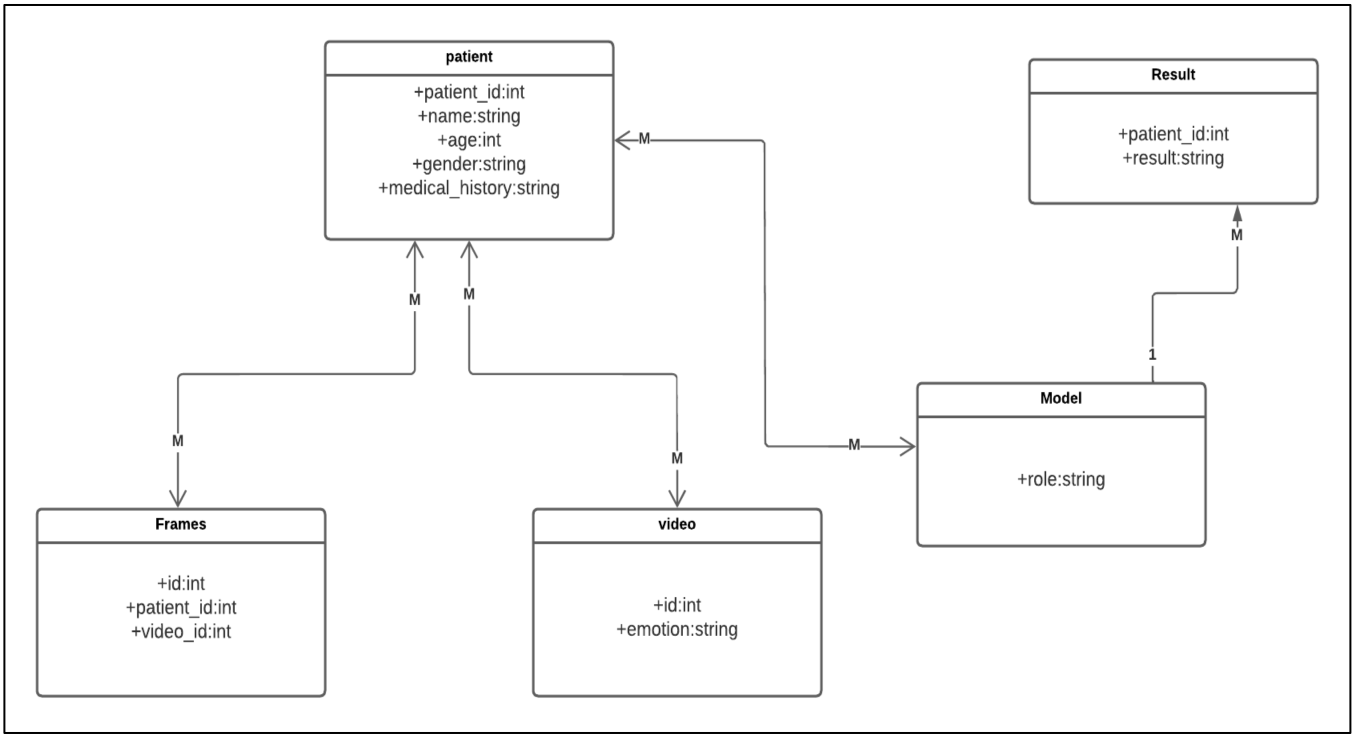


Figure 3.6 (system Domain)

3.2 UML Use case Diagram

3.2.1 Use case Diagram

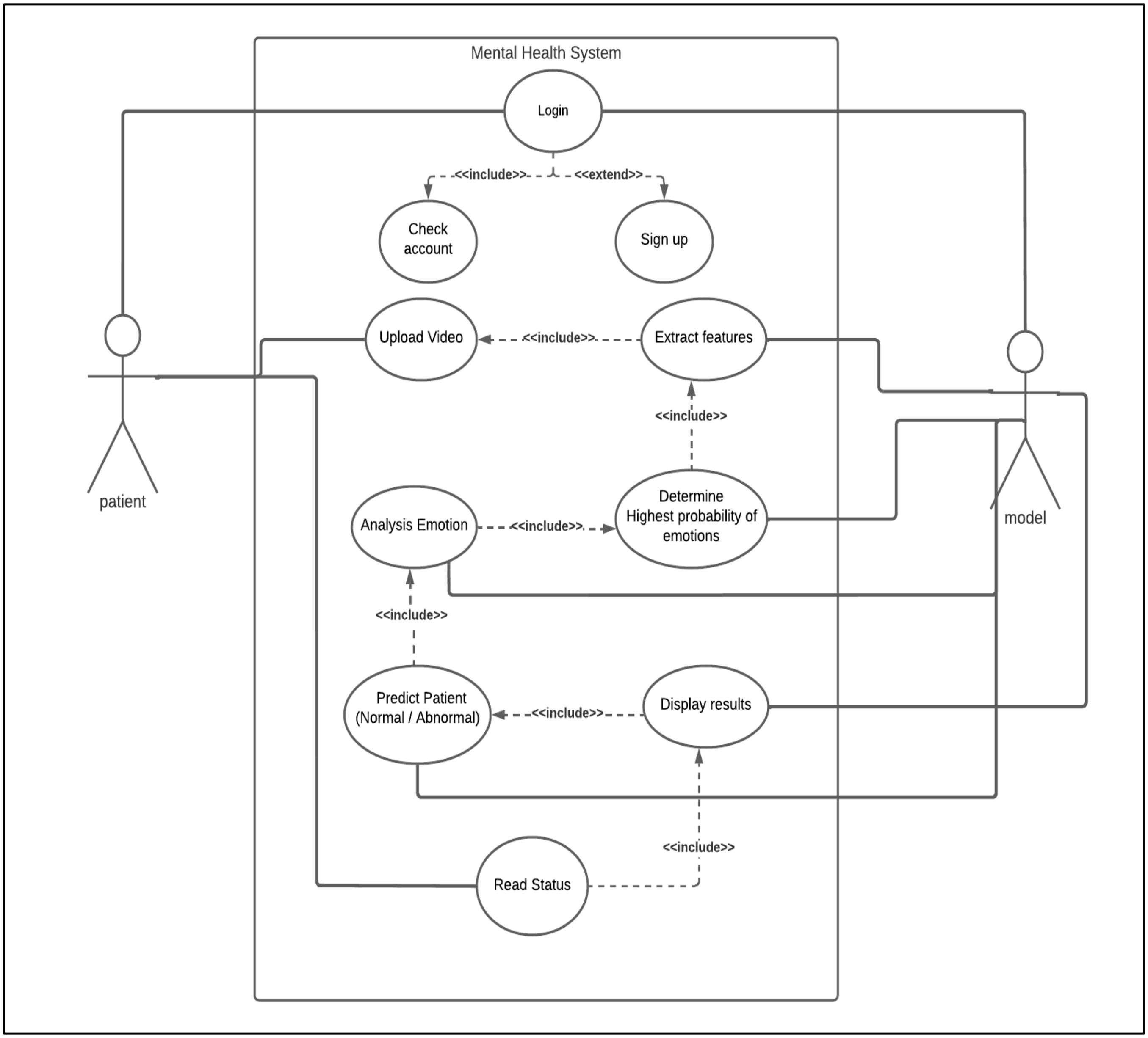


Figure 3.7(system overall use case)

3.2.2 Use case Scenario tables

Table 3.1 Login use case

Use case name	Login	
Actor(s)	patient	
Description	This use case describes how a user log in from the app.	
Typical of Events	Actor action	System Response
	Step1: this use case is initiated when the patient press login. Step2: the patient enters your username and password.	Step3: if the username and password are correct the, system login the account and enters the user to home page
Alternative	If a user name or password entre is incorrect, system will provide the user with other attempt or sign up to new account.	
Precondition	The patient enters the patient's name and password to allow to enter the app.	
Postcondition	If a user name and password are correct, System enters to home page.	
Non-Functional requirements	All Non-Functional requirements: e.g. safety, reliability.	

Table 3.2 Make test normal or abnormal use case

Use case name	Analysis Emotion	
Actor(s)	*Patient*	
Description	This function is used to analyze emotion and determine the Highest probability of emotions to classify a patient (normal/Abnormal) .	
Typical of Events	*Actor action*	*System Response*
	Step1: system stores emotion in model *Step2: model determines the highest probability of emotions.*	*Step3: classify the patient if the* patient is normal, model retrieve. Step4: system analysis of the answer to the test. Step5: displays of the percentage of Depression and anxiety, level and answers of questions have a patient.
Alternative	*No Alternative*	
Precondition	*The User selects a* Depression and anxiety *test.*	
Postcondition	*The model displays of the percentage of* Depression and anxiety*; level and answers of questions have a patient.*	
Non-Functional requirements	*All Non-Functional requirements: e.g., safety, reliability.*	

Table 3.3 User upload videos and images to app use case

Use case name	Add Comment
Actor(s)	Doctor
Description	The Doctor adds a comment to the page of patients.
Typical of Events	<table><tr><td>Actor action</td><td>System Response</td></tr><tr><td><u>Step1</u>: The doctor writes comment in patient file. <u>Step2</u>: The **system** uploads The comments.</td><td><u>Step3</u>: the system displays the comments to parent of patient.</td></tr></table>
Alternative	No Alternative
Precondition	The doctor selects tab of comment.
Post condition	The system displays the comments to patient.
Non-Functional requirements	All Non-Functional requirements: e.g., safety, reliability.

