



Faculty of Computer Science and Information Technology

DEPRESSION DETECTION USING LOGISTIC REGRESSION

DWAYNE CHAN KING CHIU

Bachelor of Computer Science with Honours

(Information Systems)

2025

UNIVERSITI MALAYSIA SARAWAK

THESIS STATUS ENDORSEMENT FORM

TITLE DEPRESSION DETECTION USING LOGISTIC REGRESSION
TECHNIQUE

ACADEMIC SESSION: 2024/2025

(CAPITAL LETTERS)

hereby agree that this Thesis* shall be kept at the Centre for Academic Information Services, Universiti Malaysia Sarawak, subject to the following terms and conditions:

1. The Thesis is solely owned by Universiti Malaysia Sarawak
2. The Centre for Academic Information Services is given full rights to produce copies for educational purposes only
3. The Centre for Academic Information Services is given full rights to do digitization in order to develop local content database
4. The Centre for Academic Information Services is given full rights to produce copies of this Thesis as part of its exchange item program between Higher Learning Institutions [or for the purpose of interlibrary loan between HLI]
5. ** Please tick (✓)

☐

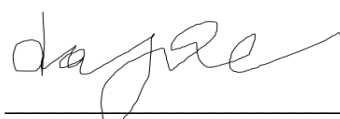
CONFIDENTIAL (Contains classified information bounded by the OFFICIAL SECRETS ACT 1972)

☒

RESTRICTED (Contains restricted information as dictated by the body or organization where the research was conducted)

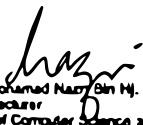
☐

UNRESTRICTED



(AUTHOR'S SIGNATURE)

Validated by


Th. Dr. Mohamed Nazri Bin Mj. Khalidudin Yap
Senior Lecturer
Faculty of Computer Science and Information
Technology
Universiti Malaysia Sarawak

(SUPERVISOR'S SIGNATURE)

Permanent Address

No. 28, Jalan Pandan Indah, 5/18

55100, Kuala Lumpur

Wilayah Persekutuan

Date: 18/7/2025

Date: 18/7/2025

Note * Thesis refers to PhD, Master, and Bachelor Degree

** For Confidential or Restricted materials, please attach relevant documents from relevant organizations / authorities

DEPRESSION DETECTION USING LOGISTIC REGRESSION

DWAYNE CHAN KING CHIU

This project is submitted in partial fulfilment of the requirements for the degree of
Bachelor of Computer Science with Honours (Information Systems)

Faculty of Computer Science and Information Technology

UNIVERSITI MALAYSIA SARAWAK 2025

PENGESANAN KEMURUNGAN MENGGUNAKAN TEKNIK REGRESI LOGISTIK

DWAYNE CHAN KING CHIU

Projek ini merupakan salah satu keperluan untuk
Ijazah Sarjana Muda Sains Komputer dengan Kepujian (Sistem Maklumat)

Fakulti Sains Komputer dan Teknologi Maklumat

UNIVERSITI MALAYSIA SARAWAK 2025

DECLARATION

I hereby declare that this research. Inclusive with all related content is none other than my own work, with consideration of the exception of research-based information which were adapted and extracted from relevant source, which have evidently been stated respectively.

Signed,

A handwritten signature in black ink, appearing to read 'Dwayne Chan King Chiu', written in a cursive style.

Dwayne Chan King Chiu

79242,

Faculty of Computer Science and Information Technology

21st of July 2025

University Malaysia, Sarawak

ACKNOWLEDGEMENT

Firstly, I would like to express my deepest gratitude to my Final Year Project's supervisor, Dr. Mohamad Nazri Khairuddin Yap, who have provided a lot of invaluable guidance and advice throughout this project. With his guidance, I was able to complete this project without many challenges which streamline the process.

Moreover, I would also like to thank my examiner, Dr. Yanti Rosmunie Bujang, for her crucial comments and suggestion which will help me improve for my future endeavour.

I also greatly appreciate Puan Fauziah Bee binti Mohd Salleh from UNIMAS counselling unit for providing her insights and suggestions, her expertise in mental health greatly contributed to ensuring the application remained both relevant and sensitive to the needs of its intended users.

Then, I would also like to acknowledge the help provided by Prof. Dr Wang Yin Chai, the final year project coordinator, who has given me timely information regarding the outline and the submission of my Final Year Project.

Furthermore, I would also like to express my gratitude to the 20 respondents who have participated in my survey prior to the development stage and another 20 respondents who have participated in my user acceptance test after development, their insights and opinion help me throughout the project.

In addition, I would also like to show my appreciation to my friends and fellow course mates for providing their insights and opinion on my project to assist me in completing this project. Finally, I am grateful for my family for their support and encouragements that empower my motivation in completing this project.

Table of Contents

ACKNOWLEDGEMENT	i
Table of Contents.....	ii
List of Figures.....	vi
List of Tables	x
Abbreviation.....	xi
Abstract	xiii
Abstrak	xiv
Chapter 1: Introduction.....	1
1.1 Introduction	1
1.2 Problem Statement.....	3
1.3 Scope.....	3
1.4 Aims and Objectives	4
1.5 Brief Methodology.....	4
1.6 Significance of Project	5
1.7 Project Schedule	6
1.8 Expected Outcome	6
1.9 Report Project Outline	7
1.10 Summary	8
Chapter 2: Literature Review.....	9
2.1 Introduction	9
2.2 Review on existing work.....	10

2.2.1 Depression and Suicide Analysis Using Machine Learning and NLP	10
2.2.2 Detection of Depression-Related Posts in Reddit Social Media Forum.....	12
2.2.3 MoodCapture: Depression Detection using In-the-Wild Smartphone Images	15
2.2.4 Wysa	20
2.3 Review Summary	23
2.4 Tools and technologies that will be used to develop the proposed application.....	25
2.4.1 Flutter	25
2.4.2 TensorFlow	25
2.4.3 Jupyter Notebook	26
2.4.4 FastAPI	26
2.4.5 Postman	26
2.4.6 SQLite.....	26
2.5 Summary	27
Chapter 3: Requirement Analysis and Design	28
3.1 Introduction	28
3.2 Waterfall Model.....	28
3.2.1 Application Requirement	30
3.2.2 Application Design.....	54
3.2.3 Application Implementation	68
3.2.4 Application Testing.....	70
3.2.5 Application Deployment.....	70

3.2.6 Application Maintenance	71
3.3 Summary	71
Chapter 4: Implementation & Testing.....	72
4.1 Introduction	72
4.2 Hardware Specifications	73
4.3 Implementation.....	74
4.3.1 Machine Learning Model	74
4.3.2 Database.....	81
4.3.3 System Architecture	83
4.4 Application Testing	102
4.4.1 Unit Testing.....	102
4.4.2 Integrations Testing	107
4.4.3 Functional Testing	109
4.4.4 System Testing	113
4.4.5 User Acceptance Test.....	117
4.5 Summary	128
Chapter 5: Conclusion & Future work	130
5.1 Introduction	130
5.2 Achievement of Objectives	131
5.3 Project Limitation	133
5.4 Future works.....	135

5.5 Contribution	137
5.6 Conclusion.....	138
References.....	139
Appendix A.....	142
Appendix B.....	144
Appendix C.....	151
Appendix D.....	154

List of Figures

Figure 1.1: Gantt Chart of Initial Project Schedule	6
Figure 2.1: The depression detection framework	13
Figure 2.2: MoodCapture framework	16
Figure 2.3: Screenshots of PHQ-8 questions in MoodCapture	17
Figure 2.4: Screenshots of Wysa chatbot 1.....	20
Figure 2.5: Screenshots of Wysa chatbot 2.....	21
Figure 3.1: Waterfall Model of the proposed application.....	29
Figure 3.2: Bar Chart on respondent familiarities on depression's symptom	32
Figure 3.3: Bar Chart on respondent's source of information regarding mental health	33
Figure 3.4: Sought professional help before.....	34
Figure 3.5: Bar Chart on confidence in identifying sign of depression	35
Figure 3.6: Bar Chart on depression's seriousness	36
Figure 3.7: Bar Chart on depression as discussion topic within circle	37
Figure 3.8: Pie Chart on mental health awareness within	38
Figure 3.9: Statement on respondent's trusted information regarding depression 1.	39
Figure 3.10: Statement on respondent's trusted information regarding depression 2.	40
Figure 3.11: Statement on respondent's trusted information regarding depression 3.....	40
Figure 3.12: Bar Chart on respondent's comfortability of the idea of using AI to detect depression	41
Figure 3.13: Pie Chart on respondent believes on AI's accuracy in detecting depression.....	42
Figure 3.14: Respondent reason on believing or not believing in AI 1	43
Figure 3.15: Respondent reason on believing or not believing in AI 2	44

Figure 3.16: Respondent reason on believing or not believing in AI 3	44
Figure 3.17: Bar Chart on respondent's privacy concern when using AI	45
Figure 3.18: Pie Chart on respondent willingness to share data for a more accurate detection	46
Figure 3.19: Bar Chart on respondent likeliness to use AI-based depression detection application	47
Figure 3.20: Respondent's statement on accuracy of AI in detecting depression 1	48
Figure 3.21: Respondent's statement on accuracy of AI in detecting depression 2	49
Figure 3.22: Respondent's statement on accuracy of AI in detecting depression 3	49
Figure 3.23: Pie Chart on respondent preference on recommendation	50
Figure 3.24: Respondent's statement on additional features of the application 1	51
Figure 3.25: Respondent's statement on additional features of the application 2	52
Figure 3.26: Respondent's statement on additional features of the application 3	52
Figure 3.27: Flowchart of the proposed application	55
Figure 3.28: Context diagram of the proposed application	56
Figure 3.29: Data Flow Diagram level-0 of the proposed application.....	57
Figure 3.30: Level-1 diagram for Process 1.0	58
Figure 3.31: Level-1 diagram for Process 2.0	59
Figure 3.32: Level-1 diagram for Process 3.0	60
Figure 3.33: Level-1 diagram for Process 4.0	60
Figure 3.34: Entity Relationship Diagram of the proposed application.....	61
Figure 3.35: Wireframe of the homepage.....	65
Figure 3.36: Wireframe of the assessment page	66
Figure 3.37: Wireframe of the result page.....	67
Figure 3.38: Pipeline for implementation process	69

Figure 4.1: Snippet of stop words removal function.....	75
Figure 4.2: Snippet of pre-processed data set being used to train BERT model	76
Figure 4.3: Snippet of labelled data using Mental BERT model	76
Figure 4.4: Snippet of using trained Mental BERT as embedding	77
Figure 4.5: Snippet of dimension reduction and validation	78
Figure 4.6: Trained Model Performance Evaluation.....	78
Figure 4.7: Snippet of API integration	79
Figure 4.8: FastAPI endpoint.....	80
Figure 4.9: Snippet of Database Table creation.....	81
Figure 4.10: Snippet of Database Table creation	82
Figure 4.11: Splash Screen of MoodMate	83
Figure 4.12: Home Screen of MoodMate.....	84
Figure 4.13: Demographic Test Screen 1 of MoodMate	86
Figure 4.14: Demographic Test Screen 2 of MoodMate	87
Figure 4.15: PHQ-9 Part Screen 1 of MoodMate	88
Figure 4.16: PHQ-9 Part Screen 2 of MoodMate	89
Figure 4.17: ASQ Part Screen 1 of MoodMate.....	90
Figure 4.18: ASQ Part Screen 2 of MoodMate.....	91
Figure 4.19: Incomplete Message	92
Figure 4.20: Result Screen of MoodMate	93
Figure 4.21: Helpline option in MoodMate result screen	94
Figure 4.22: Contact options	95
Figure 4.23: View result report and retake assessment button	96
Figure 4.24: Result report page.....	97

Figure 4.25: Share report.....	98
Figure 4.26: Download folder in device.....	99
Figure 4.27: MoodMate report in PDF 1.....	100
Figure 4.28: MoodMate report in PDF 2.....	101
Figure 4.29: Usability UAT question	118
Figure 4.30: Clarity UAT question.....	119
Figure 4.31: Performance UAT question.....	120
Figure 4.32: Result UAT question.....	121
Figure 4.33: Trust in accuracy UAT question.....	122
Figure 4.34: Emotional impact UAT question.....	123
Figure 4.35: Overall Impression UAT question.....	124
Figure 4.36: Overall feedback 1 UAT question	125
Figure 4.37: Overall feedback 2 UAT question	126
Figure 4.38: Overall feedback 3 UAT question	126

List of Tables

Table 2.1: the results from each machine learning technique.....	11
Table 2.2: Performance results of classification model.....	14
Table 2.3: MoodCapture’s ML and DL’s accuracy	18
Table 2.4: Summary of features in existing works and proposed application.	23
Table 3.1: Hardware requirement	53
Table 3.2: Software requirement.....	53
Table 3.3: Data Dictionary for user entity	62
Table 3.4: Data Dictionary for assessment entity	63
Table 3.5: Data Dictionary for result entity.....	64
Table 4.1: Hardware Specification.....	73
Table 4.2: Unit Testing 1 of the proposed application	102
Table 4.3: Unit Testing 2 of the proposed application	105
Table 4.4: Unit Testing 3 of the proposed application	106
Table 4.5: Integration Testing of the proposed application	107
Table 4.6: Functional Testing 1 of the proposed application.....	109
Table 4.7: Functional Testing 2 of the proposed application.....	111
Table 4.8: System Testing of the proposed application.....	113
Table 5.1: Achievement of Project Objective of the MoodMate application	125

Abbreviation

Acronym	Full term
AI	Artificial Intelligence
API	Application Programming Interface
ASQ	Ask-Suicide-Screening Questions
BERT	Bidirectional Encoder Representations from Transformers
CPU	Central Processing Unit
DFD	Data Flow Diagram
DL	Deep Learning
ERD	Entity-Relationship Diagram
FAU	Facial Action Units
GB	Gigabyte
GPU	Graphics Processing Unit
IDE	Integrated Development Environment
LIWC	Linguistic Inquiry and Word Count
LDA	Latent Dirichlet Allocation
MAE	Mean Absolute Error
MCC	Matthew's Correlation Coefficient
ML	Machine Learning
NLP	Natural Language Processing
OS	Operating System
PHQ	Patient Health Questionnaire
RAM	Random Access Memory

SDLC	Software Development Life Cycle
SVM	Support Vector Machine
TF-IDF	Term Frequency - Inverse Document Frequency
UAT	User Acceptance Test
UI	User Interface

Abstract

Depressive disorder, commonly known as depression, is one of the most prevalent mental disorders. Moreover, it can be challenging for an individual to determine if they are experiencing depression, as some symptoms overlap with those of other mental disorders or even physical illnesses. Thus, there is a need to develop a mobile application capable of determining user's depression level with the use of Artificial Intelligence (AI). The proposed application will determine depression level by letting users answer several text-based questionnaires by relying on a machine learning technique such as logistic regression to determine depression level.

Abstrak

Kemurungan adalah salah satu gangguan mental yang paling lazim. Seterusnya, ia adalah sukar untuk seseorang individu menentukan sama ada mereka mengalami kemurungan atau tidak, kerana banyak juga symptom yang bertindih dengan gangguan mental lain dan penyakit fizikal. Dengan itu, terdapat keperluan untuk membangunkan aplikasi mudah alih yang mampu menentukan tahap kemurungan pengguna dengan penggunaan Kecerdasan Buatan. Aplikasi yang dicadangkan akan menentukan tahap kemurungan dengan membenarkan pengguna menjawab beberapa soal selidik berasaskan teks dengan bergantung pada teknik pembelajaran mesin seperti regresi logistik untuk menentukan tahap kemurungan.