Table 3.4 Select the video that the child watching use case

Use case name	**Select video**	
Actor(s)	Doctor, patient	
Description	The user selects a video to his/ her patient watching.	
Typical of Events	Actor action	System Response
	Step1: this use case is initiated when the user looks for a specific of video.	Step2: system provides the search results
Alternative	Step2: if a search entry is incorrect, system will provide the user with all the suggestions.	
Precondition	User has selected a process of search for any product.	
Post condition	User receives the result of the search.	
Non-Functional requirements	All Non-Functional requirements: e.g., safety, reliability.	

Table 3.5 Watch a video use case

Use case name	**Watch a video**	
Actor(s)	Patient	
Description	This function is watching the Depression and anxiety for videos to learning emotion and how he expresses feelings correctly.	
Typical of Events	Actor action	System Response
	Step1: the patient is watching a video.	Step2: the system detects the Patient face emotion. Step3: the system stores the patient emotion to database. Step4: the system analysis to patient face emotion. Step5: the system displays the patient face status.
Alternative	Step1: if the patient isn't watching a video, he/she watch an image expresses about feelings correctly to learning emotions and expresses well.	
Precondition	The user selects video that patient watching.	
Post condition	The system displays the patient face status.	
Non-Functional requirements	All Non-Functional requirements: e.g., safety, reliability.	

3.3 UML Sequence and System Sequence Diagrams

3.3.1 System Sequence Diagram

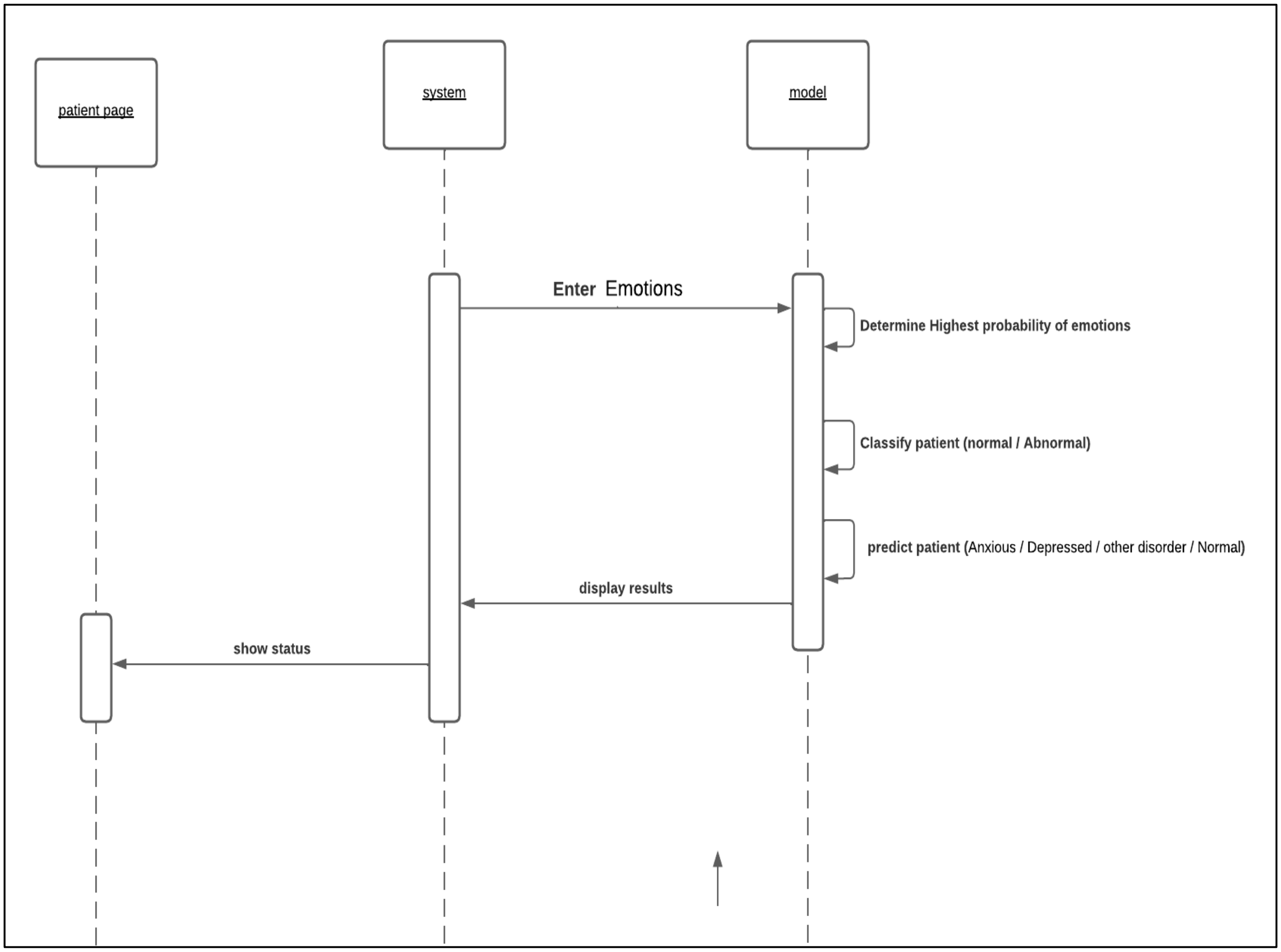


Figure 3.9 (analysis features sequence diagram)

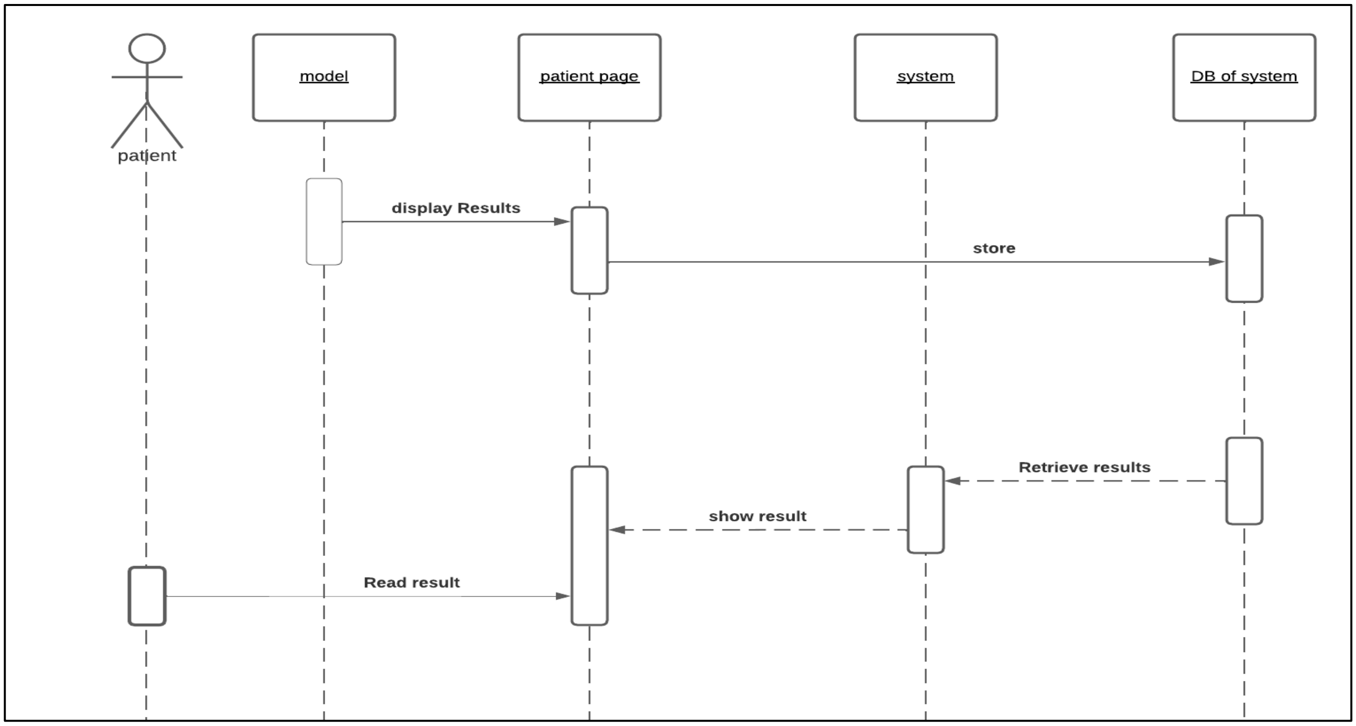


Figure 3.10 (Display results sequence diagram)

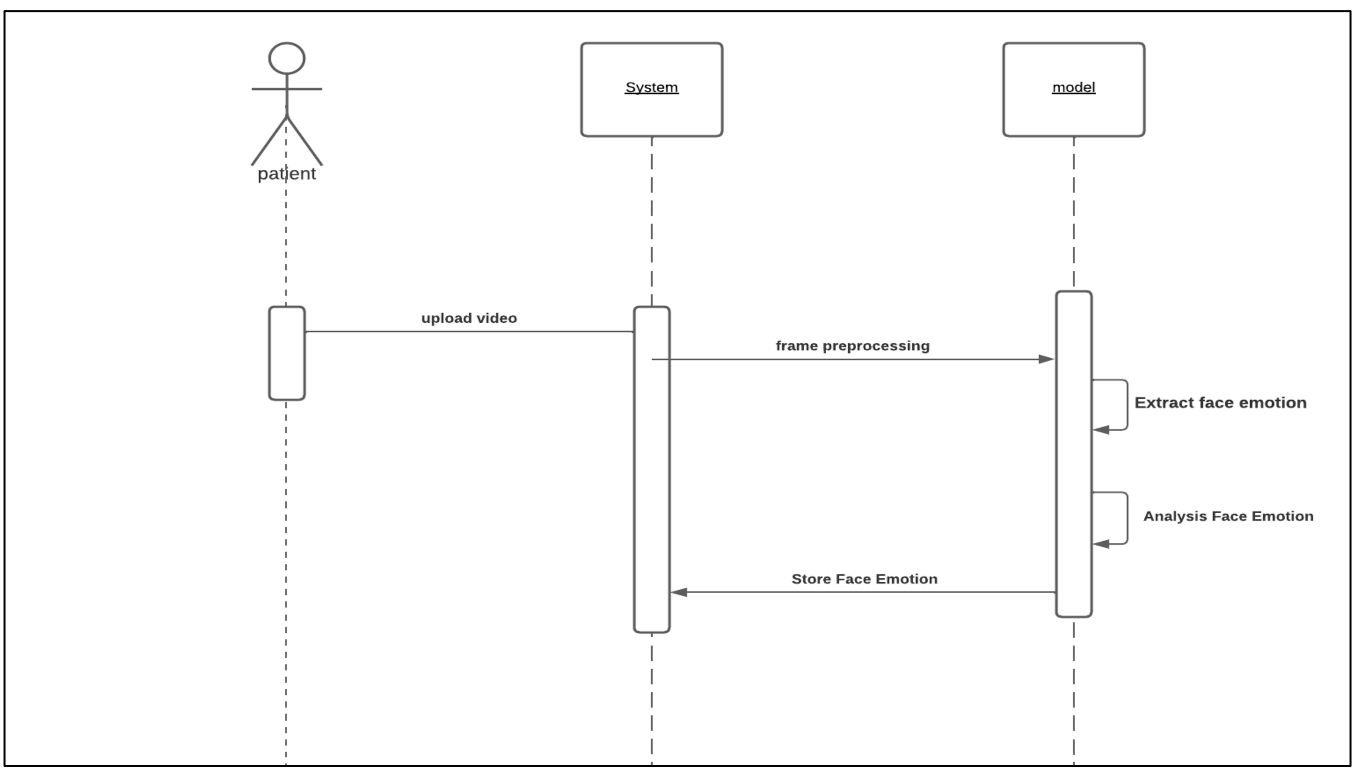


Figure 3.11 (extract features sequence diagram)

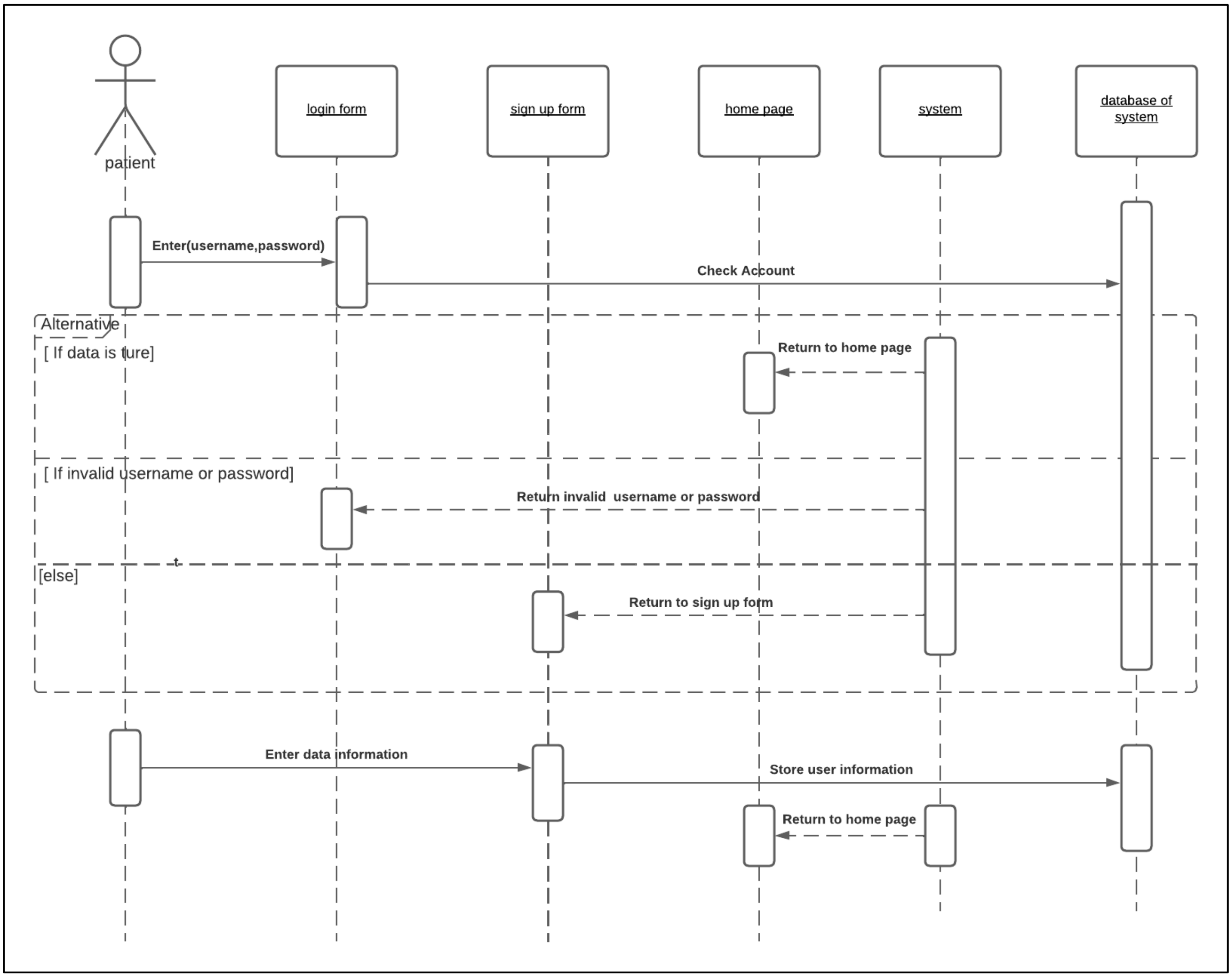
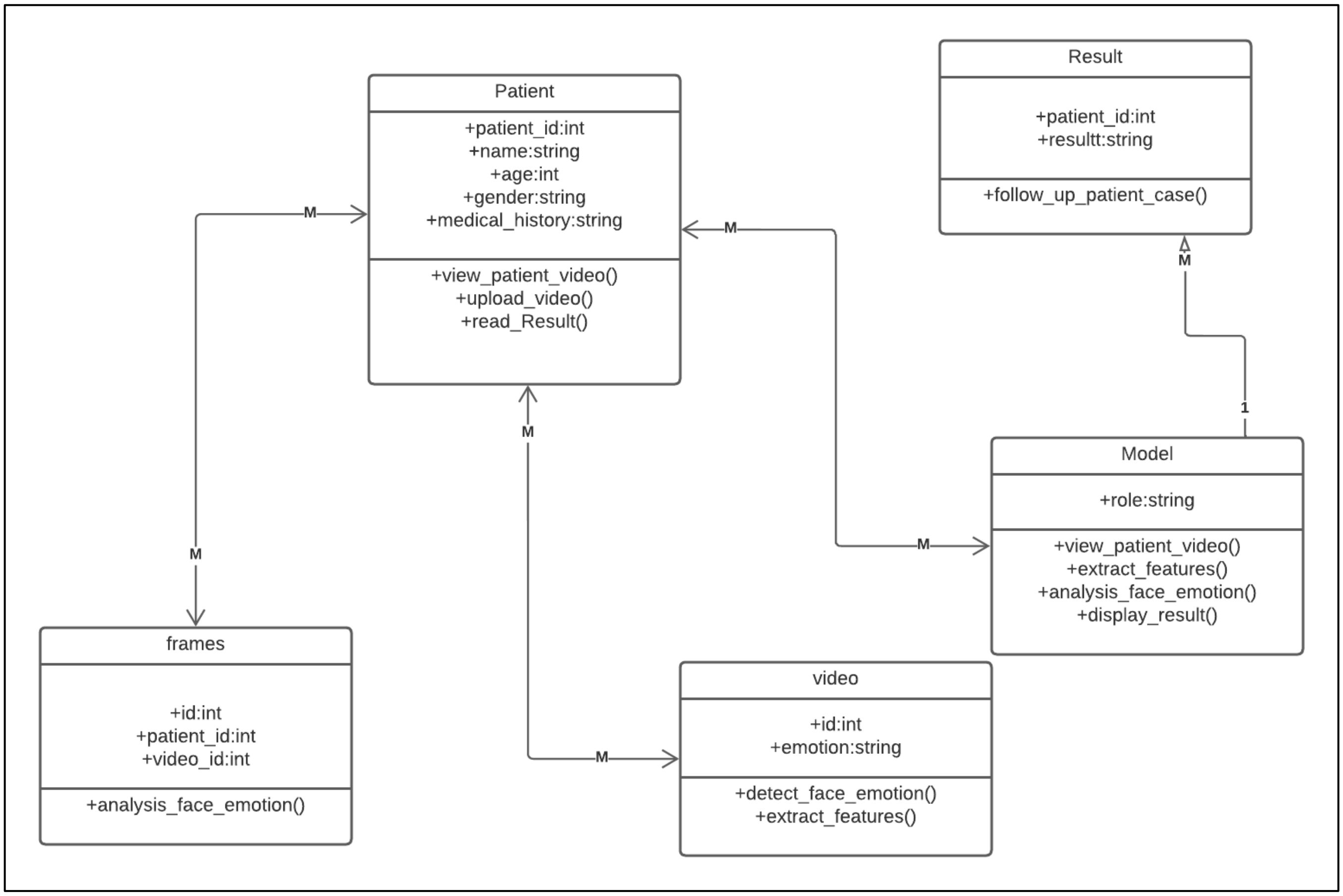