Chapter 1: Introduction

1.1 Introduction

A mental disorder is described as a psychological disturbance that disrupts an individual's mental state, including their cognition, emotions, and behaviour, ultimately impacting their routine and daily life in a negative way (World Health Organization, 2022). Depressive disorder, commonly known as depression, is one of the most prevalent mental disorders. It involves persistent feelings of hopelessness, a loss of pleasure in activities, and diminished interest in hobbies that approximately 280 million people worldwide suffers from (World Health Organization, 2023). In Malaysia's context, the reported depression in Malaysia has risen twofold from 2016 until 2023 with young adults with age groups 16-19 and 20-29 prone to depression, this is concerning because they are also the future of Malaysia (Muhammed Radzi & Rabindra, 2024). There are many factors affecting. According to National Health Service (n.d.), there are many factors that causes an individual, especially adults to have depression, it could be from a stressful or extremely upsetting life event, personality that is susceptible to depression or even genetics can also partly contribute to depression. Moreover, there are many symptoms to depression and different individual may experience different type and numbers of symptoms due to several factors, a few examples are such as persistent sadness, feeling of worthlessness, huge change in appetite and many more (National Institute of Mental Health, n. d.). Therefore, it can be challenging for an individual to determine if they are experiencing depression, as some symptoms overlap with those of other mental disorders or even physical illnesses. Additionally, individuals may face challenges in assessing mental health resources or support for early assessment due to limited availability or financial constraints. Given these challenges, there is a need for accessible, preliminary tools that can

help individuals assess their depression status. Recent advances in technology, particularly in machine learning, offer promising ways to support mental health assessment by identifying patterns and risk factors associated with depression.

Machine learning which is a part of Artificial Intelligence (AI) has been evolutionary and influenced many industries for various applications such as weather forecasting, environmental monitoring, sales forecasting and so on (Zhou, 2021). Therefore, healthcare, particularly mental health, is no exception, as machine learning leverages historical data and continually improves with increasing input, making it a powerful tool for predicting and addressing mental health conditions, and in our case, depression (Chung & Teo, 2022). Moreover, Natural Language Processing (NLP) has been a prominent tool in analysing text and make prediction since it can make sense of text data and understand the sentiment behind it (Rendyk, 2024). Thus, making NLP a highly suitable approach for predicating depression. Furthermore, with the growing emergence of mobile application usage, deploying the trained model into a mobile platform offers a convenient way for user to conduct self-assessment on their mental condition, hence, providing a non-intrusive method for early detection of depression.

1.2 Problem Statement

According to M. Matlala, et. Al (2018), mental health issues, particularly depression, are often underdiagnosed due to stigma, lack of resources, and inadequate access to mental health professionals. This could be detrimental to the society as untreated depression can lead to profound emotional distress, significantly impairing an individual's health, well-being, and functional capacity that results in disrupting their physical and mental health, this could in turn undermine their ability to perform daily tasks, maintain relationships, and participate effectively in the community (Ritcher et al, 2021). Additionally, according to Ritcher et al (2021), untreated depression significantly increases the risk of suicide with approximately up to 800,000 cases per year which in turn may create a broader impact on societal productivity and healthcare resources.

This project seeks to create a tool that can provide preliminary assessments of depression levels through machine learning technique, enabling users to gain insights into their mental health and prompting them to seek professional help if necessary. By leveraging machine learning, specifically Logistic Regression, this tool aims to provide users with an initial indication of their depression level, potentially encouraging early intervention and professional support.

1.3 Scope

The scope of this project will focus mostly on assessing depression on the Faculty of Computer Science & Information Technology (FCSIT). The FCSIT students were selected due to academic pressure and workload associated with the course, making early detection and awareness of mental health quite relevant. This application only seeks to detect their level of

depression and only recommend them to seek help from expert if their depression level is found to be severe.

1.4 Aims and Objectives

The aim of this project is to develop a machine learning model using Logistic Regression to detect depression levels and integrate it into a mobile application for user assessment. The objectives are as follows:

- This project aims to raise user awareness on their depression's levels which can be achieved by analysing user's text input and displaying depression levels depending on the input.
- To enable early detection on their mental health by identifying early signs or symptoms of depression.
- To develop and implement a tool that is capable of assessing depression level with the help of machine learning model, serving as a functional solution for early self-assessment, by providing users with potential depression score and contributing factors to their depressive state.

1.5 Brief Methodology

The project will adopt waterfall model which is a sequential process that follows a linear process consist of six phases which are application requirement, application design, application implementation, application testing and application deployment and application maintenance. The procedure of this project involves gathering data from social media platform. Social media platforms are chosen because they contain real-time expression and interaction between users

which often reflect on their personal experience, emotional state and behaviour useful for mental health analysis. Then, the collected data will undergo preprocessing to handle inconsistencies to ensure that the model will be able to capture and learn

A Logistic Regression model will then be trained on this labelled dataset to predict depression levels accurately. Logistic Regression is useful in predicting depression because it is a classification algorithm that can predict the probability of depression levels based on the given input. In this case, a specialized form of Logistic Regression called Multinomial Logistic Regression will be used, as it supports multiclass classification needed to predict depression levels, unlike standard Logistic Regression, which is limited to binary classification. Therefore, it will be able to classify 4 depression levels.

Finally, the trained model will be deployed in a mobile application, enabling users to receive preliminary assessments of their depression level based on their input. The mobile application will ask users several questions and the results will be based on Patient Health Questionnaire-9 (PHQ-9) and Ask Suicide-Screening Questions (ASQ) with the addition of optional user's input from the text to analysis to determine their depression level, therefore, Natural Language Processing (NLP) method will be used for this project.

1.6 Significance of Project

This project aims to assist individuals in assessing their mental health status, particularly depression, especially for those who cannot afford professional services. By offering preliminary assessments of depression levels, the project seeks to enhance self-awareness about mental health and potentially mitigate the risk of mental health deterioration. Ultimately, this could help bridge the mental health care gap, providing essential support to those in need.

1.7 Project Schedule

This project will start on 19th of October 2024 until 30th of June 2025 as per the current Gantt Chart attached in Figure 1.1. The full Gantt Chart can be found in Appendix A.

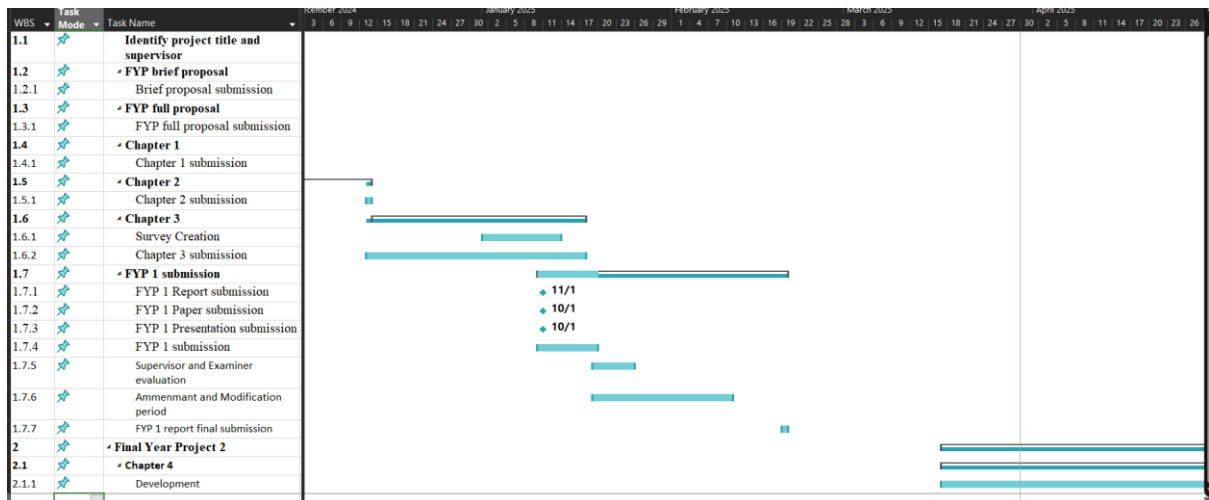


Figure 1.1: Gantt Chart of Initial Project Schedule

1.8 Expected Outcome

The project outcomes will include a functional mobile application that allows users to input data and receive real-time feedback on their depression level. The trained model contributes to this project by analysing user's input to predict their depression level, thus providing an accurate mental health assessment.

1.9 Report Project Outline

Chapter 1: Introduction

This chapter will serve as the introduction to the proposed depression detection via Logistic Regression technique application. This section will include – introduction, problem statement, objectives, methodologies, scope, significance of the project, project schedule and the expected outcome.

Chapter 2: Literature Review

This chapter will explore and review similar existing system to this project with the goals to identify similarity, differences, benefits and limitations of the existing and the proposed system for comparison purposes.

Chapter 3: Requirement and Analysis Design

This section will delve deeper into the methodologies and the steps to design and develop the proposed the application in this project. This will include, the process of implementation, tools and framework used and so on.

Chapter 4: Implementation and testing

This chapter will be the implementation of the proposed application. The proposed application will be developed and then a testing phase will be conducted to make sure the developed application run smoothly and run as intended. Moreover, feedback will be gathering from reviewers to ensure the application is feasible in real life situation.

Chapter 5: Conclusion and future work

This chapter will be the conclusion of this project, and final assessment on how well this project runs. Furthermore, this chapter will also explore the lessons learnt from this project which will serve as an inspiration for future work and find improvement for future project.

1.10 Summary

This chapter concludes the idea of the proposed application. With introduction and background study as the basic concept of the system and its purposes with project statement serving as the issues that inspired the project's objective to solve ongoing issues. Moreover, significance of the project will highlight the importance of this project and how much it will contribute to the community. Scope focuses on the range or the boundary of this project. Then, methodologies which includes Natural Language Processing (NLP) and Logistic Regression to detect depression. Lastly, the outline of each chapter highlights the purposes of each project and the flow of the project.

Chapter 2: Literature Review

2.1 Introduction

This chapter will focus on reviewing other existing work related to this proposed application. There exist several related works with the purpose of detecting illness and other phenomenon by utilising machine learning such as customer behaviour prediction, environmental phenomenon detection, disease diagnosis and detection and so on. Moreover, all of them employ distinct algorithms in their development with some of the work focusing solely on researching the most suitable algorithm in predicting a certain phenomenon by using accuracy metrics with the results given. Furthermore, many existing works also uses different approaches in their detection such as facial recognition, scoring metrics and even sound-based detection. Therefore, this chapter will find out how different machine learning algorithms are utilized in existing works to achieve high accuracy and how certain feature extraction, or optimization technique can help in getting the most optimal accuracy in AI detection. Additionally, this chapter will examine the significance and feasibility of diverse approaches to find out how existing work employ different approach to achieve same objectives as this proposed application, eventually learning the benefits and limitation of other approaches. Then, this chapter will also dive into the tools and technologies used for the proposed application, explaining each of them. This literature review aims to evaluate prior studies and methodologies related to depression detection using machine learning by identifying key advancements, limitations, and gaps that justify the direction of this project.

2.2 Review on existing work

Several studies have demonstrated the use of artificial intelligences in detecting and assessing depression, this section will delve into the existing works of depression detection, examining the approaches and algorithms employed and analysing how they achieve their objectives.

2.2.1 Depression and Suicide Analysis Using Machine Learning and NLP

One notable work by Jain et al (2022) explored the usage of NLP to analyse text for depression and suicide analysis via social media post, the author has used multiple machine learning technique to predict depression such as Logistic Regression, Random Forest, Naïve Bayes and Support Vector Machine (SVM). The author explored r/suicidewatch and r/depression subreddit from Reddit and declared it as a space for users to genuinely seek help and be honest about their mental state, thus the objective is to predict depressions and the accuracy of several machine learning techniques from the two subreddits' post.

The methodology of this study starts with collecting data from over 60, 000 Reddit post from r/depression and r/suicidewatch then preprocess the data. Pre-processing data include lowercasing, tokenization, removing stop word and stemming. After that, pre-processed data were then applied to 4 machine learning techniques: Logistic Regression, Naïve Bayes, Support Vector Machine and Random Forest.

The yield results are as shown:

Table 2.1: the results from each machine learning technique

(Depression and Suicide Analysis Using Machine Learning and NLP: Jain et al, 2022)

ML Technique	Subreddit	Precision	Recall	f1-score
Logistic Regression	r/suicidewatch	0.80	0.79	0.79
	r/depression	0.79	0.80	0.79
Naïve Bayes	r/suicidewatch	0.78	0.72	0.75
	r/depression	0.74	0.80	0.77
Support Vector Machine	r/suicidewatch	0.77	0.78	0.77
	r/depression	0.77	0.76	0.77
Random Forest	r/suicidewatch	0.78	0.77	0.77
	r/depression	0.77	0.77	0.77

The reported performance metrics showed that Logistic Regression and Random Forest achieved similar results, both with around 77% accuracy and an F1-score of 0.77. SVM followed closely, with 77.12% accuracy and an F1-score of 0.77, while Naïve Bayes lagged behind with 74.35% accuracy and an F1-score of 0.74. The authors may have averaged results from two different subreddits, but the exact calculation method remains unclear. Despite this, Logistic Regression and Random Forest showed the highest effectiveness among the models tested. The research highlights the potential of NLP and machine learning in mental health analysis and proven Logistic Regression to be the best in machine learning technique in indicating depression, thus aligning with the project that aims to determine depression using the same technique. However, this review only showcases the accuracy of each machine

learning models without showcasing the application of model in real-world situation, thus the feasibility of the model after implementation is unknown.

2.2.2 Detection of Depression-Related Posts in Reddit Social Media Forum

Another relevant work by (Tadesse, 2019), delved into the impact of Natural Language Processing (NLP) technique and how it affects the accuracy of prediction alongside it's machine learning technique. For more context, NLP techniques also known as feature extraction refers to converting words into numerical form or other form for machine to understand (Tabassum & Patil, 2020). There are several methods or techniques in achieving this, each techniques have their differences and uses according to the context of a machine learning project. The NLP techniques used in this research are the N-grams which consist of unigram and bigram, Linguistic Inquiry and Word Count (LIWC) and Latent Dirichlet Allocation (LDA).

The objective of this research is to analyse Reddit's post and determine factor that indicate depression with the use of NLP and machine learning technique. The work compares the accuracy of sole NLP technique with machine learning and author's proposed combination of NLP technique with machine learning which yielded the best results out of all.

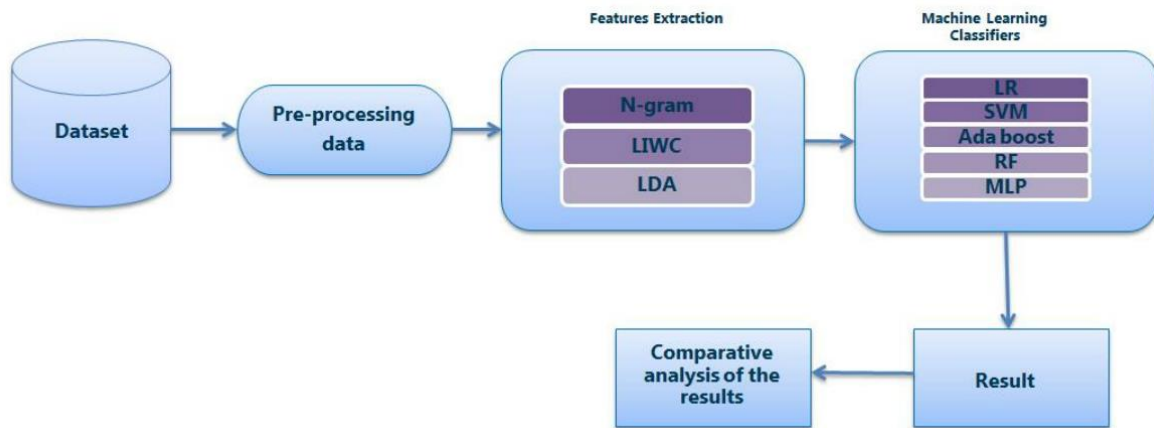


Figure 2.1: The depression detection framework

(Detection of Depression-Related Posts in Reddit Social Media Forum: Tadesse et al, 2019)

Figure 2.1 above highlights the process and methodology used by author to conduct their research; this would include pre-processing data where the process is as followed: Tokenization, URL, punctuations and stop words removal then stemming. After that, the pre-processed data were feed into model with feature extractions. The N-gram that analyse the sequence of words with Term Frequency - Inverse Document Frequency (TF-IDF) to rank the importance of word to scale down less important or very frequent and yet irrelevant words. LIWC to analyse emotion behind texts to understand each post's emotional state. Alongside LDA to discover hidden topic behind each post. Then, the data was process to machine learning classifier which includes Logistic Regression, Support Vector Machine, Random Forest, Adaptive Boosting and Multilayer Perceptron classifier.