Figure 3.12 (Log in sequence diagram)

3.4 Class Diagram

The class diagram is a static diagram. It represents the static view of an application. The class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. The class diagram describes the attributes and operations of the class and also the constraints imposed on the system.



Figures 3.13 (system class diagram)

3.5 System Requirements

3.5.1 Functional Requirements

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.

* Make online communications more efficient
* The project will involve making the model user-friendly and interactive.
* The model must have an unbiased dataset.
* The model must be correctly able to load the face classifier model.
* Load face image as input.
* Frame Preprocessing
* Detecting the frame facial landmarks
* Perform image processing.
* The system must be able to detect a face on human faces &eyes in every frame in a video.
* The results must be viewed by showing the probability along with the output of „normal ‟ or „unnormal “and then go to the second stage to determine if the user has depression/anxiety.

3.5.2 Non-Functional Requirements

One of the best ways to gather requirements is to get all of the stakeholders together for a guided brainstorming session. Remember that in many cases the upper-level stakeholders are not the users. Include user representatives on the team, who are one of the best sources for non-functional requirements.

* Usability: The system should be usable.
* Reliability: the testing process should be accurately monitored, especially when the estimated result of mentally stable or not.
* Accessibility: the doctor can know the percentage of patient-level in the stage of determining if the patient has depression/anxiety.
* Flexibility: The system should be flexible enough to accommodate evolving data - e.g., the sets of concerned participants.
* Performance: The number of participants, fast send report with the result of the testing process.
* Accuracy: Accurate result for each participant in the test about his mentally stable or not / if the patient has depression/anxiety.
* Security: Only the user and the model admin have the authority to view the test reports of the participants.

Chapter 4

The Dataset

This chapter reviews the Dataset information and Setup of the dataset.

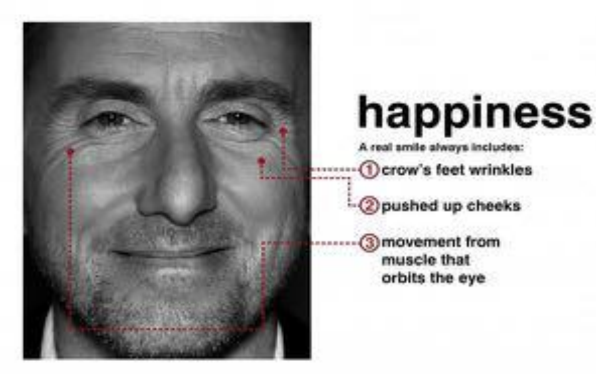
The chapter is organized into 4.2: Dataset definition, 4.3 Dataset Properties.

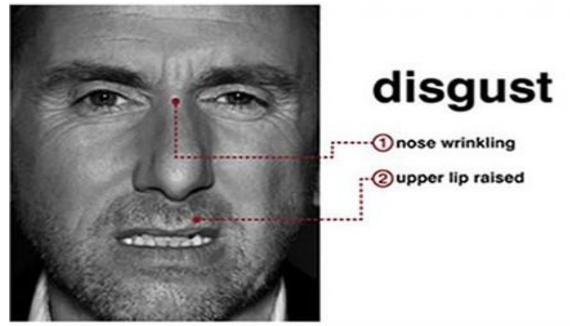
4.1 Dataset Definition [23]

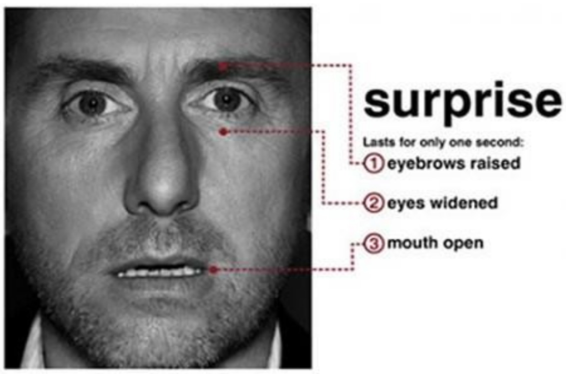
Our model's dataset is the **FER+** dataset, which was designed to detect depression and anxiety by training the dataset (FER+ 2013). The data comprises 38,537 grayscale images of faces at a resolution of 48x48 pixels. **The aim** is to categorize each face into one of seven emotion categories, all labeled, depending on the emotion expressed in the facial expression. The **FER2013** dataset contains images that **vary** in viewpoint, lighting, and scale. Emotions in the dataset are "angry", "disgust", "fear", "happiness", " sad ", "surprise" and "neutral". The training set **consists** of 32,114 examples. The public test set consists of 6,423 examples.

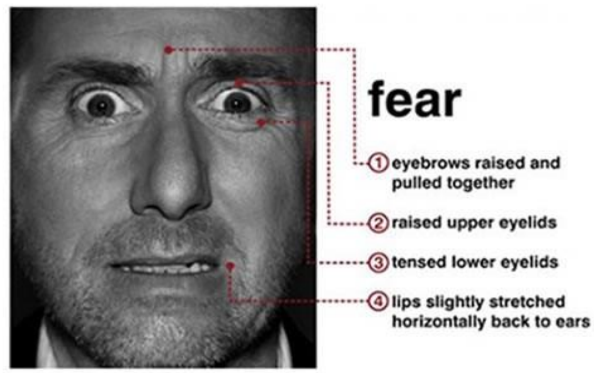
4.2 Dataset Properties

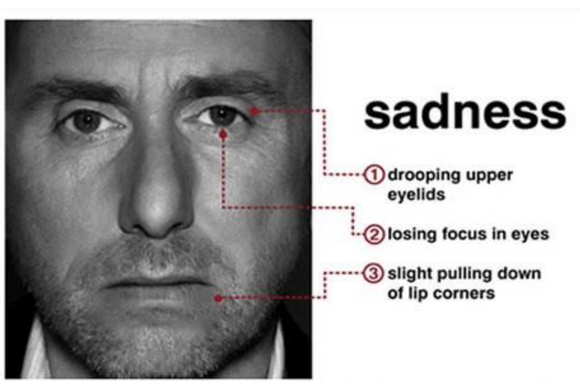
The model will generate seven probability values, each corresponding to seven expressions. The image with the highest probability value for the corresponding expression will be the predicted expression for that image. The region of the image containing the face is resized to 48x48 and is passed as input to the CNN. The network generates a list of SoftMax scores for each of the seven emotion classes. On the screen, the emotion with the highest score is presented. This research proposes a system that can predict and recognize the classification of facial emotions based on feature extraction using the Convolution Neural Network (CNN) algorithm in real-time with the OpenCV library.

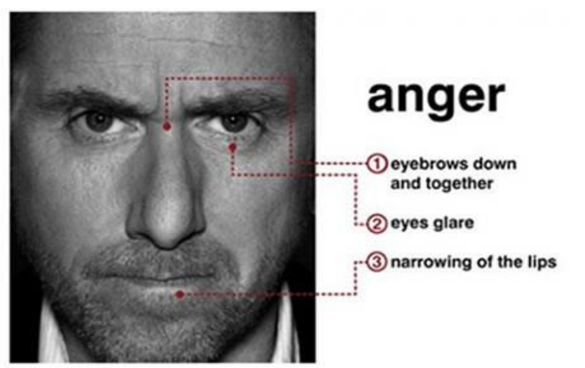

happiness
A real smile always includes:
1 crow's feet wrinkles
2 pushed up cheeks
3 movement from muscle that orbits the eye


disgust
1 nose wrinkling
2 upper lip raised


surprise
Lasts for only one second:
1 eyebrows raised
2 eyes widened
3 mouth open


fear
1 eyebrows raised and pulled together
2 raised upper eyelids
3 tensed lower eyelids
4 lips slightly stretched horizontally back to ears


sadness
1 drooping upper eyelids
2 losing focus in eyes
3 slight pulling down of lip corners


anger
1 eyebrows down and together
2 eyes glare
3 narrowing of the lips

Chapter 5

The Proposed model

In this chapter we discussed the architecture of the proposed system, Frame Preprocessing, Building the Model, and mental Classification. ▪ System Architecture ▪ Frame Preprocessing ▪ Building the model ▪ mental Classification

5.1: System Architecture

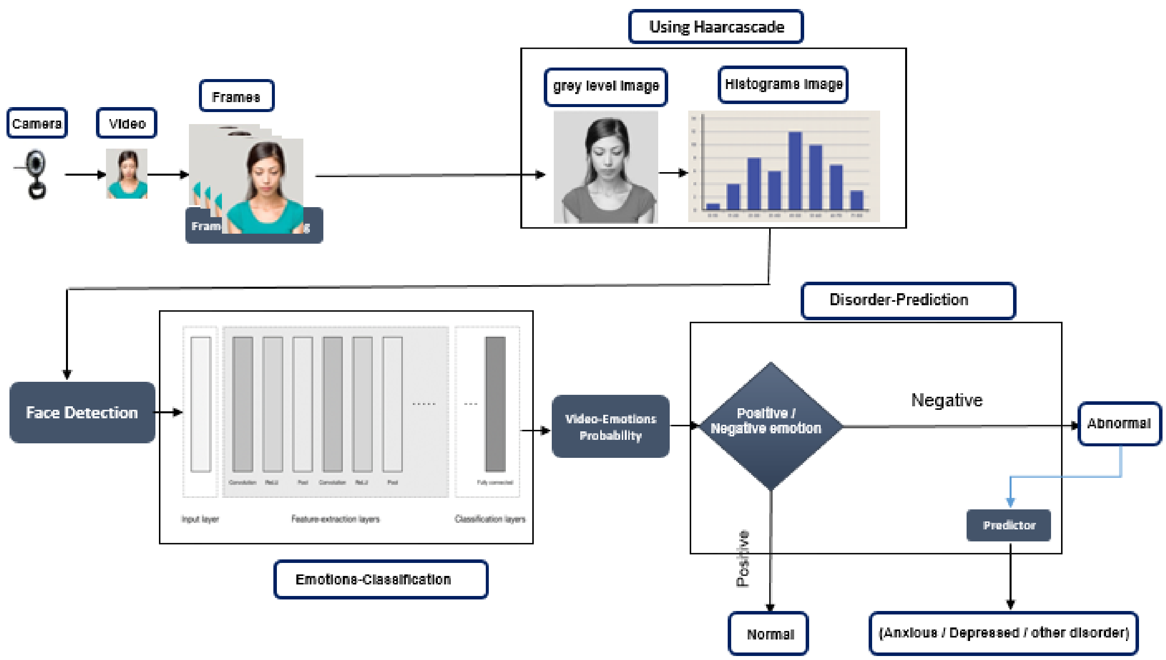


Figure 5.1 (System Architecture)

The Figure 5.1 explains in detail the major steps of our model and shows the block diagram of the proposed system. As can be seen, first, the user's face is uploaded by the camera and converted into many frames. In the second step, each frame in the video is preprocessed, and in the final third step, the frames get into the model to classify whether the user is normal or abnormal and if the user is abnormal detect if he has depression, anxiety, normal, or other disorders.

5.2: Frame Preprocessing:

5.2.1: Frame Preprocessing

- Is the term for operations on frames, these operations do not increase frame information content but decrease it.
- The aim of pre-processing is an improvement of the frame data that suppresses undesired distortions or enhances some frame features relevant for further processing and analysis tasks.
- we are using facial recognition technology which is known as a computer technology that uses artificial intelligence (AI) to recognize and identify human faces in digital photographs. Face detection technology can be used in a variety of industries to enable real-time surveillance and tracking of people, including security, biometrics, law enforcement, entertainment, and personal safety.
- We take 14 frames per second (FPS) from an uploaded video as the landmark of the user in the video will be more clear and more useful for the process of detection we are working on [21].

```
import cv2
import numpy as np
from keras.models import model_from_json

emotion_dict = {0: "Angry", 1: "Disgusted", 2: "Fearful", 3: "Happy", 4: "Neutral", 5: "Sad", 6: "Surprised"}

# load json and create model
json_file = open('D:/Ayat_/-fci/مشروع التخرج/model/Emotion_detection_with_CNN-main/weights/model.json', 'r')
loaded_model_json = json_file.read()
json_file.close()
emotion_model = model_from_json(loaded_model_json)

# load weights into new model
emotion_model.load_weights("D:/Ayat_/-fci/مشروع التخرج/model/Emotion_detection_with_CNN-main/weights/model.h5")
print("Loaded model from disk")

# pass here your video path
cap = cv2.VideoCapture("D:/Ayat_/-fci/مشروع التخرج/model/Emotion_detection_with_CNN-main/an.mp4")
cap.set(cv2.CAP_PROP_FPS, 1)

# get frames from videos
def getFrame(start_sec, End_sec):
    cap.set(cv2.CAP_PROP_POS_MSEC, start_sec * 1000)
    hasFrames, image = cap.read()
    while hasFrames:
        if start_sec <= End_sec:
            cv2.imwrite("image/frame " + str(start_sec) + " sec.jpg", image)  # save frame as JPG file
            return image
        else:
            break
```

5.2.2: Face Detection

- Object detection is one of the computer technologies that is connected to image processing and computer vision. It is concerned with detecting instances of an object such as human faces, buildings, trees, cars, etc. The primary aim of face detection algorithms is to determine whether there is any face in an image or not.

- We use the algorithm to detect faces is Haar Cascades [11] Where it is a machine learning method that involves drilling a classifier from a large number of positive and negative pictures. It's an Object Detection Algorithm that detects faces in images and real-time videos. Paul Viola and Michael Jones are the ones who forward

- we used Haar feature-based cascade classifiers as classifiers for object detection. This classifier follows a machine learning approach in which a cascade operation is instilled from the photographs to find things in additional photos. The detection of faces and facial emotions in images is also successful. The exercise is completed by presenting the classifier with positive and negative images. The properties are then extracted from the image.

- Each feature is a distinct value obtained by subtracting the sum of pixels in the white rectangle from the total of pixels in the black rectangle. In which it recognizes the faces of various people in various settings. Because of integral pictures, the Haar-like feature of any size may be determined in constant time.

- In frame Preprocessing we used the OpenCV library to enhance frames, it provides a training method or pre-trained models, that can be read using the **cv::CascadeClassifier::load** method. Some algorithms we used as:
  - cv2.cvtcolor(): to convert frame to grayscale.
  - cv2.resize(): resize frame 48 * 48.
  - And the result from the previous steps rescales it using a normalization algorithm.