The measurement metric used to compare in this research is accuracy, precision, recall and F1. The results yielded are as shown:

Table 2.2: Performance results of classification model

(Detection of Depression-Related Posts in Reddit Social Media Forum: Tadesse et al, 2019)

FEATURE	LR				SVM				RF				Ada Boost				MLP			
	Acc.	F1	P	R	Acc.	F1	P	R	Acc.	F1	P	R	Acc.	F1	P	R	Acc.	F1	P	R
LIWC	69%	0.80	0.95	0.69	74%	0.74	0.75	0.72	78%	0.84	0.77	0.95	67%	0.81	0.68	0.99	70%	0.72	0.74	0.71
LDA	77%	0.83	0.82	0.84	72%	0.80	0.75	0.88	68%	0.67	0.68	0.68	66%	0.74	0.61	0.95	75%	0.74	0.75	0.72
unigram	68%	0.80	0.93	0.79	70%	0.81	0.70	0.89	71%	0.81	0.71	0.96	72%	0.81	0.73	0.92	70%	0.81	0.71	0.95
bigram	80%	0.79	0.81	0.78	80%	0.80	0.79	0.82	74%	0.73	0.75	0.72	71%	0.68	0.75	0.63	79%	0.78	0.80	0.76
LIWC+LDA+unigram	80%	0.84	0.88	0.81	79%	0.81	0.81	0.81	83%	0.84	0.82	0.86	73%	0.72	0.87	0.62	78%	0.81	0.84	0.79
LIWC+LDA+bigram	89%	0.89	0.89	0.92	90%	0.91	0.89	0.93	85%	0.85	0.83	0.87	79%	0.81	0.72	0.93	91%	0.93	0.90	0.92

^aAcc. represents accuracy; LR=Logistic Regression, SVM=Support Vector Machine, RF=Random Forest, Ada Boost=Adaptive Boosting, MLP=Multilayer Perceptron

Based on the results, it is shown that Support Vector Machine with Bigram feature gives the best results with 80% accuracy. However, author's proposed combination of NLP features with a classifier outperforms all other classifier with single feature, with the best being Multilayer Perceptron classifier with LIWC+LD+bigram shows a high accuracy of 91%. This research emphasizes on the importance of selecting the correct NLP techniques and its classifier partner to create an accurate prediction. It also emphasizes on value of exploring multiple NLP techniques rather than relying on a single approach thus prompting further exploration into other appropriate NLP techniques in the proposed application to get the most optimal accuracy. As per the first review, this review only emphasizes on the accuracy of each model this time with the involvement of feature extraction technique but did not assess real-world applications of these method and how the addition of feature extractions technique affects real-world application on how it predicts depression on real-life scenario which leaves the efficiency and feasibility uncertain as in the first review.

2.2.3 MoodCapture: Depression Detection using In-the-Wild Smartphone Images

MoodCapture is an AI powered Smartphone application developed to assess user's depression level by capturing their facial cue (Nepal et al, 2024). Facial cues are captured while users are answering the PHQ-8 which is Patient Health Questionnaire (PHQ) for patients to self-assess their illness based on them on how they feel. The PHQ-8 is a self-test for depression level consist of 8 questions that focus on respondent's emotional state in the last two weeks with frequency scale ranging from 0 (Not at all) to 3 (Nearly every day) (Kroenke et al, 2009). Thus, MoodCapture assess user's facial cue that indicate depression while they are answering PHQ-8 by using both machine learning and deep learning technique.

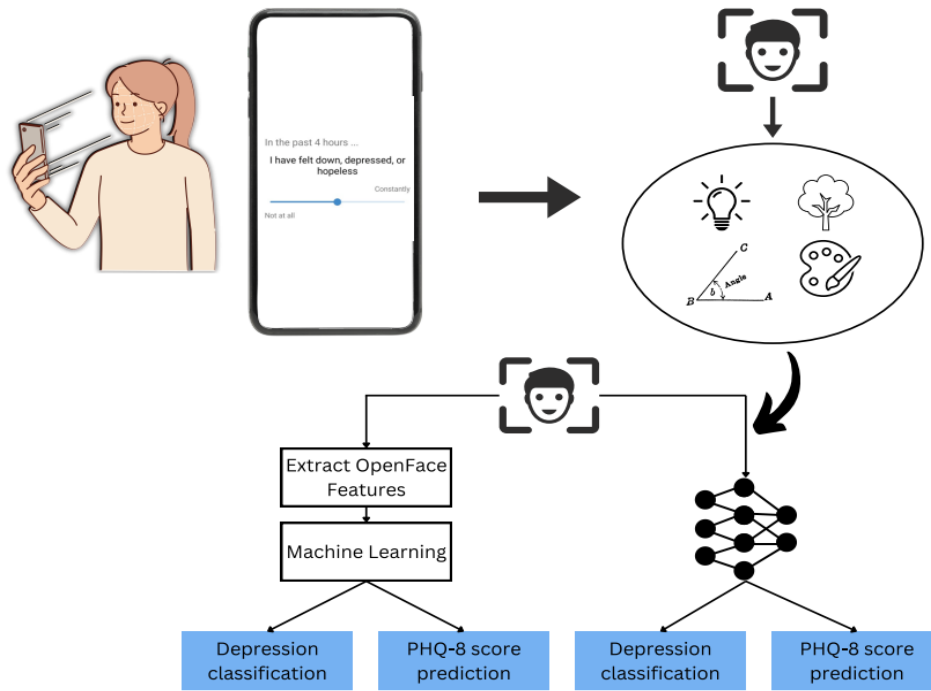


Figure 2.2: MoodCapture framework

(MoodCapture: Depression Detection using In-the-Wild Smartphone Images: Nepal et al, 2024)

Figure 2.2 above shows the framework of MoodCapture and the processes it uses to assess one's depression. Firstly, users answer PHQ-8 depression survey while the app will attempt to take photo of users using the mobile's phone front camera. Then, the photos of users taken will be used to determine user's depression with 5 traits of the photo affecting the results such as brightness, location (outdoor or indoor), angle, colour and background items. After that, OpenFace is used for feature extraction to extract facial feature to be fed into machine learning model while raw images were directly fed to deep learning model. Lastly, depression classification is a binary predictor to predict whether the users have depression or not and a regression model is used to predict their true PHQ-8 score.

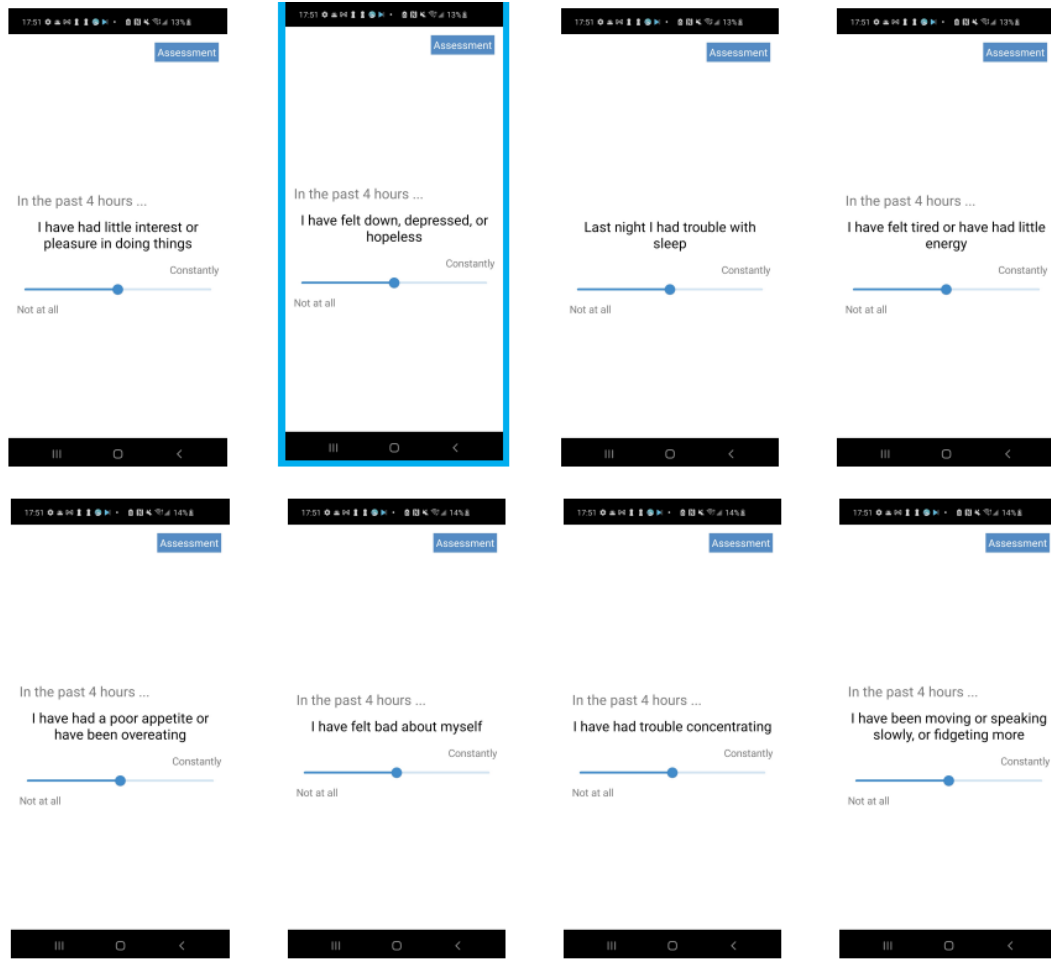


Figure 2.3: Screenshots of PHQ-8 questions in MoodCapture

(MoodCapture: Depression Detection using In-the-Wild Smartphone Images: Nepal et al,2024)

PHQ-8 is needed to be predict because the authors have modified the questions from a 4 answers frequency scale to a 0-100 Likert scale as shown in Figure 2.3 to improve accuracy and precision of their depression level.

As mentioned earlier both machine learning and deep learning techniques were used in this project, with the goals of determining whether the user is depressed or not from their image. On the machine learning side, the classification task uses Logistic Regression while the regression task to predict PHQ-8 score uses ElasticNet with Random Forest to conduct both tasks. Moreover, OpenFace which is a tool is used to extract facial expression to assist in

predicting by feeding extracted features into the model which consist of Facial Action Units (FAU), gaze, eye landmarks, head pose, rigidity parameters, 2D Landmarks and 3D Landmarks.

On the deep learning side, author initially used both pre-trained model such as EfficientNet and InceptionResNetc3 but since EfficientNet provide better performance, they decided to fine-tune for depression dataset.

The accuracy metrics used for this application to evaluate accuracy of the classification by using balanced accuracy and Matthew’s Correlation Coefficient (MCC) since MCC were used to predict binary accuracy whereas mean absolute value (MAE) were used to evaluate regression’s accuracy. The results as shown:

Table 2.3: MoodCapture’s ML and DL’s accuracy

(MoodCapture: Depression Detection using In-the-Wild Smartphone Images: Nepal et al,2024)

Method	Balanced Accuracy ↑	MCC ↑	MAE ↓
Baseline	0.52 (0.05)	0.03 (0.11)	138.18 (3.71)
LR + EN (MI)	0.52 (0.02)	0.04 (0.03)	135.40 (2.65)
Random Forest (MI)	0.54 (0.02)	0.06 (0.04)	134.45 (2.05)
Random Forest (3D Landmarks)	0.60 (0.04)	0.14 (0.08)	130.31 (3.94)
EffNet	0.61 (0.02)	0.03 (0.00)	137.19 (3.67)

Even though Deep learning method like EfficientNet shows the best balanced accuracy at 0.61 indicating the best at predicting whether the user is depressed or not but Random Forest with 3D landmark excels at predicting PHQ-8 scores with MAE of 130.31.

MoodCapture adopt a somewhat similar approach to this project in predicting depression by utilising questionnaire such as PHQ-8 and image to determine depression and

implement it into a mobile application for user's convenience. Although, the difference of this project lies in this project relying more on NLP and text-based questionnaire to predict depression level to focus more on severity of user's depression rather than just if user is depressed. Moreover, MoodCapture explore the use of both traditional machine learning and deep learning technique to test the accuracy of the prediction, it is worth noting this approach demonstrate the potential of combining multiple models to improve accuracy of detection in the proposed application.

Even though, the idea of predicting PHQ via facial expression is intriguing and MoodCapture did consider multiple reasonable features when capturing facial expression but factors such as facial structure and ethnicity is not accounted for which might affect the accuracy of the prediction. Then, PHQ-8 can indeed provide a general idea of someone's mental wellbeing but it still lacks contexts since it is purely based on predefined questions without considering user's reason for feeling down.

2.2.4 Wysa

Another application worth reviewing is Wysa which is an AI powered mental health chatbot that help users improve their mental state (Shaker, 2024). Wysa was mostly build on several psychology treatment to help its user with not just depression but also other mental illness which includes stress, anxiety, low self-esteem and so on. Moreover, this also allow the chatbot to detect early sign of depression by analysing the text sent by users which indicate the usage of NLP during development, thus making it a relevant review to this project.

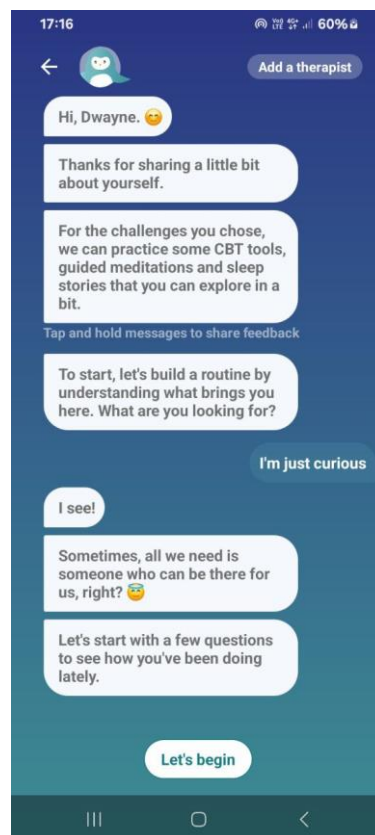


Figure 2.4: Screenshots of Wysa chatbot 1

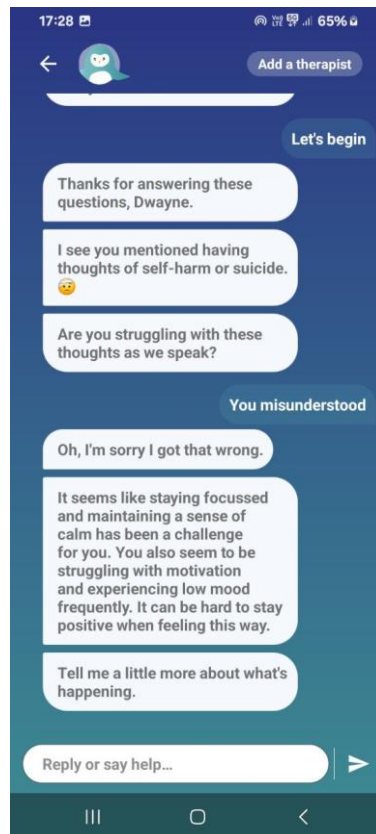


Figure 2.5: Screenshots of Wysa chatbot 2

Figure 2.4 and Figure 2.5 above shows the general user interface of Wysa chatbot, it begins with users selecting mental illness they are going through and answer a few questionnaires on how they are during the last 2 weeks to personalize the chatbot to the users. Furthermore, Wysa also allow for hybrid approach when tackling mental health, with the default chatbot guiding users through their struggle and the option to connect to a professional help.

Although Wysa is developed with the goal mainly for emotional support and mental health improvement, it is still worth nothing that it is relevant to depression detection because chatbot can analyse text to detect pattern from users to indicate their current mental state, this is done to keep track of the user's wellbeing. Therefore, this make Wysa a competent

application in predictive analysis. Moreover, Wysa was proven to help users in decreasing their depressive symptoms which make them one of the most popular AI powered self-help applications (Haque & Rubya, 2023).

In the context of depression detection project, Wysa's implementation of AI to identify mental health patterns provides a relevant case study, highlighting the importance of user engagement and hybrid care in developing effective mental health interventions. Furthermore, Wysa approach to personalise user's profile beforehand is noteworthy as it enhances user's engagement. This approach is a valuable idea that can be taken into consideration during development. While Wysa incorporates AI to analyze user text for mental health patterns, it is primarily designed as a self-help tool rather than a diagnostic system, hence its depression detection capabilities might be limited.