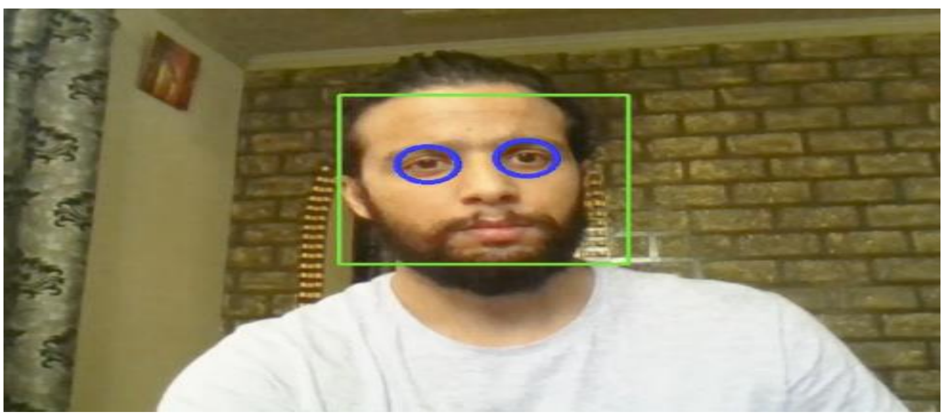


Figure 5.2 Detecting the face using haar cascades algorithm

```python
#variables to detect first and second predictor
first_predictor = [0,0]
final_prediction = [0, 0, 0]
section_of_first_predictor = ['Normal' ,'Abnormal']
sections_of_data = ['anxious', 'Depressed', 'other disorder']

start_sec =0
End_sec = 59
frameRate = 1/14
Nemotion0=0
Nemotion1=0
Nemotion2 =0
Nemotion3=0
i = 0
while True:
    if i > 826:
        break
    i += 1
    success = getFrame(start_sec, End_sec)
    face_detector = cv2.CascadeClassifier(cv2.data.haarcascades +'haarcascade_frontalface_default.xml')
    gray_frame = cv2.cvtColor(success, cv2.COLOR_BGR2GRAY)
    start_sec = start_sec + frameRate
    start_sec = round(start_sec, 2)

    #detect faces available on frame
    num_faces = face_detector.detectMultiScale(gray_frame, scaleFactor=1.3, minNeighbors=5)
```

```python
# take each face available on the frame and Preprocess it
for (x, y, w, h) in num_faces:
    cv2.rectangle(success, (x, y - 50), (x + w, y + h + 10), (0, 255, 0), 4)
    roi_gray_frame = gray_frame[y:y + h, x:x + w]
    cropped_img = np.expand_dims(np.expand_dims(cv2.resize(roi_gray_frame, (48, 48)), -1), 0)
    cropped_img=cropped_img/255

    #predict the emotions
    emotion_prediction = emotion_model.predict(cropped_img)
    maxindex = int(np.argmax(emotion_prediction))

    if emotion_dict[maxindex] == 'Fearful' or emotion_dict[maxindex] == 'Disgusted' or emotion_dict[maxindex] == 'Sad' or emotion_dict[maxindex] == 'Angry':
        first_predictor[1] += 1
        if emotion_dict[maxindex] == 'Fearful':
            Nemotion0 += 1
        elif emotion_dict[maxindex] == 'Disgusted':
            Nemotion1 += 1
        elif emotion_dict[maxindex] == 'Sad':
            Nemotion2 += 1
        elif emotion_dict[maxindex] == 'Angry':
            Nemotion3 += 1
    elif emotion_dict[maxindex] == 'Happy' or emotion_dict[maxindex] == 'Neutral' or emotion_dict[maxindex] == 'Surprised':
        first_predictor[0] += 1

cv2.imshow('Emotion Detection', success)
```

5.3: Building the model

The model was designed using Keras as an API and TensorFlow as a backend we use some the libraries such as NumPy, matplotlib, Keras, and TensorFlow.

Keras definition: is an API designed for human beings, not machines. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear & actionable error messages. It also has extensive documentation and developer guides.

Tensor Flow definition: is an end-to-end open-source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries, and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML-powered applications.

Steps:

1. parameters initialization:
    - some parameters such as number of features = 32, number of labels = 7, number of frames = 14, batch size = 64
      and the number of epochs = 70.

2. Model learning:

- VGG16: is a convolution neural net (CNN) architecture that was used to win ILSVR(ImageNet) competition in 2014. It is considered to be one of the excellent vision model architectures to date. we constructed the model using (CNN) which is a type of neural network which allow working with images and videos.
- we use specifically VGG16 architecture was composed of 6 convolution layers, interleaved with max-pooling, batch normalization, and activation function layers. More specifically, after the in-put layer, there are 2 convolution layers with 64 kernels of size 3×3. The structure repeats but changes in the number of convolution layers and number of kernels. After all the convolution layers, 2 dense layers are added, each with 128 hidden nodes.

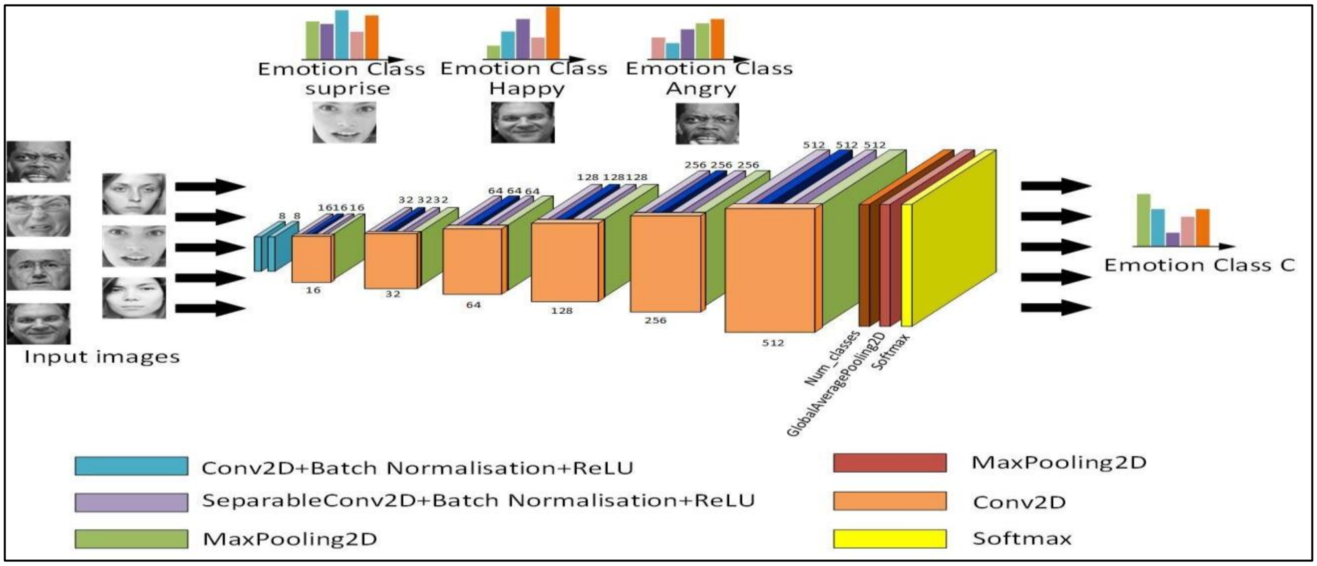


Figure 5.3 the structure of CNN

3. Model optimization:
    - The final dense layer is followed by a soft-max layer to generate the output. We compile the model with **Adam optimizer** with learning rate (0.001), beta_1 = 0.9 and beta_2 = 0.999 and epsilon = 1e-7.

4. In the end, we fit the model on the training dataset and validation dataset where we divided the dataset by 80:20.

```
from keras.layers import Conv2D, MaxPooling2D, BatchNormalization
from keras.layers import Dense, Flatten, Activation
from keras.losses import categorical_crossentropy
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
from tensorflow import keras
from matplotlib import pyplot as plt

num_features = 32
num_labels = 7
batch_size = 64
epochs = 70
width, height = 48, 48

# Initialize image data generator with rescaling
train_data_gen = ImageDataGenerator(rescale=1. / 255)
validation_data_gen = ImageDataGenerator(rescale=1. / 255)

# Preprocess all test images
train_generator = train_data_gen.flow_from_directory(
    'data/train',
    target_size=(48, 48),
    batch_size=64,
    color_mode="grayscale",
    class_mode='categorical')

# Preprocess all train images
validation_generator = validation_data_gen.flow_from_directory(
    'data/test',
    target_size=(48, 48),
    batch_size=64,
    color_mode="grayscale",
    class_mode='categorical')
```

```python
# Build the model
model = Sequential()
model.add(Conv2D(2 * num_features, kernel_size=(3, 3), padding='same', data_format='channels_last',
                 input_shape=(width, height, 1)))
model.add(Conv2D(2 * num_features, kernel_size=(3, 3), padding='same'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D())

model.add(Conv2D(2 * 2 * num_features, kernel_size=(3, 3), padding='same'))
model.add(Conv2D(2 * 2 * num_features, kernel_size=(3, 3), padding='same'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D())

model.add(Conv2D(2 * 2 * 2 * num_features, kernel_size=(1, 1), padding='same'))
model.add(Conv2D(2 * 2 * 2 * num_features, kernel_size=(1, 1), strides=(2, 2)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D())

model.add(Flatten())
model.add(Dense(units=128))
model.add(BatchNormalization())
model.add(Dense(units=128))
model.add(BatchNormalization())

model.add(Dense(num_labels, activation='softmax'))

model.summary()
```

```python
# Compiling the model with adam optimizer and categorical crossentropy loss
model.compile(loss=categorical_crossentropy,
              optimizer=keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-7),
              metrics=['accuracy'])

# Train the neural network/model
emotion_model_info = model.fit(
    train_generator,
    steps_per_epoch=32114 // 64,
    epochs=epochs,
    validation_data=validation_generator,
    validation_steps=6423 // 64,
    # callbacks=[es]
)
```

5.5: mental Classification

This is the final step in the system architecture is mental Classification in this step the model classifies if the user is normal or abnormal first then in the case of abnormal the model predicts if he has depression, anxiety, normal, or other disorder according to the facial expression on his face that was detected.