2.3 Review Summary

Table 2.4: Summary of features in existing works and proposed application.

Features	Depression and Suicide Analysis Using Machine Learning and NLP	Detection of Depression-Related Posts in Reddit Social Media Forum	MoodCapture: Depression Detection using In-the-Wild Smartphone Images	Wysa	Proposed application
Facial Analysis	✗	✗	✓	✗	✗
Text Analysis	✓	✓	✗	✓	✓
Social media Data	✓	✓	✗	✗	✓
Machine Learning	✓	✓	✓	✓	✓
Feature Extraction	✗	✓	✗	✗	✓
PHQ Questionnaire	✗	✗	✓	✗	✓
ASQ Questionnaire	✗	✗	✗	✗	✓
Top contributing Factors	✗	✗	✗	✗	✓
Interactive System	✗	✗	✓	✓	✓

Table 2.4 outline some features to be compared between the reviews, the first feature - facial analysis which is a feature that analyses pattern behind human facial expression and text analysis refers to analysing inputted text to understand the context and pattern behind the texts.

Then, social media data refers to usage of social media content to train the model, machine learning refers to the usage of AI when for their respective works and feature extraction is technique utilises to optimize the data to improve model performance. PHQ questionnaire refers to the usage of PHQ as a metric to predict depression and interactive system refers to implemented system that users are able to interact with to get utilize for their own needs.

From Table 2.4, it is shown that several reviews employ respective features to enhance their work's functionality. While only Review 3 utilises facial recognition to detect depression while the other reviews and including the proposed application utilises more on text analysis which suggest that many prefer text-based approach in depression detection. This could indicate that text-based detection offers a simpler and accurate assessment as opposed to facial recognition which relies' on user's face that may compromise user's privacy and faces with more challenges to improve accuracy as highlighted in Review 3 whereby the author uses PHQ-8 metric to further validate the results. Therefore, text-based approach offers a more adaptable application to a wide range of users without relying on additional hardware or visual data.

Furthermore, only Review 1 and Review 2 uses social media such as Reddit to train their model, which is what the proposed application needs to do as social media provide a rich source of real-world, text data that reflects the diverse users employ to express their mental health experiences. Additionally, it is without a doubt, all reviews rely on machine learning techniques to develop respective works, even though techniques use may differ. Moreover, Review 2 highlighted the importance of selecting the correct feature extraction technique to get the most accurate detection which is what the proposed application aims to do.

Then, Review 3 utilises PHQ Questionnaire to validate their PHQ results based on facial recognition and extended PHQ, whereas proposed application will also rely on PHQ with the addition of optional text-based elaboration for each question as per the domain expert's

suggestion. The proposed application will also have two additional features that other work does not which is the inclusion of Ask Suicide-Screening Questions (ASQ) questionnaire and top contributing factors for user's mental state.

Lastly, only Review 3 and Review 4 provides interactive system for users since Review 1 and Review 2 emphasises more on other machine learning and feature extraction techniques, with proposed application as interactive system as well to assess user's depression level.

2.4 Tools and technologies that will be used to develop the proposed application

2.4.1 Flutter

The proposed application is in the form of mobile application; therefore, Flutter will be used to develop the mobile application for Android and iOS which this application aims to. The application will serve as the user's interface for user to input their answers to detect their depression level.

2.4.2 TensorFlow

TensorFlow will serve as the framework for model development, the model behind the proposed application will rely on Tensorflow to build and train the machine learning model and converting the trained model to TensorFlow Lite format which is optimises for mobile application.

2.4.3 Jupyter Notebook

Jupyter will be used for data crawling from Reddit to collect post data from r/depression and r/mentalhealth. Where data will be preprocessed here as well before being used for model training.

2.4.4 FastAPI

FastAPI will be used for Application Programming Interface (API) development to ensure smooth communication between the model and the mobile application, enabling the delivery of accurate results to users.

2.4.5 Postman

Postman will be used to test if the API between the model and mobile application is working properly.

2.4.6 SQLite

SQLite will be used for local data storage within the mobile application. It's a lightweight, serverless database, ideal for managing small datasets like user inputs (e.g., depression questionnaire responses). It ensures data persistence across app sessions without needing a server, which simplifies the app's setup and makes it easier to deploy.

2.5 Summary

To summarize, case studies and examples in literature review can foster a deeper understanding of project as it helps in bridging theoretical research and practical implementation. Moreover, case studies of research topic encourage careful consideration of existing methods and approaches within a project as it offers valuable insight on the various approaches and methods, thus encouraging refinement on the project's chosen approaches and methodology. Furthermore, practical implementation as demonstrated with applications such as MoodCapture and Wysa enhance the understanding of feasibility and practical aspect of project development which also offer inspirations on the project in designing an efficient application for users. Thus, engaging with these cases helps in refining perspectives and further advance the state of the knowledge of relevant projects.

Chapter 3: Requirement Analysis and Design

3.1 Introduction

This chapter will analyse the requirement of the projects and discuss the system design, which in other word, it is the methodologies of this project. It will discuss. This chapter will outline the development approach used in this project which is System Development Life Cycle (SDLC) framework, thus covering the 5 steps of SDLC which consist of requirement, design, development, testing, and deployment. However, maintenance steps of SDLC will be left out first since this project is meant to be developed as a standalone implementation with no immediate plans for production deployment unless needed in the future. Moreover, this project will adopt the Waterfall Model of SDLC as a guide for the proposed application's development process.

3.2 Waterfall Model

Waterfall Model is chosen as this project development steps because it is a sequential process that follows a linear process to completing the project which aligns well with the project's purpose of developing a standalone application. Furthermore, each phase being completed sequentially ensures a clear deliverable at every stage (Khan, 2023). As mentioned earlier, this project specifically will consist of six phases which are application requirement, application design, application implementation, application testing and application deployment and application maintenance as referred in Figure 3.1 below and six phases must be executed sequentially which means, current phase have to be completed first before going into the next phase and next phases cannot be started if the previous phase is not completed.

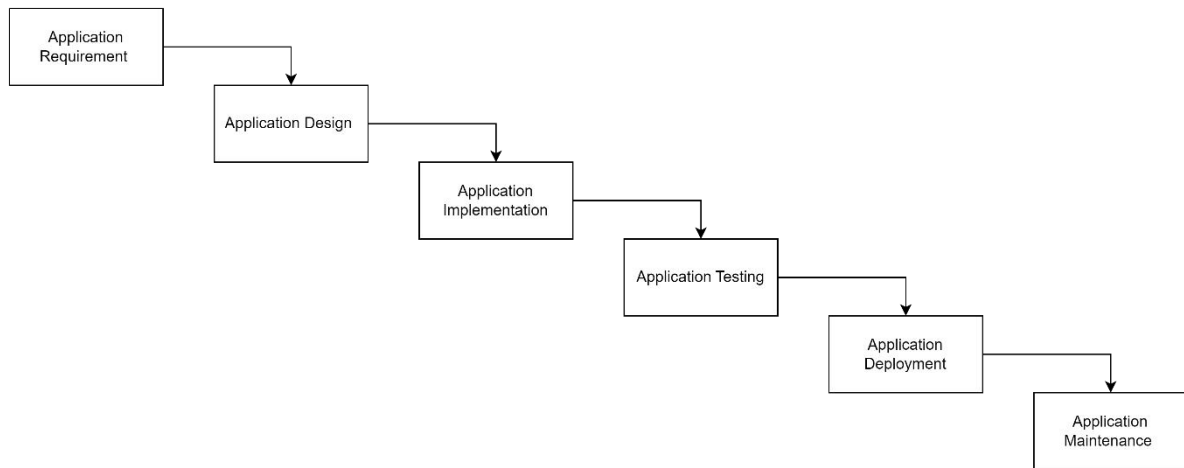


Figure 3.1: Waterfall Model of the proposed application

(Waterfall Model Used in Software Development Reference: Software Requirements Engineering Waterfall Model: Khan, 2023)

In application requirement phase, the application's requirement will be analysed. Then, in application system, several diagrams such as context diagram, data flow diagram and wireframe will be illustrated based on the proposed application will be discussed to understand the inner working of the application. Application implementation phase is when the application will be implemented followed by application testing where implemented application will be tested. Lastly, application will be deployed once testing is finished without issue.

3.2.1 Application Requirement

This section will dive all the requirements for the proposed application. First and foremost, functional and non-functional requirement will be explored first with functional requirement highlighting on the application's main features and functions, whereas non-functional focuses on the performance and reliability of the proposed application.

Secondly, this section will also focus on user's requirement analysis gathered from survey via google form distributed which consist of several close-ended and open-ended questions and the proposed application's software and hardware requirement. User's requirement will be thoroughly analysed to understand user's understanding on depression in general and their concerns and expectations regarding the usage of AI in the proposed application. 20 respondents have participated the survey, and their insight will be explained.

The depression detection application is developed in smart devices. Hence, any smartphones and smart tablets would be able to utilise this application to detect depression. Moreover, this application will be developed to support various smart devices Operation System (OS) such as Android, iOS and others, so that this application will not limit to certain smart devices users.

The depression detection application will consist of two parts which are the front-end and the depression detection AI at the back end. The front-end will focus on the design of the user interface (UI) for user to input their responses prior to getting their depression level result and several programming language and scripting will be used for front-end development. Then, the depression detection AI will be developed with the selected machine learning technique where the AI will be trained to recognize text that indicate depression so that it can make accurate judgement on user's depression level. It is without a doubt that a programming language and several tools are needed to develop and train the AI.

3.2.1.1 Functional Requirements

- i. User should be able to use this application without needing to create an account.
- ii. The application should be able to accurately assess and classify user's depression level.
- iii. User should be able to download their assessed result before ending the session.

3.2.1.2 Non-Functional Requirements

- i. The application shall be compatible to both iOS and Android.
- ii. The application will be supported in English.
- iii. The application ensures user's privacy by not requiring any personal information to conduct the depression assessment.

3.2.1.3 User Requirement

Familiarity on depression's symptoms

This question uses Likert Scale from one to five with:

One - Not familiar at all

Five – Very familiar

Figure 3.2 shows that majority of the respondents are familiar with the symptoms of depression while there are still a few who are still unfamiliar and unsure with depression's symptoms. This indicates that majority of the respondent is somewhat knowledgeable about the symptoms of depression since there are at thirteen respondents (65%) who are at least familiar with the symptoms with just five respondents (25%) as neutral and only two respondent (10%) who are not familiar with the symptoms. Therefore, it is assumed that most have some awareness to depression while only a few does not.

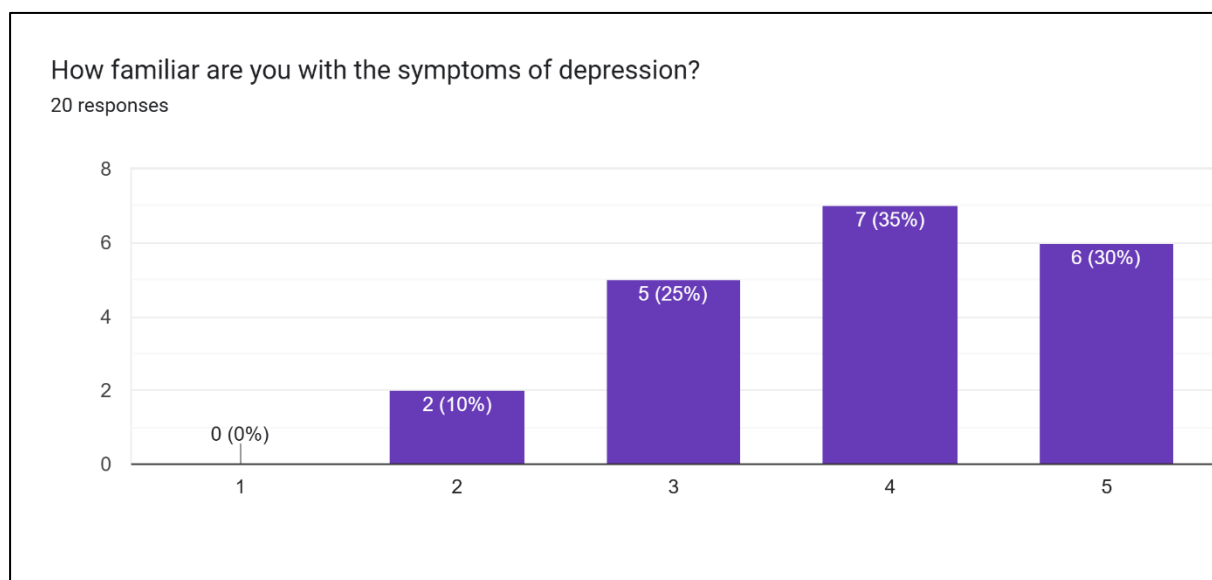


Figure 3.2: Bar Chart on respondent familiarities on depression's symptom

Source of information regarding mental health

Figure 3.3 shows almost all respondent (90%) get their information about depression from social media because almost everyone uses mobile devices these days, therefore, it is a good chance for this application to be developed in mobile application. Moreover, with website being the second most used source to get information with fifteen respondents (75%) also indicate that most people get knowledge regarding mental health from technology because information can be obtained with just a tip of a finger. Furthermore, half of the respondents (50%) learn about mental health via elective classes, which indicate that elective classes from other faculty is somewhat useful in providing knowledge. Healthcare professional and Books being the least used source on mental health with only six (30%) and five (25%) respondents respectively might also mean that respondents do not have access to a more practical resource which this application aim to provide.

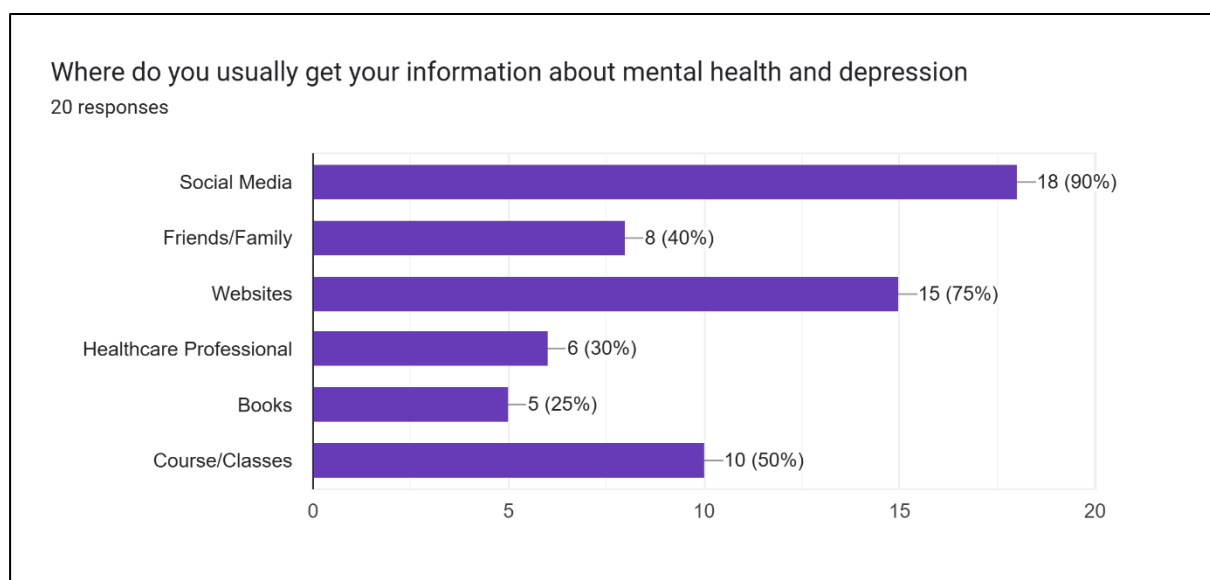


Figure 3.3: Bar Chart on respondent's source of information regarding mental health

Sought professional help before

Figure 3.4 shows that five respondents (25%) sought professional help on mental health concerns before while the rest of the fifteen respondents (75%) did not. This can be assumed that they are unsure if they should share their burden to professional help yet, problem which this application aims to solve because this application can serve as a preliminary test for users to be able to determine their depression level and the application will strongly advice user to seek professional help if things get out of hand.

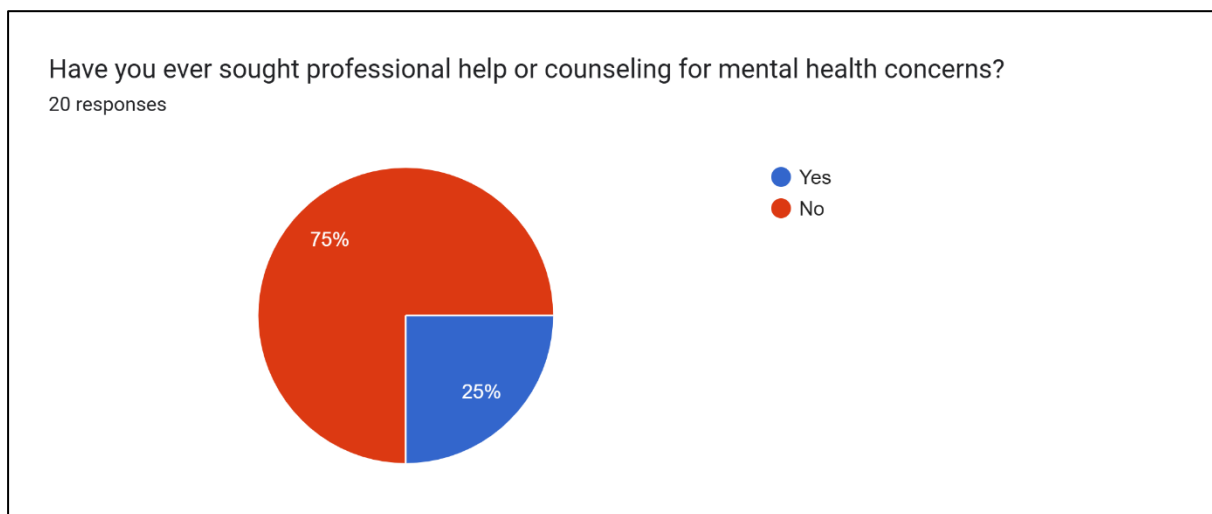


Figure 3.4: Sought professional help before

Confidence in identifying sign of depression

This question uses Likert Scale from one to five with:

One - Not confident at all

Five – Very confident

Figure 3.5 shows that while majority of the respondents (35%) is unsure if they are confident in identifying signs of depression or not and four respondents (20%) is not confident, therefore this indicate that more than half of the people is still in doubt of their ability in identifying depression. However, there are nine respondents (45%) who are at least confident that they can identify sign of depression on themselves or others.

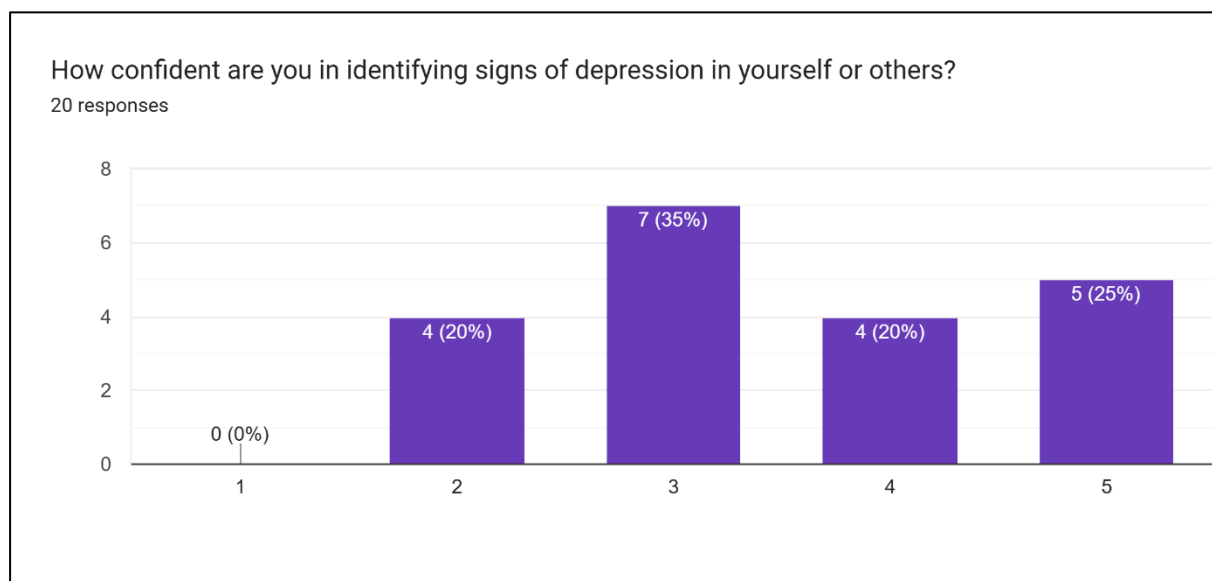


Figure 3.5: Bar Chart on confidence in identifying sign of depression

Seriousness of depression

This question uses Likert Scale from one to five with:

One - Not serious at all

Five – Very serious

Figure 3.6 shows that almost every respondent (85%) thinks that depression is a very serious issue while there is one respondent (5%) who does not think so and two respondents (10%) being neutral. Hence, this indicate that majority of the people are aware that depression is an underlying issue where there is a need to tackle this issue in which the application can contribute to.

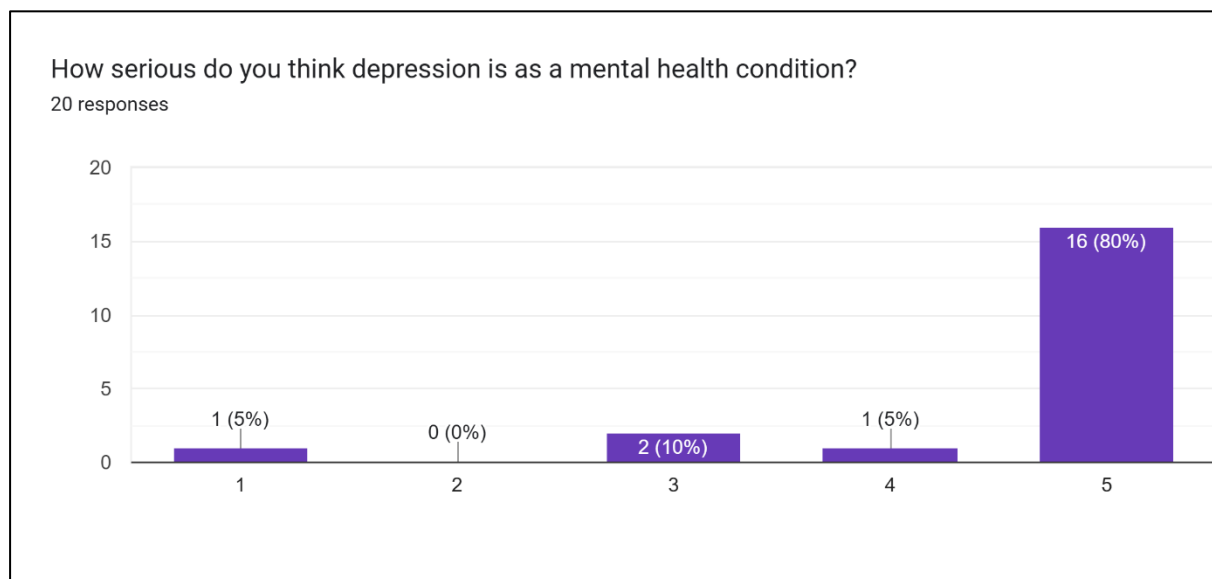


Figure 3.6: Bar Chart on depression's seriousness

Depression as discussion topic within circle

This question uses Likert Scale from one to five with:

One – Very seldom

Five – Very often

Figure 3.7 shows that seven respondents (35%) do talk about depression occasionally but not often while five respondents (25%) seldom talk about depression and four respondents does not talk about depression within their circle at all, with only four respondents (20%) discussed about depression but not too often as well. This can be interpreted that almost everyone does not want to disclose their mental wellbeing to their loved ones might be because of does not weight mental wellbeing as the top priority in our society, therefore this application will serve as an assistant where they can at least get the status of their current depression level.

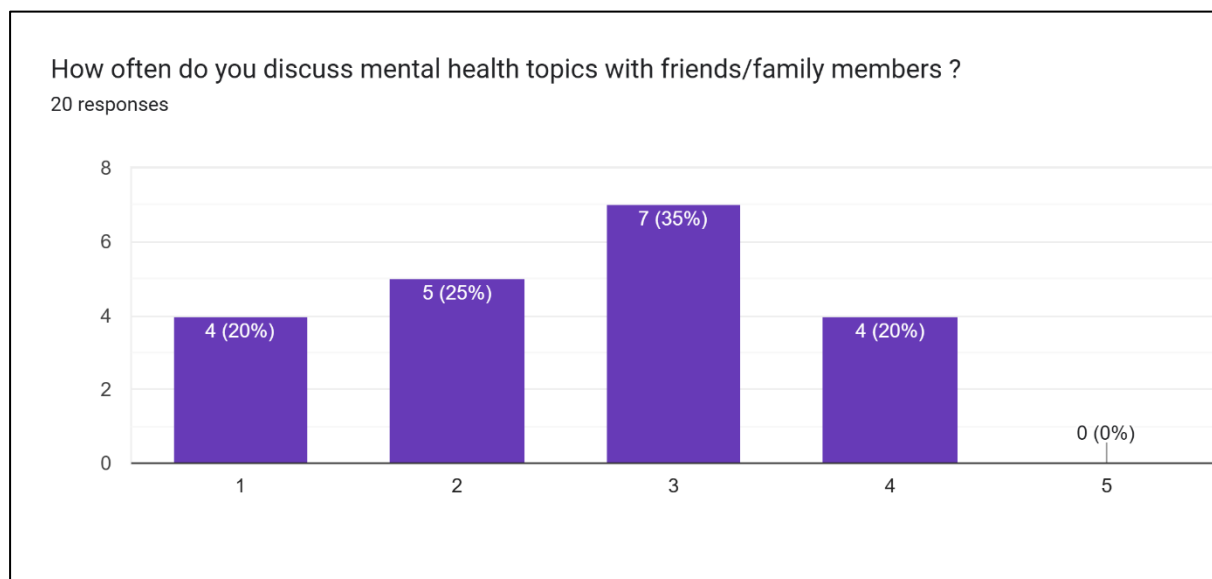


Figure 3.7: Bar Chart on depression as discussion topic within circle

Mental health awareness within the country

Figure 3.8 shows that majority of the respondents (70%) seems to think that Malaysia does not have enough awareness about depression while the remaining 6 respondents (30%) seems to think otherwise. This indicate that our country does not priorities the mental wellbeing and awareness regarding depression that much yet as compared to other country.

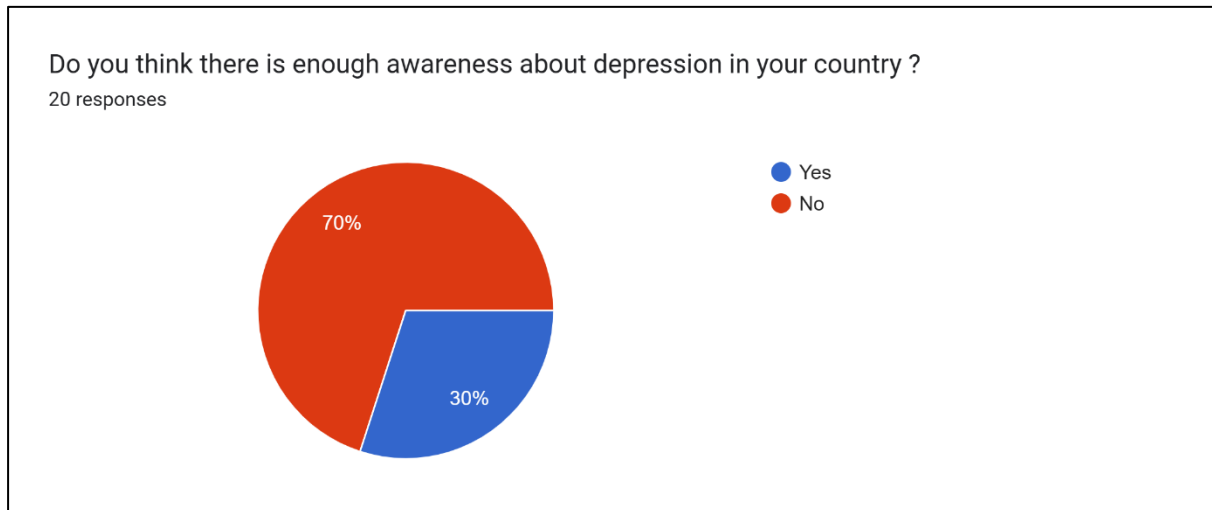


Figure 3.8: Pie Chart on mental health awareness within the country

Trusted source on depression

Figure 3.9, Figure 3.10 and Figure 3.11 shows the respondents trusted sources on depression vary from certified websites, books, research and straight from professional themselves. From the 3 figures below, it is shown that most trust mental health information from professionals and verified official websites. Thus, this enhances the credibility of this application since the project will involve domain expert on the questions and approaches of the assessment to ensure a more verified approach on detecting depression.

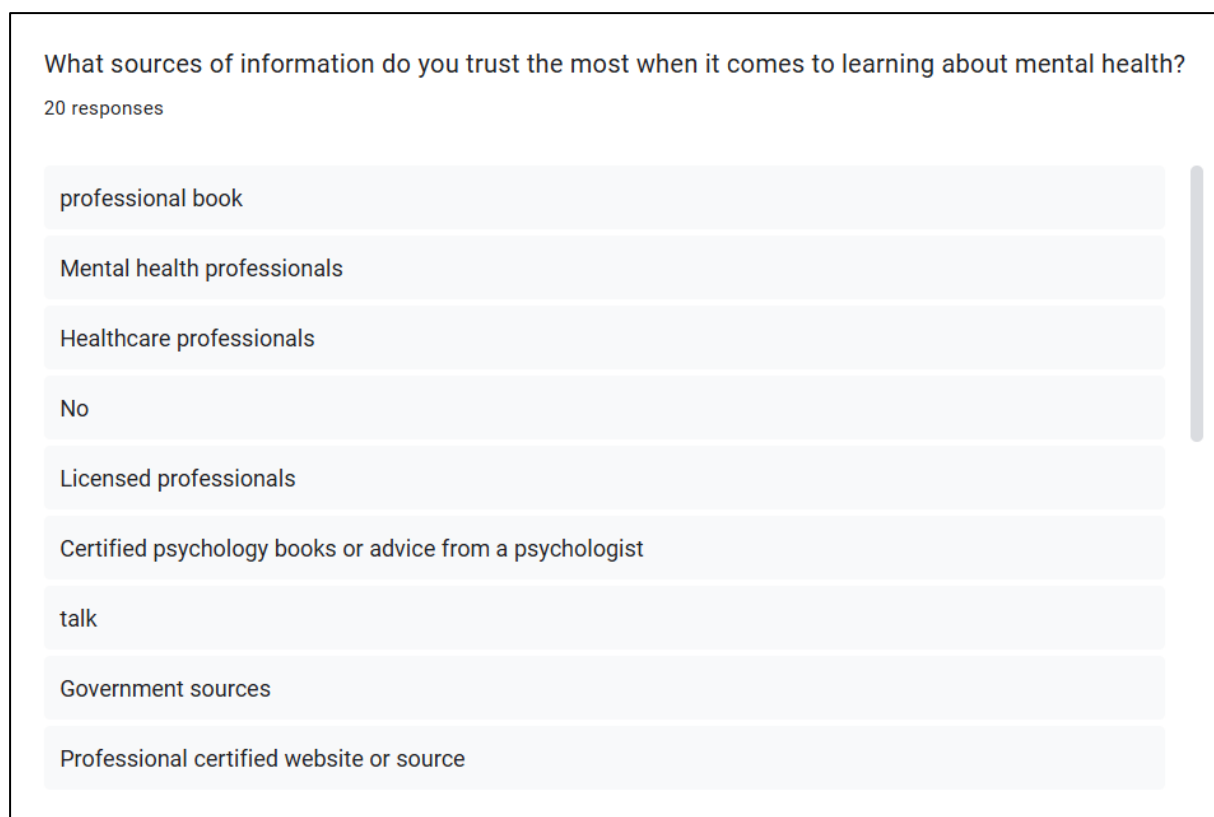


Figure 3.9: Statement on respondent's trusted information regarding depression 1.