5.5.1: Classifications

Our system is constructed in Python Programing Language in Two Mainly phases:

1-Emotion with Highest Probability:

Use the CNN algorithm to extract emotion from the frame to detect emotion with the highest probability to obtain one emotion from seven emotions, Disgusted, Fearful, Happy, Neutral, Sad, and Surprised.

2-we classified emotions in two labels [19,20]:

- Positive Emotions: if the emotion is “Happy” or “Neutral” or “Surprised” the results became that detect Human is Normal.

- Negative Emotions: if the emotion is “Fearful “or “Disgusted “or “Sad “or “Angry” the results became that detect Human is Abnormal

.

```
    if emotion_dict[maxindex] == 'Fearful' or emotion_dict[maxindex] == 'Disgusted' or emotion_dict[maxindex] == 'Sad' or emotion_dict[maxindex] == 'Angry':
        first_predictor[1] += 1
        if emotion_dict[maxindex] == 'Fearful':
            Nemotion0 += 1
        elif emotion_dict[maxindex] == 'Disgusted':
            Nemotion1 += 1
        elif emotion_dict[maxindex] == 'Sad':
            Nemotion2 += 1
        elif emotion_dict[maxindex] == 'Angry':
            Nemotion3 += 1
    elif emotion_dict[maxindex] == 'Happy' or emotion_dict[maxindex] == 'Neutral' or emotion_dict[maxindex] == 'Surprised':
        first_predictor[0] += 1

cv2.imshow('Emotion Detection', success)
```

5.5.2: Predictor

If the result with the previous classification is Abnormal classify negative emotions into three labels are 'Anxiety', 'Depression', 'other disorders'

1) If the result of the video is a combination of Fearful and Disgusted emotions then the final predicate is that the human is suffering from an anxiety disorder.

2) If the result of the video is a combination of Sad and Angry emotions then the final predicate is that the human is suffering from depression disorder.

3) Otherwise, the final predicate is that the human is suffering from other disorders and We will get to know it in the future.

```python
x = first_predictor.index(max(first_predictor))
# check if user Normal or Abnormal
print(section_of_first_predictor[x])

# if user Abnormal
if section_of_first_predictor[x]=='Abnormal':
    final=0
    if (Nemotion0 + Nemotion1 )>(Nemotion2+Nemotion3) and Nemotion0 > 0 and Nemotion1 >0:
        final=0
    elif (Nemotion0 + Nemotion1 )<(Nemotion2+Nemotion3) and Nemotion1 > 0 and Nemotion2 >0:
        final=1
    else :
        final =2
    print(sections_of_data[final])
```

Chapter 6

Experimental Results

This chapter reviews the model virtualization, model Testing, Validation and. compare the accuracy of our model to other models

6.1: training a model

```
Epoch 60/70
501/501 [==============================] - 2676s 5s/step - loss: 0.0956 - accuracy: 0.9729 - val_loss: 0.1075 - val_accuracy: 0.9694
Epoch 61/70
501/501 [==============================] - 3010s 6s/step - loss: 0.0994 - accuracy: 0.9710 - val_loss: 0.1665 - val_accuracy: 0.9439
Epoch 62/70
501/501 [==============================] - 1763s 4s/step - loss: 0.0951 - accuracy: 0.9731 - val_loss: 0.1131 - val_accuracy: 0.9644
Epoch 63/70
501/501 [==============================] - 1729s 3s/step - loss: 0.1033 - accuracy: 0.9700 - val_loss: 0.2049 - val_accuracy: 0.9312
Epoch 64/70
501/501 [==============================] - 1725s 3s/step - loss: 0.0978 - accuracy: 0.9707 - val_loss: 0.1568 - val_accuracy: 0.9491
Epoch 65/70
501/501 [==============================] - 1782s 4s/step - loss: 0.0985 - accuracy: 0.9711 - val_loss: 0.1797 - val_accuracy: 0.9436
Epoch 66/70
501/501 [==============================] - 1998s 4s/step - loss: 0.0975 - accuracy: 0.9714 - val_loss: 0.1398 - val_accuracy: 0.9586
Epoch 67/70
501/501 [==============================] - 1733s 3s/step - loss: 0.0945 - accuracy: 0.9742 - val_loss: 0.1266 - val_accuracy: 0.9608
Epoch 68/70
501/501 [==============================] - 1720s 3s/step - loss: 0.0880 - accuracy: 0.9744 - val_loss: 0.1590 - val_accuracy: 0.9527
Epoch 69/70
501/501 [==============================] - 1745s 3s/step - loss: 0.0924 - accuracy: 0.9748 - val_loss: 0.0915 - val_accuracy: 0.9737
Epoch 70/70
501/501 [==============================] - 1734s 3s/step - loss: 0.0927 - accuracy: 0.9738 - val_loss: 0.1584 - val_accuracy: 0.9530
```

```
# confusion matrix
c_matrix = confusion_matrix(test_generator.classes, predictions.argmax(axis=1))
print(c_matrix)
cm_display = ConfusionMatrixDisplay(confusion_matrix=c_matrix, display_labels=emotion_dict)
cm_display.plot(cmap=plt.cm.Blues)
plt.show()
```

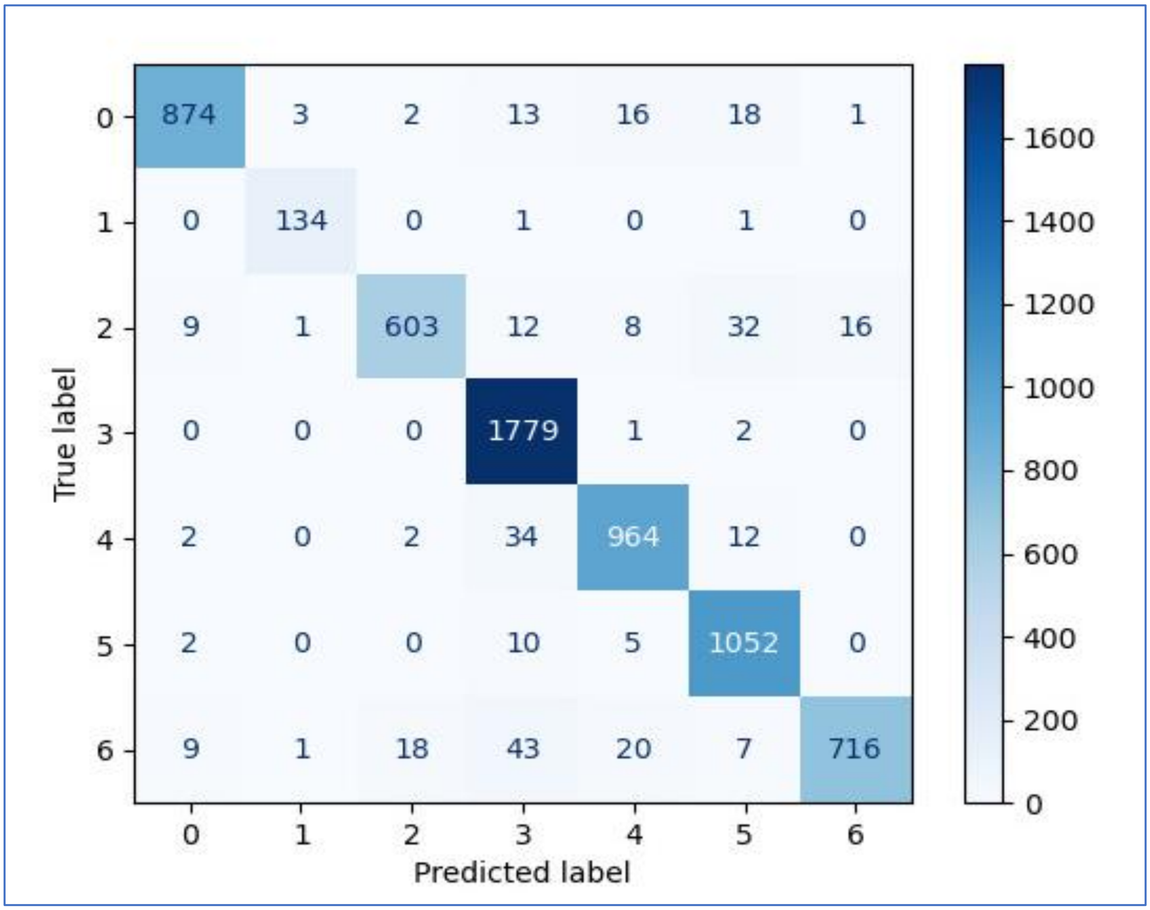


Figure 6.2: confusion matrix

6.3: classification report

```
# Classification report
print("---------------------------------------------------------------")
print(classification_report(test_generator.classes, predictions.argmax(axis=1)))
```

```
------------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.98      0.94      0.96       927
           1       0.96      0.99      0.97       136
           2       0.96      0.89      0.92       681
           3       0.94      1.00      0.97      1782
           4       0.95      0.95      0.95      1014
           5       0.94      0.98      0.96      1069
           6       0.98      0.88      0.93       814

    accuracy                           0.95      6423
   macro avg       0.96      0.95      0.95      6423
weighted avg       0.95      0.95      0.95      6423
```