Figure 3.10: Statement on respondent's trusted information regarding depression 2.



Figure 3.11: Statement on respondent's trusted information regarding depression 3.

Comfortability of usage of AI in detecting depression

This question uses Likert Scale from one to five with:

One – Not Comfortable at all

Five – Very Comfortable

Figure 3.12 shows that majority of the respondents (70%) are at least comfortable with the idea of using AI to detect depression with only two respondents (10%) not comfortable and four respondents (20%) being neutral to the idea which could be due to their doubts about the accuracy of using AI, however the rest of the respondents are quite positive to the idea. Moreover, this also indicate that most approve of that an application that are able to utilise AI to detect depression.

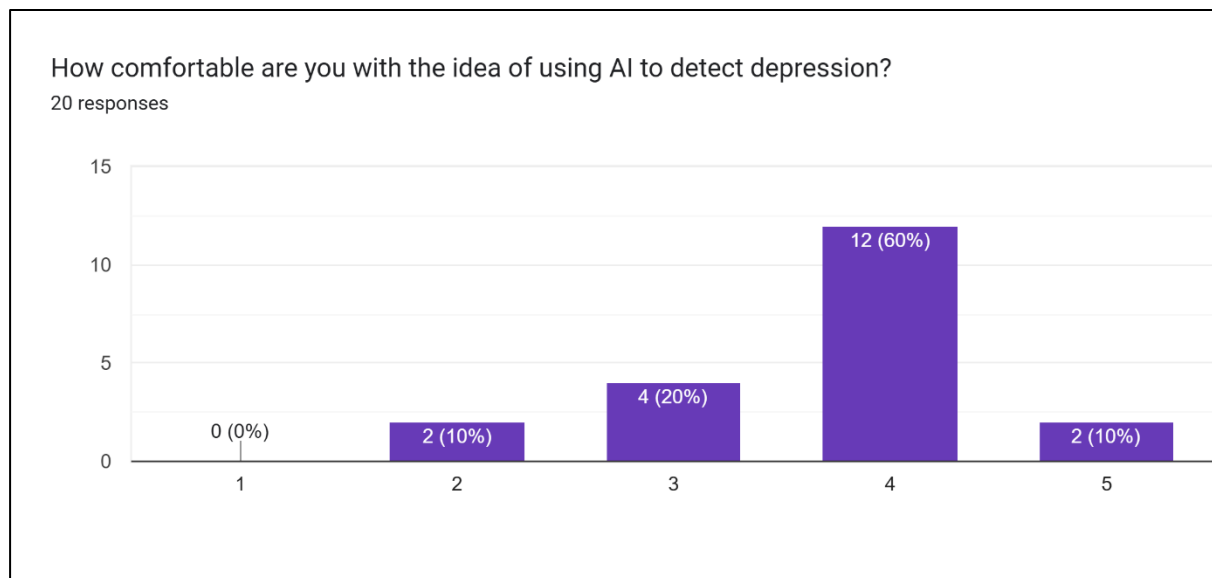


Figure 3.12: Bar Chart on respondent's comfortability of the idea of using AI to detect depression

Believes on AI accuracy to detect depression

Figure 3.13 shows that majority of the respondents (40%) believe that AI can indeed accurately detect depression while 35% are unsure and 25% does not seem to think so. Even though, majority do believe that AI can accurately detect depression but there are still some doubts of utilising AI for depression detection which might be caused by experience with AI or the believe that AI cannot detect or interpret human psychologies.

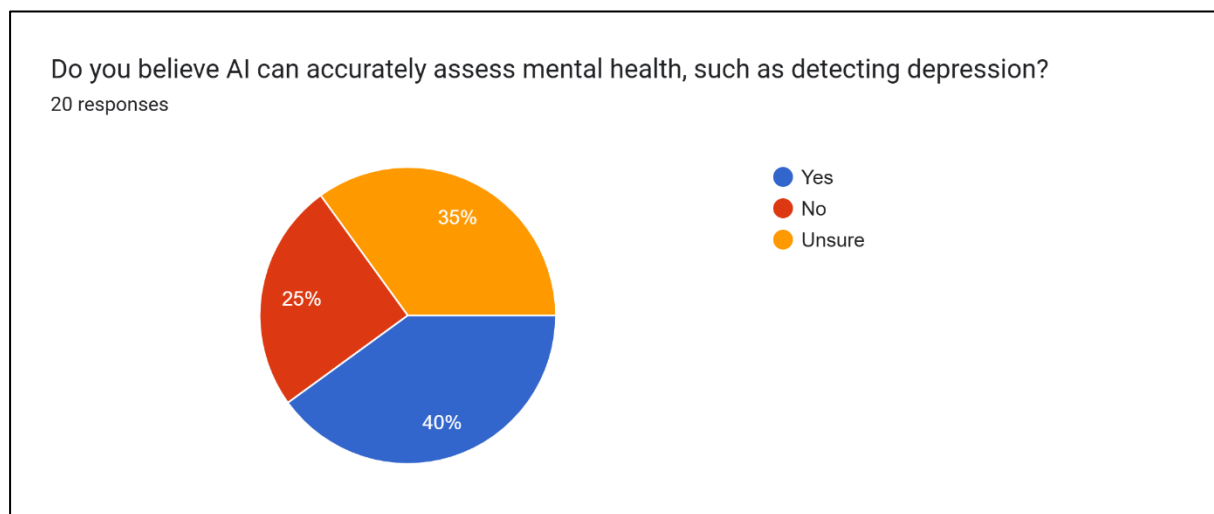


Figure 3.13: Pie Chart on respondent believes on AI's accuracy in detecting depression

Reason on believing or not believing in AI (Continuation)

Figure 3.14, Figure 3.15 and Figure 3.16 shows the reason for respondents' previous question, the reasons vary from thinking AI would have hard time predicting human's psychology on the other hand some respondents showcase their knowledge on AI by thinking AI could predict depression with sufficient data to be fed. Moreover, some are not familiar with the workings of AI, so they are unsure. In general, it can be interpreted that those who knows the inner workings of AI believes that AI have the potential to detect depression whereas others think that depression is subjective which include psychology, nonverbal behaviours and any physical indication that AI might have hard time predicting. Although the concerns are valid, but the scope does not cover this since this application will determine depression via text.

Why ? (Continue from previous question)

20 responses

Because AI can detect the depression correctly

AI cant observe one's nonverbal behaviour

Because AI only depends on existing data and may not be able to detect current level of depression.

Since human can't consider ones is depress hence how can an AI can easily detect the depression.

never try

With our technology now, human brain is too complex for AI to detect depression, atleast the information u can get from AI is not as detailed as from a psychologist

AI is the artificial intelligence that can do a lot

because its just prediction there are limited factors to assess mental health

Still not familiar with the working of AI yet, especially when it comes to psychology

Figure 3.14: Respondent reason on believing or not believing in AI 1

Ai can detect some usual symptoms of depression but it would need lot more programming and improvements to fully be able to reliably detect mental illness
can narrow down the scope
With various data fed into AI coupled with advanced AI algorithms, it is very likely to be very accurate.
Ai can rapidly search all the information about depression from whole online platform including professional, it can be a foundational to identify the sign of depression
Based on experience using chatgpt, some of the info are misleading thus making it hard to put trust on AI in detecting the depression.
Because AI is reliable
Depression is more subjective issue, AI maybe cannot assess whether a person is suffering from depression. For example, one of the depression symptoms is feeling down. Some person with depression can pretend that they are very happy, in fact, they are suffering from depression.

Figure 3.15: Respondent reason on believing or not believing in AI 2

AI can analyze large amounts of data quickly and identify patterns that might be missed by humans. This includes analyzing text, speech, and even facial expressions to detect signs of depression.
AI can be inaccurate sometimes, juz like chatgpt might generate inaccurate responses as well.
It is 5050 and also depend on how many data the developer feed the model.
Using AI to detect depression is still a pretty new venture and there are no conclusive evidence of it being accurate

Figure 3.16: Respondent reason on believing or not believing in AI 3

Privacy and data security concern when using AI

This question uses Likert Scale from one to five with:

One – Not Important at all

Five – Very Important

Figure 3.17 shows that majority of the respondent (90%) think that privacy of their data is important when using AI which highlighted their concern for privacy while there is one respondent who is not concern and another one being neutral. It is without a doubt that their concern is valid since they need to provide some of their daily activity and self-behaviours data to conduct the assessment. Which is why this application will not use account system that requires users to provide their emails and other personal data, this can ensure that data collection is kept to minimal while allowing users to do the assessment without worry data privacy.

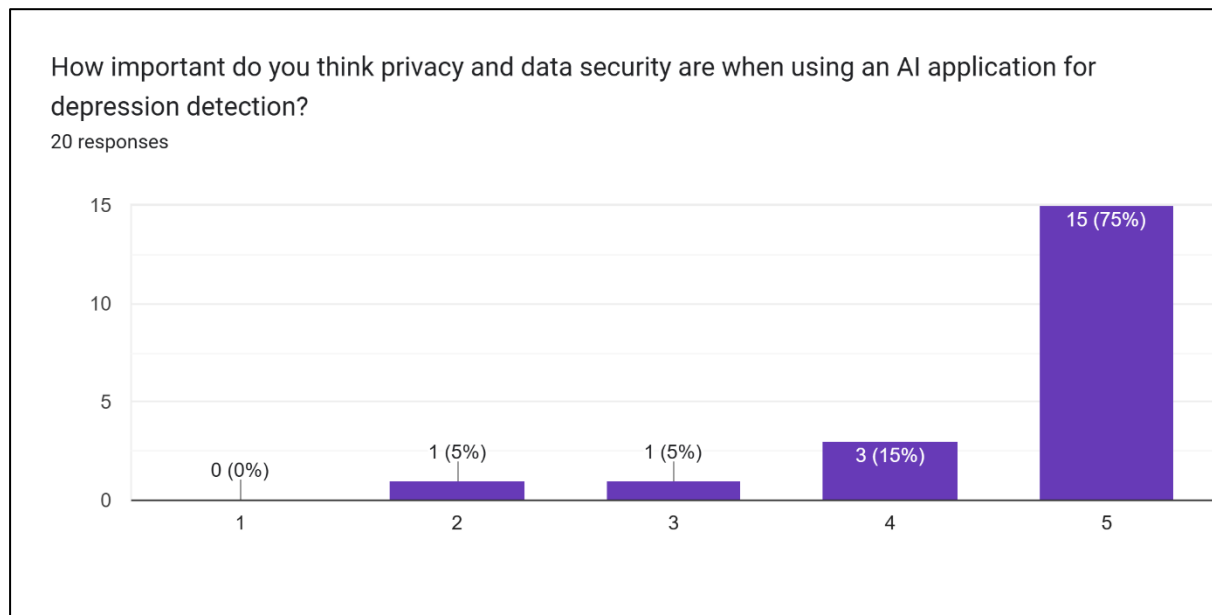


Figure 3.17: Bar Chart on respondent's privacy concern when using AI

Willingness to share data for a more accurate detection

Despite the concern from previous question but in Figure 3.18, it is shown that they are still willing to share their data to get a more accurate detection with 70% of respondent willing and 30% unsure, none of the respondent are not willing to share. This indicate that while there are concern but they are willing to compromise to do their assessment. However, personal data will not be taken thus account system will not be implemented.

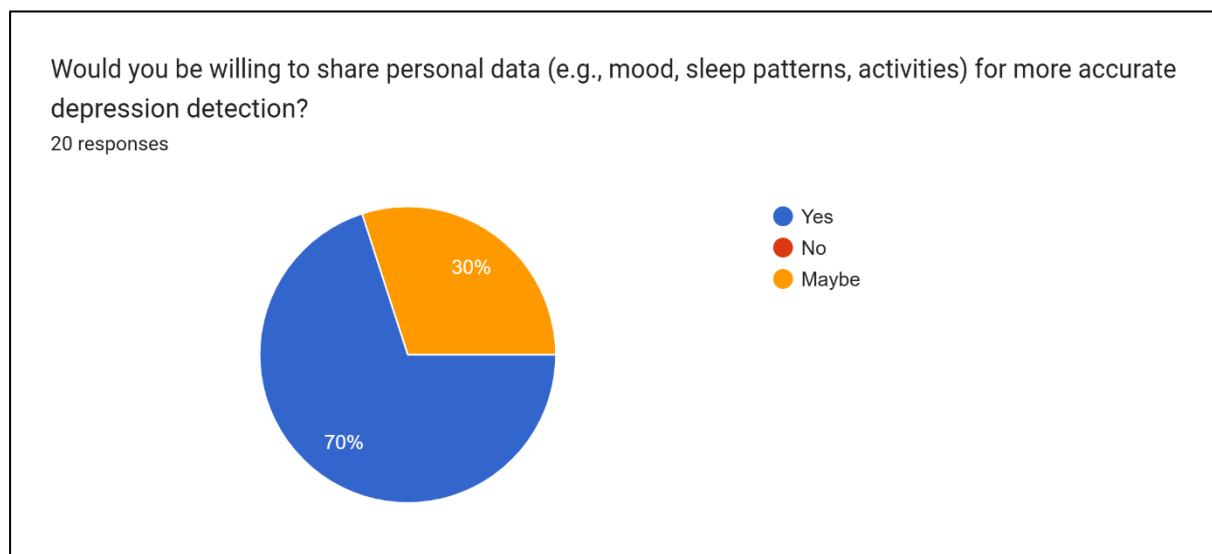


Figure 3.18: Pie Chart on respondent willingness to share data for a more accurate detection

Likelihood to use AI-based depression detection application

This question uses Likert Scale from one to five with:

One – Not likely at all

Five – Very likely

Figure 3.19 shown that majority (80%) of the respondent are at least likely to use an AI-based depression detection application if they are available while two respondents (10%) are neutral and another two respondents (10%) are not likely to use the application. This is assumed that the usage of AI to detect depression which is within the domain of human psychology intrigues majority of the respondents. However, the minority that does are unsure or not likely to use this application might be due to not feeling the need to detect depression now.

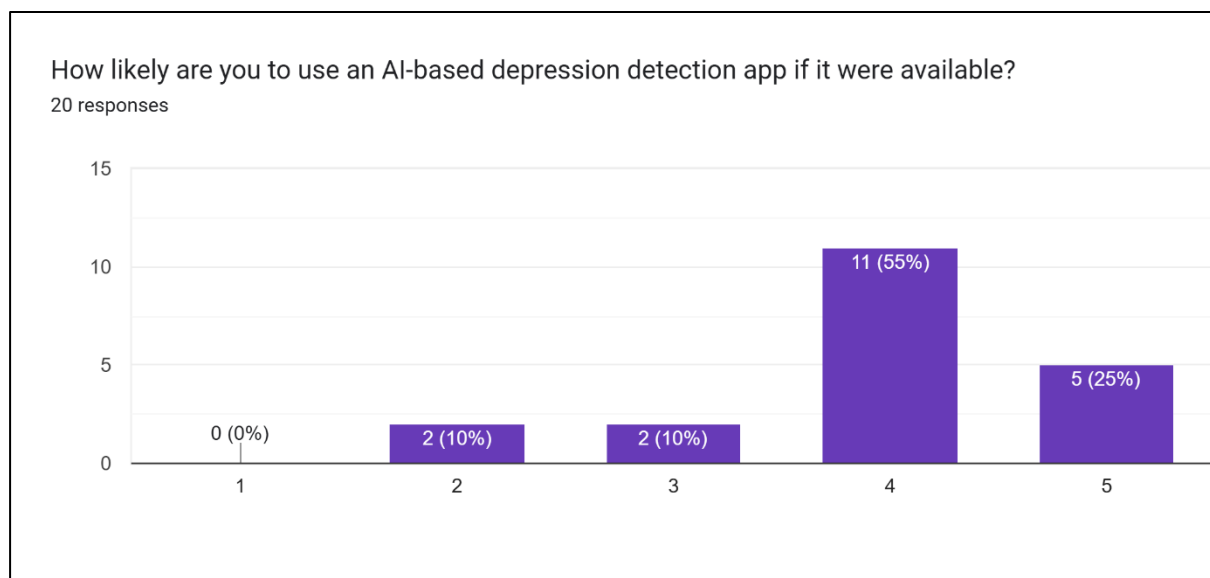


Figure 3.19: Bar Chart on respondent likeliness to use AI-based depression detection application

Concerns on accuracy of AI in detecting depression

Figure 3.20, Figure 3.21 and Figure 3.22 show the statement of respondent regarding their concern on the accuracy of AI in detecting depression. Most of them are worried about inaccurate results which might in turn give user the wrong especially in the absence of human professional. However, this can be assured since the application will use questions suggested by domain expert to conduct the assessment. Moreover, some other concerns regarding data privacy which as mentioned earlier, can be solved by not requiring users to log in. Some other concerns regarding the inaccuracy due to AI issue itself which can be solved by careful planning and optimization of the model.