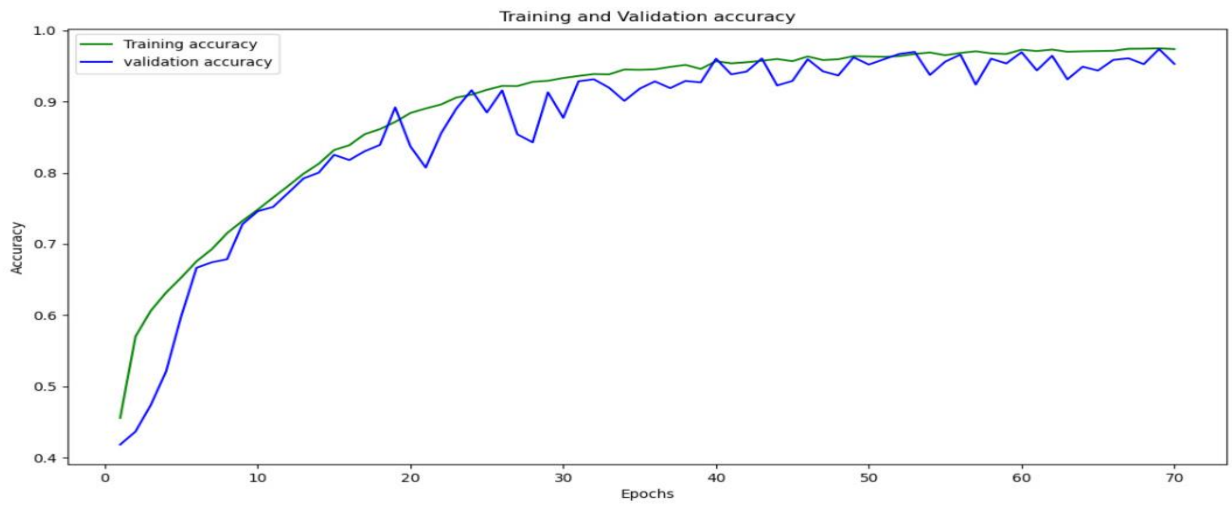


Figure 6.4 The accuracy of training and validation

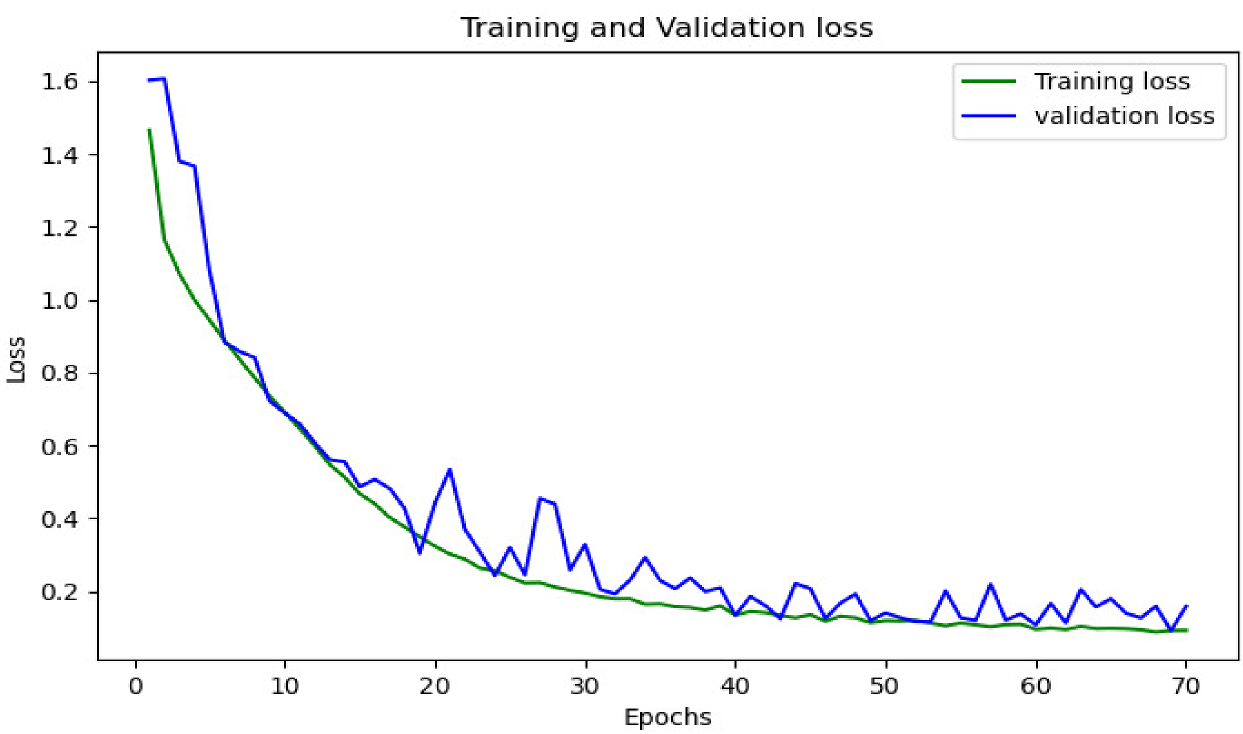


Figure 6.5 The loss of training and validation

6.6 Model Testing and Validation

▪ Visibility of model status

The system should always give users information about the status of a tracked person, through give them feedback if this person has depression, anxiety, or normal.

▪ Match between model and the real world

The System is making a real-time order to alert the user about their mental status at a particular time, which helps them to take action to help themselves.

▪ Flexibility and Efficiency of use

The model is considered to be simple for inexperienced users‟ experience.

▪ Error Prevention

Model content error prevention in case of model can't detect the face gives the exception that he doesn't find a face or if detecting more than one face it gives an exception that he found more than one face.

▪ Help users recognize, diagnose, and recover from errors

Error messages are expressed in plain language and suggest a solution

6.7: Comparison between the proposed model and other models:

Table 6.1 classification accuracies summarization

Paper Name	Dataset	Method	Accuracy Rate
AUTOMATIC PREDICTION OF DEPRESSION AND ANXIETY [9]	FER2013	CNN	63%
Facial Emotion Recognition: State of the Art Performance on FER2013 [5]	FER2013	VGG13	73.28 %
Local Learning to Improve Bag of Visual Words Model for Facial Expression Recognition [13]	JAFFE+(CK+)+MMI	Bag of word	67.484 %
Deep Learning Approaches for Facial Emotion Recognition: A Case Study on FER-2013 [14]	FER2013	Google Net	65.2%
Local Learning with Deep and Handcrafted Features for Facial Expression Recognition [15]	FER+	VGG-SVM	66.31%
Going Deeper in Facial Expression Recognition using Deep Neural Networks [16]	(CK+) + DISFA, +FER	Conv+inception layer	66.4%
Learning to Amend Facial Expression Representation via De-albino and Affinity [17]	RAF-DB+AffectNet+SFEW	ARM(ResNet-18)	71.28%
Facial Expression Recognition using Convolutional Neural Networks: State of the Art [18]	FER+	ResNet VGG	72.2% 72.7%
Automated Detection of Human Mental Disorder	**FER+ +(CK+)**	**VGG16**	**97%**

Table 6.1 Represents a summary of previously reported classification accuracies FER2013 data set. Most reported methods perform better than the estimated human performance by (65.5 %). The previous best-reported single-network accuracy is 73.28 % [22]. In this work, we achieve an accuracy of 97 % and all of this is already mentioned in the previous table.

Chapter 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion:

Since the last few years, and especially during a period of COVID-19 where we had lockdowns, it has caused a considerable degree of fear, concern, and anxiety among the entire population their mental health deteriorates. Disconnected from everything that may slip into depression or anxiety. and the ability to get in contact with therapists and psychology wasn't that easy to do since then. the internet was the only thing available for everyone who need to look for anything, many papers had discussed this option and provided some ideas, such as using facial expressions, mobile/computers logs, and eye expressions with Gaze Tracking, and others which we thought was the best choice, so we solved this problem using facial expression and the FER+ dataset using a VGG-16 algorithm, we thoroughly tune all hyperparameters towards an optimized model for facial emotion recognition. Different optimizers and learning rate schedulers are explored and the best initial testing classification accuracy achieved is 97 %, surpassing all network accuracies previously reported that helped us to detect the mental health of the patient if he/she has depression, anxiety, or normal.

7.2 Future Work:

We aim to add more different mental health diseases in the detection state not only depression, anxiety, or normal as autism, obsessive-compulsive disorder (OCD), Obsessive-compulsive personality disorder (OCPD), and other possibilities can also be added in the future. We also will try to Make the detection not only based on facial expressions but also on eye gaze which can help in making the detection process more accurate. Enhance the accuracy of the model by using more optimizers, and adding more options to the model to help the user like (recommendation, tips, others) and we may also determine the level of the disease the patient has.

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