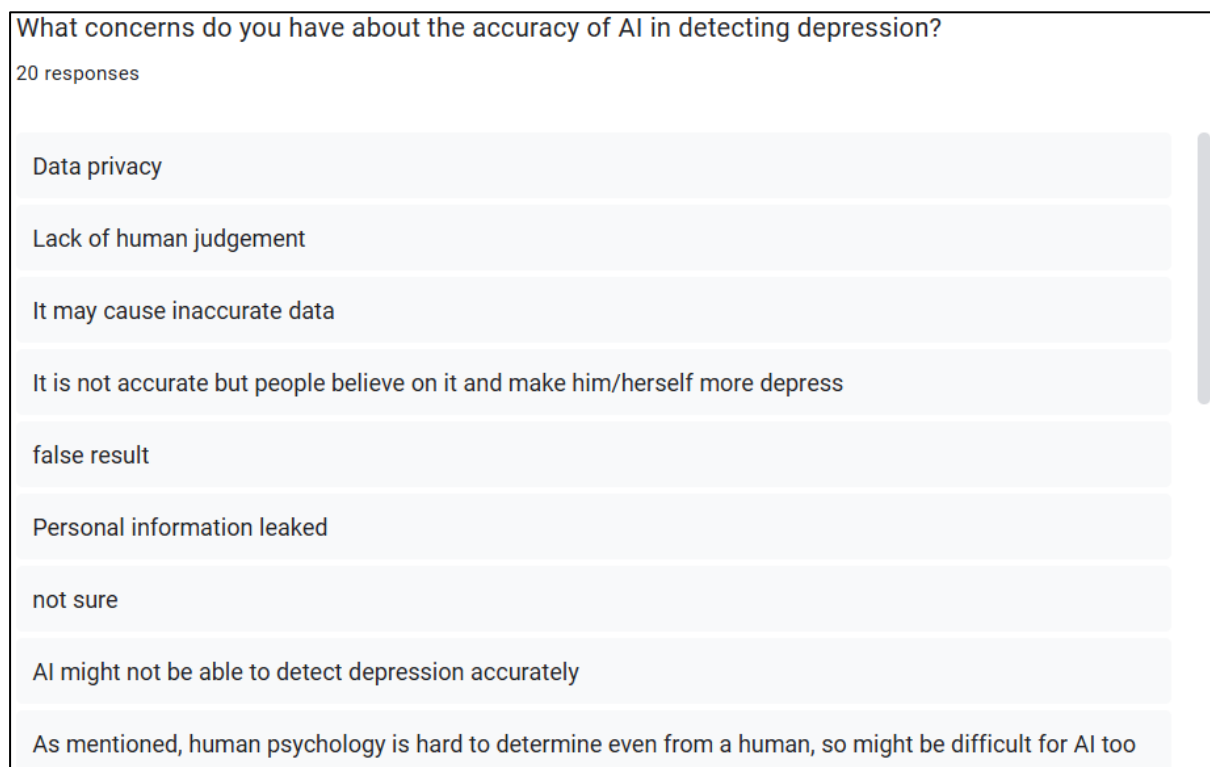


Figure 3.20: Respondent's statement on accuracy of AI in detecting depression 1

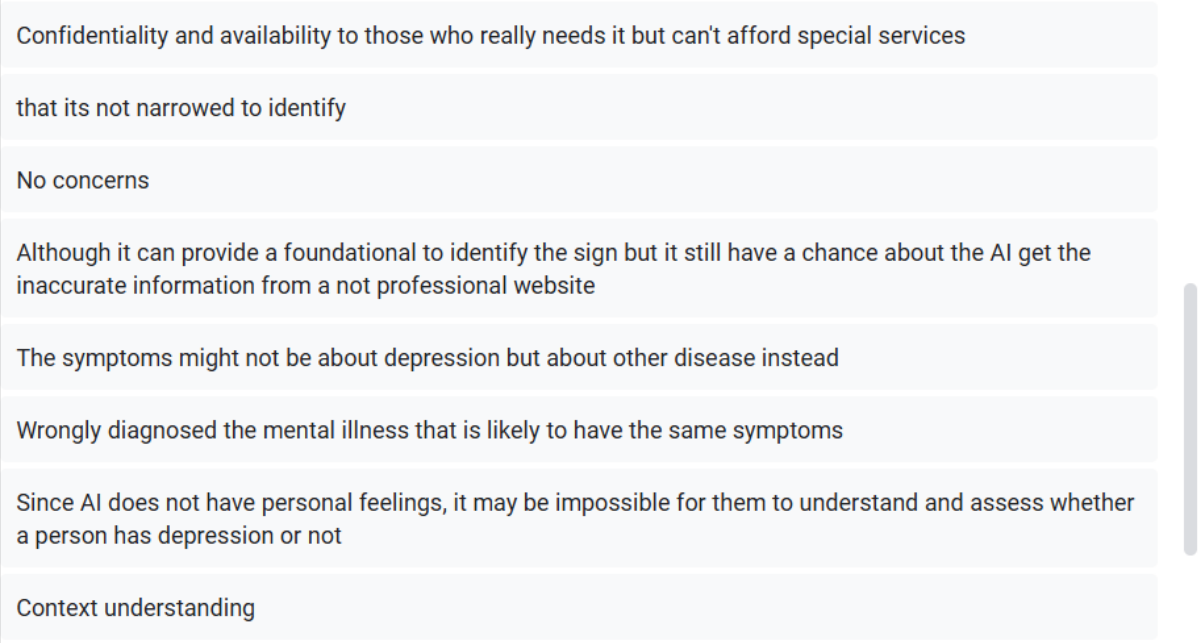


Figure 3.21: Respondent’s statement on accuracy of AI in detecting depression 2

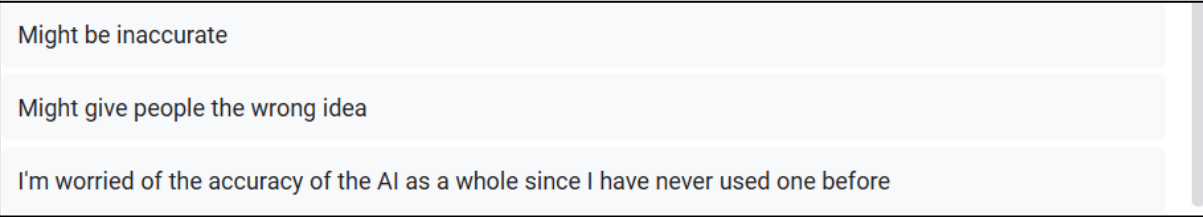


Figure 3.22: Respondent’s statement on accuracy of AI in detecting depression 3

Additional recommendation

Figure 3.23 shows that almost all respondents (95%) prefer to have recommendation or motivation in the application. Therefore, this feature can be implemented by giving a few recommendations at the end of the result page, by giving statis recommendation depending on the user's depression level such as "You are severely depressed, please seek professional help immediately." With some recommendation and motivation quote such as "Remember to take care of yourself, and don't be afraid to confine in your loved one" and "You are the best, stay strong".

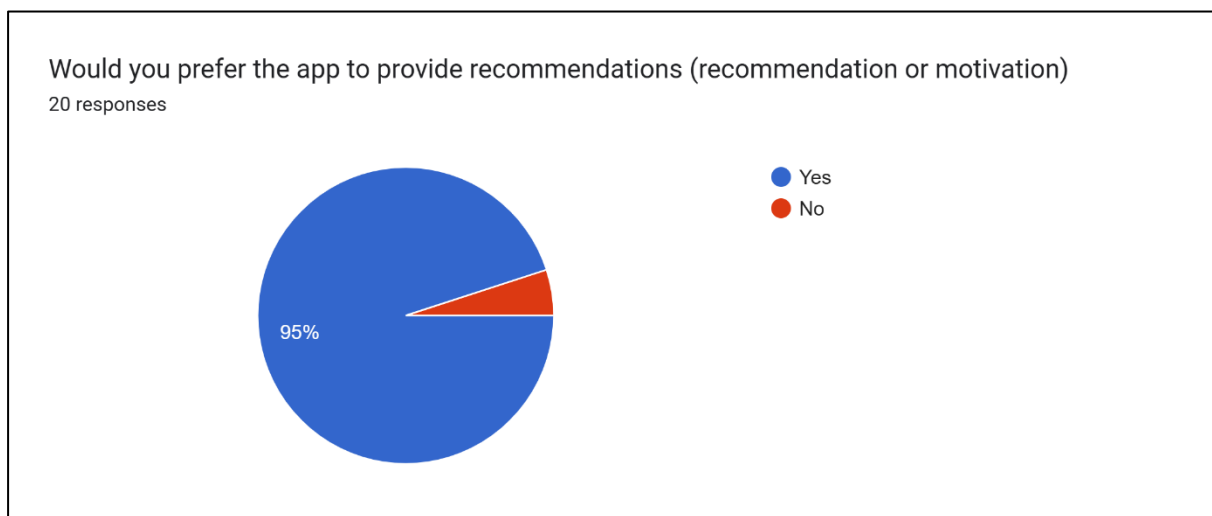
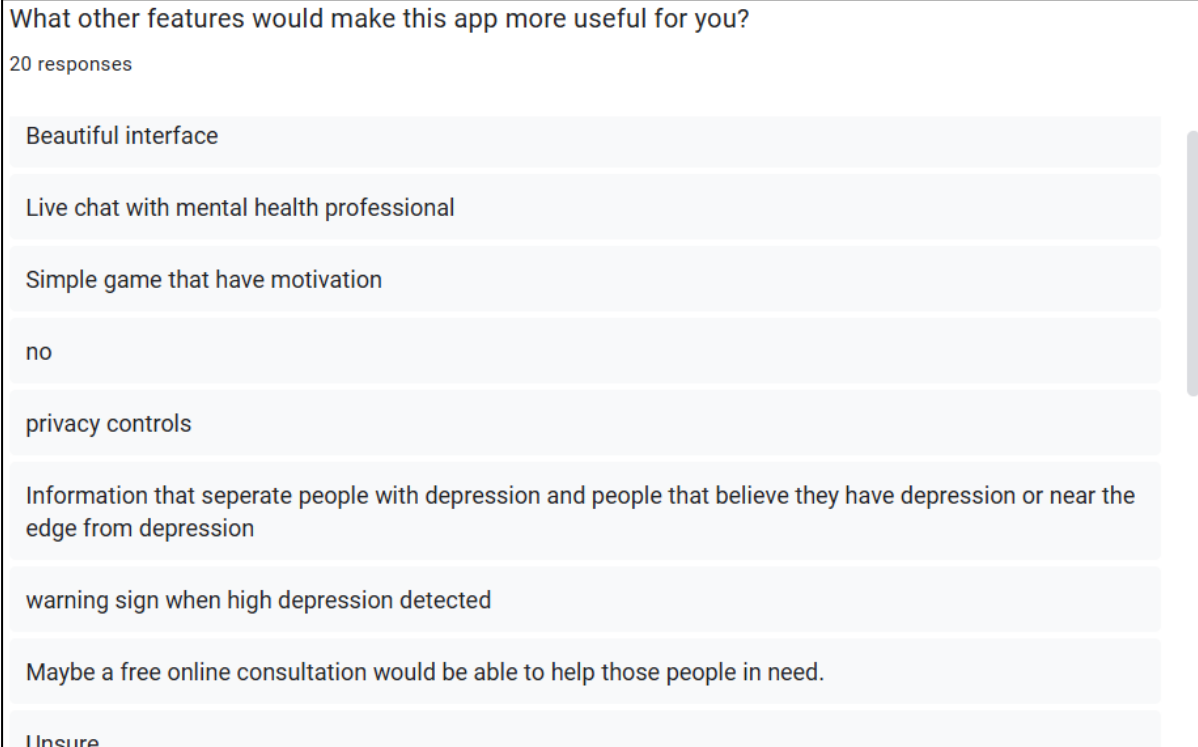


Figure 3.23: Pie Chart on respondent preference on recommendation

Additional feature of the application

Figure 3.24, Figure 3.25 and Figure 3.26 shows other feature suggestion from respondent. Although most of them are involving professional help but this is out of scope since the project only aim to detect depression but other ways to add the feature can be done by adding recommendation and nearest professional help's hotline. Moreover, feature such as warning signs, sharing positive affirmation and user-friendly user-interface can be implemented.



What other features would make this app more useful for you?

20 responses

- Beautiful interface
- Live chat with mental health professional
- Simple game that have motivation
- no
- privacy controls
- Information that separate people with depression and people that believe they have depression or near the edge from depression
- warning sign when high depression detected
- Maybe a free online consultation would be able to help those people in need.
- Unsure

Figure 3.24: Respondent's statement on additional features of the application 1

A licenced professional to be 24/7 online
activities recommendation to do based on level of my symptom
Burnout detection feature
If it can be remind me to do some prevention technique every day if i have some symptoms of depression but not until to find therapist
Mini notes so that user can read about diseases
An appointment online booking to the nearest psychiatrist hospital
Sharing positive and interesting news
User-Friendly Interface: Ensure the app is easy to navigate with a clean, intuitive design that makes it accessible to users of all ages and tech-savviness levels.

Figure 3.25: Respondent’s statement on additional features of the application 2

Provide suicide hotlines in the apps
-
Maybe adding second opinions with real doctors

Figure 3.26: Respondent’s statement on additional features of the application 3

3.2.1.4 Hardware Requirement

The hardware requirement for the development of the proposed application:

Table 3.1: Hardware requirement

No.	Hardware	Specification
1.	CPU	Intel Core i7 or equivalent (4 cores or higher)
2.	RAM	16 GB or higher
3.	Storage	256 GB SSD (for faster performance)
4.	GPU	NVIDIA GeForce RTX 2060 (or higher, optional for AI acceleration)
5.	Operation System	Windows 10 (64-bit)

3.2.1.5 Software Requirement

The software requirement for the development of the proposed application:

Table 3.2: Software requirement

No.	Software	Specification
1.	Integrated development environment (IDE)	Microsoft Visual Studio Code
2.	Programming language	Python
3.	Frameworks/Libraries	TensorFlow, Keras, Scikit-learn, Pandas, NumPy
4.	Mobile development tools	Flutter, Android Studio
5.	AI model training tools	Jupyter Notebook, Google Colab
6.	Database	SQLite
7.	Testing tools	Postman (for API)

3.2.2 Application Design

The purpose of this phase is present a detailed overview of the proposed application through various illustrations to provide context on the system's structure, process flow, data flow and user interface to ensure a clear visualisation and understanding of how the application operates. Moreover, it can also serve as a guide during implementation phase as to stay on within scope and not deviate from priorities.

3.2.2.1 Flowchart

Figure 3.27 shows the flowchart of the proposed application, which illustrate the inner operation of the application and how user's action influence the application. Firstly, when user start the application on their smart devices the application will start with the main menu which allow user to proceed to the questionnaire by tapping on "Start Assessment" button. Then, questionnaire will be display where user can input their response into the questionnaire and once they submit the application will check if they have completed all the questions in the questionnaire, if they do then the responses will be sent to model for processing, else an error message would prompt reminding user to complete all the question and navigate them back to the questionnaire with their current responses saved. Then, if users answer the optional elaboration text box then the text will be processed by the ML model and will be sent to compute the results, if user did not use the optional elaboration text box then only the selected answers will be used to compute final result. Furthermore, once processing is successful, the depression level results will be displayed and user can decide to whether to view their results in PDF and then they can choose downlaod the results to their devices and share the results, if they choose not to or if they are done viewing their results, then the there is another button for

them to retake the assessment again where user will be navigated back to the questionnaire if they choose to do so else the process would end.

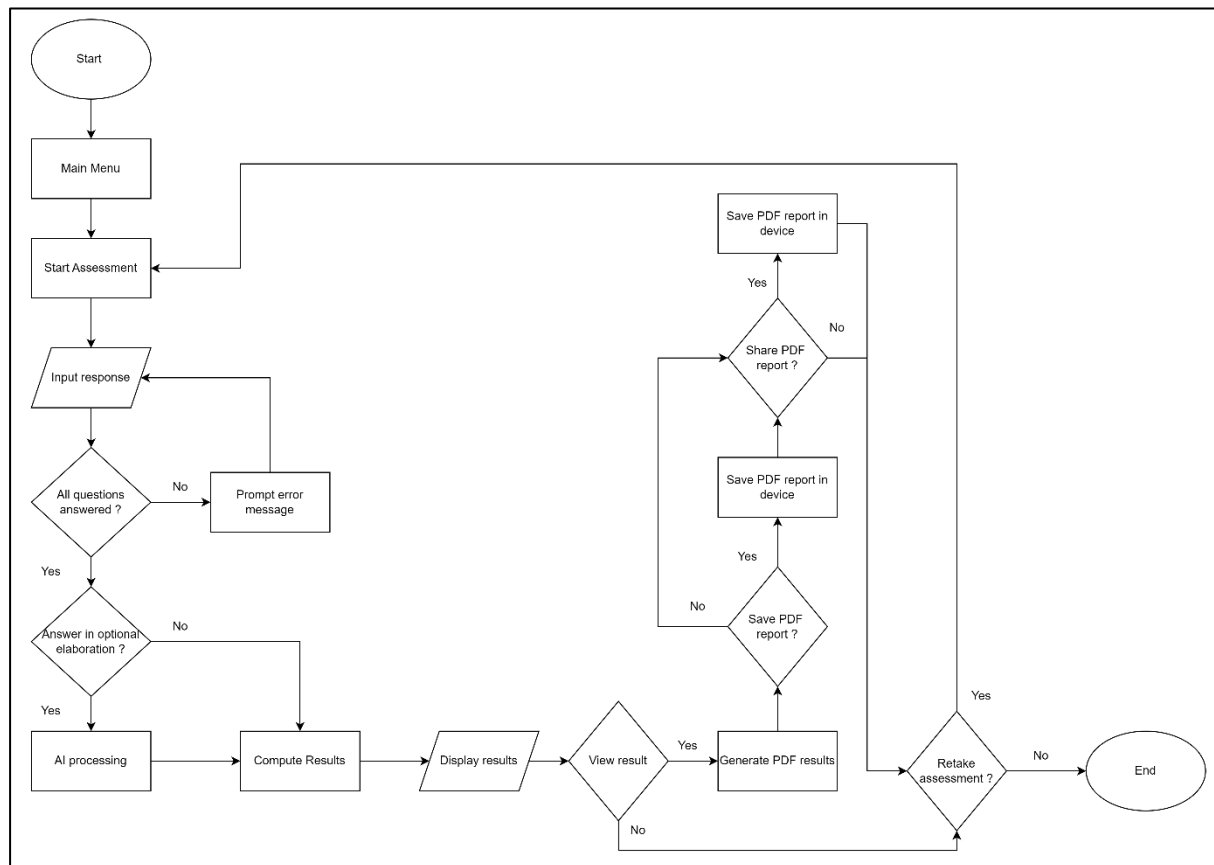


Figure 3.27: Flowchart of the proposed application

3.2.2.2 Context Diagram

The context diagram in Figure 3.28 provides an overview of the interactions between the user and the depression detection application. The figure highlights 4 main processes which are user taking the assessment, submitting it to the application and view the final results such as depression level, depression score and top contributing factors to depressions, will be generated by the application, then with the option to download the result. Moreover, users also have the choice to retake the assessment should they need it. Context diagram will step the stage for Data Flow Diagram (DFD) next which will provide more context on the process involving data in the proposed application.

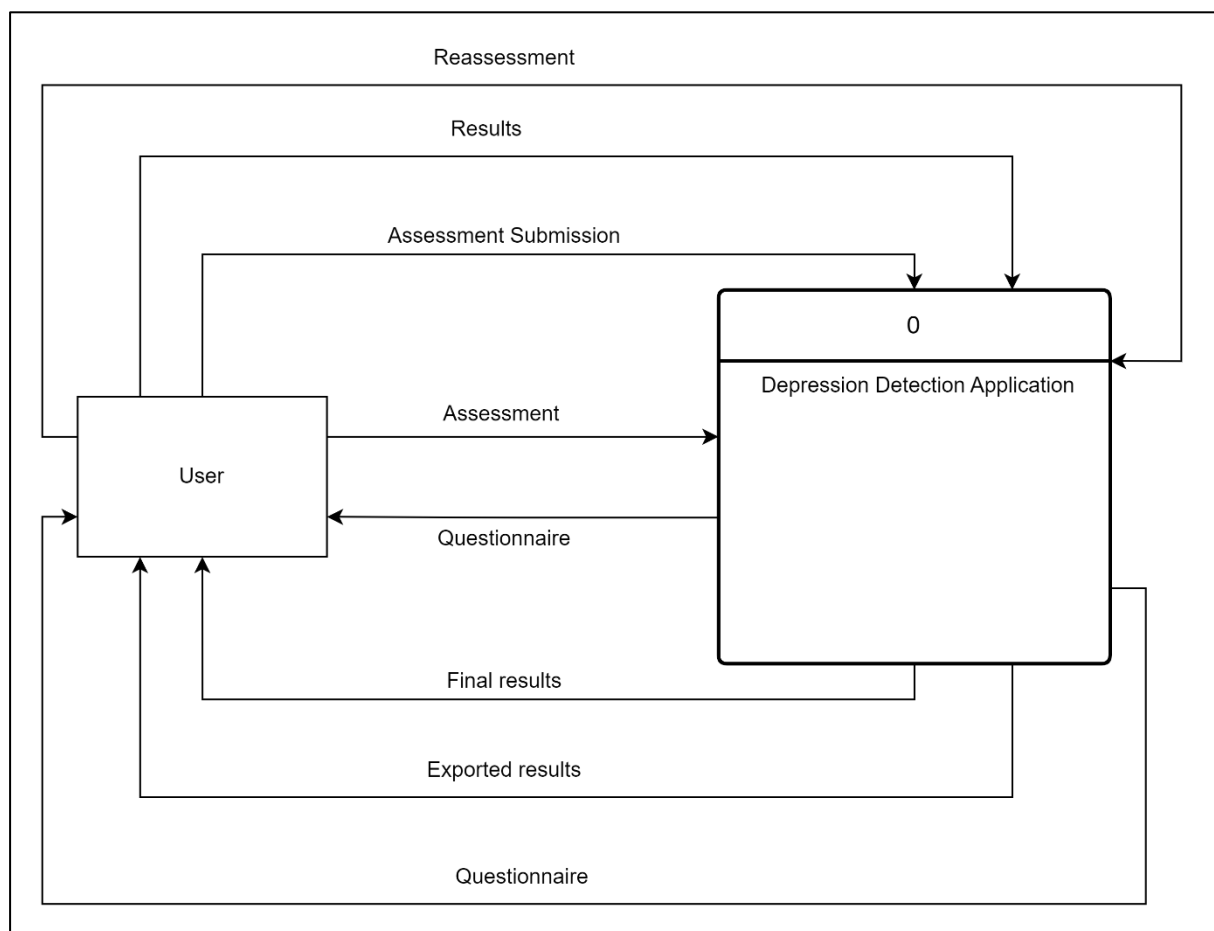


Figure 3.28: Context diagram of the proposed application

3.2.2.3 Data Flow Diagram (DFD) level 0

The data flow diagram in Figure 3.29 provides a more detailed look into the depression detection application from Figure 3.28 context diagram that shows the main component and inner working of the data flow process. The figure highlights 5 processes within the depression detection application and how user's interaction influence it. Firstly, user would have to take assessment first by initialising it and the system would display the questionnaire for user. Secondly, once user is done with their assessment will be submitted whereas their response will be stored and then sent to process 3.0 to be processed and processed results will be stored accordingly before being displayed to user. Then, user will have the option to download where process 4.0 to allow user to download their results. Lastly, process 5.0 is where user can retake the assessment.

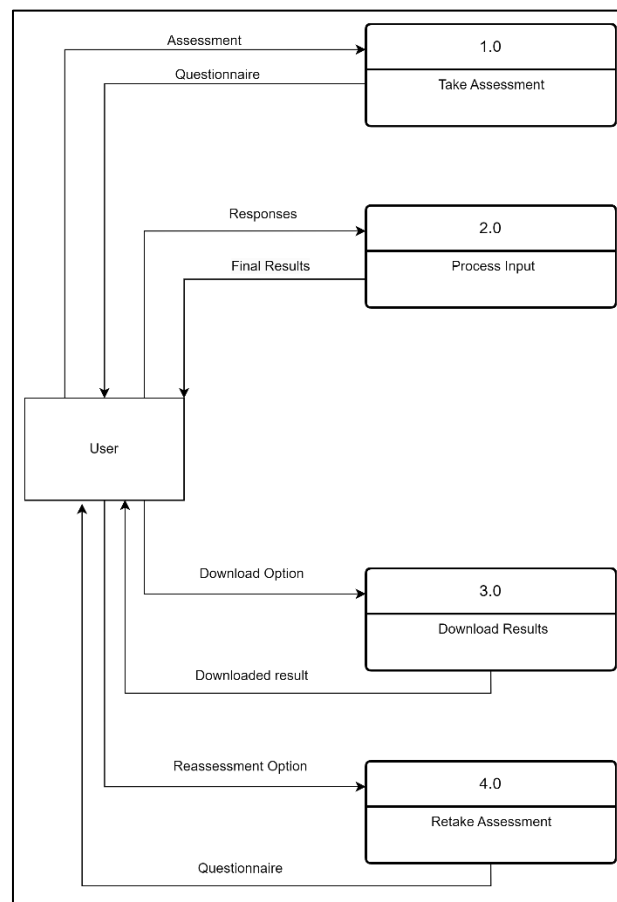


Figure 3.29: Data Flow Diagram level-0 of the proposed application

Process 1.0: Take Assessment

Figure 3.30 shows when user start the assessment, the application will initialise the questionnaire first and then send the questionnaire data to the application to be displayed for user.

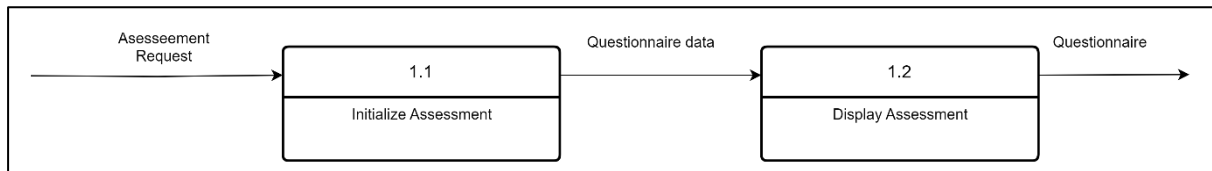


Figure 3.30: Level-1 diagram for Process 1.0

Process 2.0: Process Input

Figure 3.31 shows once user have finish answering the questionnaire, they may submit their response whereby in 2.1 will submit and collect their responses store it into the user response database prior to processing. The stored responses consisting of objective answers from PHQ and ASQ, elaborated texts and demographic information will be retrieved and processed in process 2.0 whereby, user's elaborated responses will be fed to the ML model to be processed, while the demographics and keywords from elaborated text are processed through a rule-based system to identify potential contributing factors to depression. Once processing is done, the model will be able to provide results based on the responses and generate depression level results and top potential contributing factors, then results will be stored into Result repository for record purposes before displaying it to users.

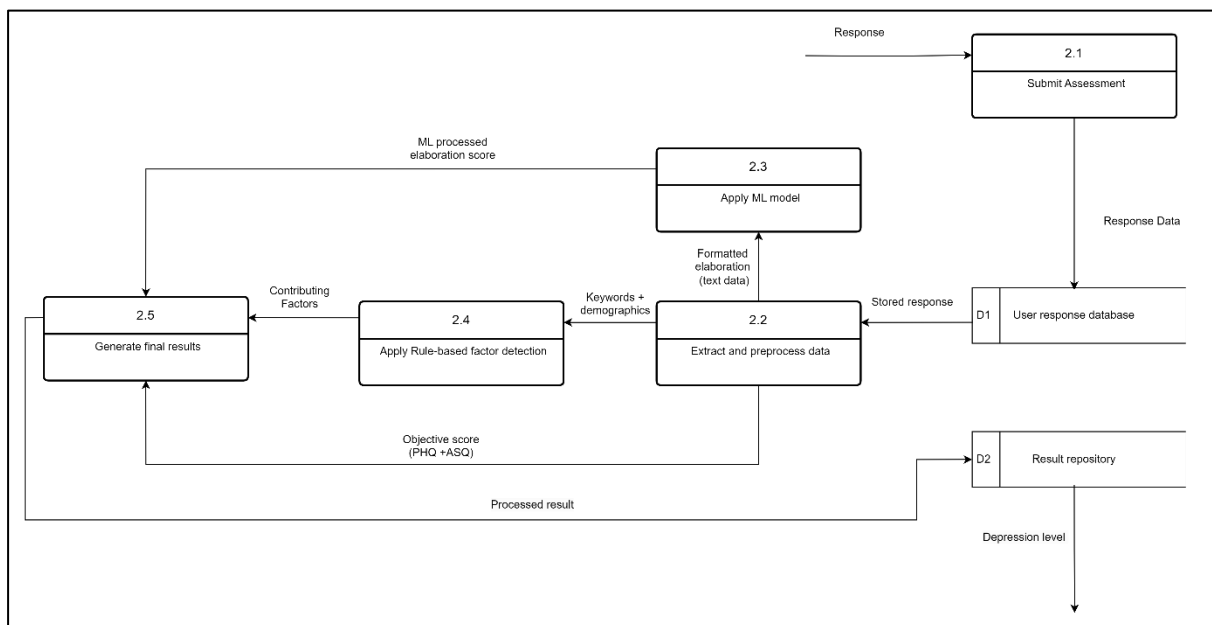


Figure 3.31: Level-1 diagram for Process 2.0

Process 3.0: Download Result

Figure 3.32 shows once user got their results, they may choose to download the results by requesting for download or confirm download, whereby the application will first verify results availability before moving on to initiate the download to the user locally.



Figure 3.32: Level-1 diagram for Process 3.0

Process 4.0: Retake Assessment

Figure 3.33 shows users may choose to retake the assessment, where the application will re-initiate the assessment and redirect user back to the questionnaire page.

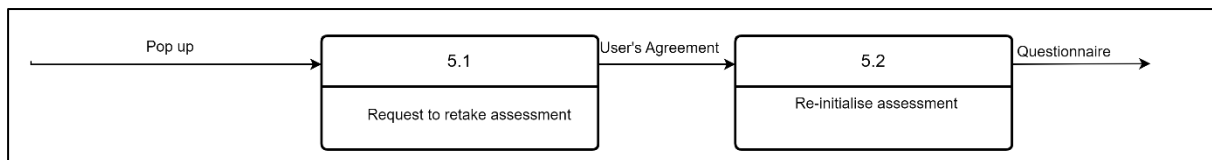


Figure 3.33: Level-1 diagram for Process 4.0

3.2.2.4 Entity Relationship Diagram (ERD)

Figure 3.34 shows the ERD for the depression detection application consists of three entities which are user, assessment and result. Firstly, the user entity consists of the user's demographics details as attributes (genders, years, faculty, cgpa & income tier) and one primary key which is the sessionid which will be utilise as foreign key to other entities. Secondly, with sessionid as foreign key to with a 1-to-1 relationship from user to the assessment entity as one user can only attempt one assessment per session, the assessment with an auto-incremented ID as primary key to uniquely identify each answered question, with each entry linked to a session through the session_id foreign key. The attributes in assessment entity serve as user's response for each question alongside other question details. Then, result entity contains the depression level, depression score and three contributing reasons for depression as attributes after processing assessment's responses which is also tied to the session, thus 1-to-1 relationship as one session can attempt one assessment which in turn can only get one result.

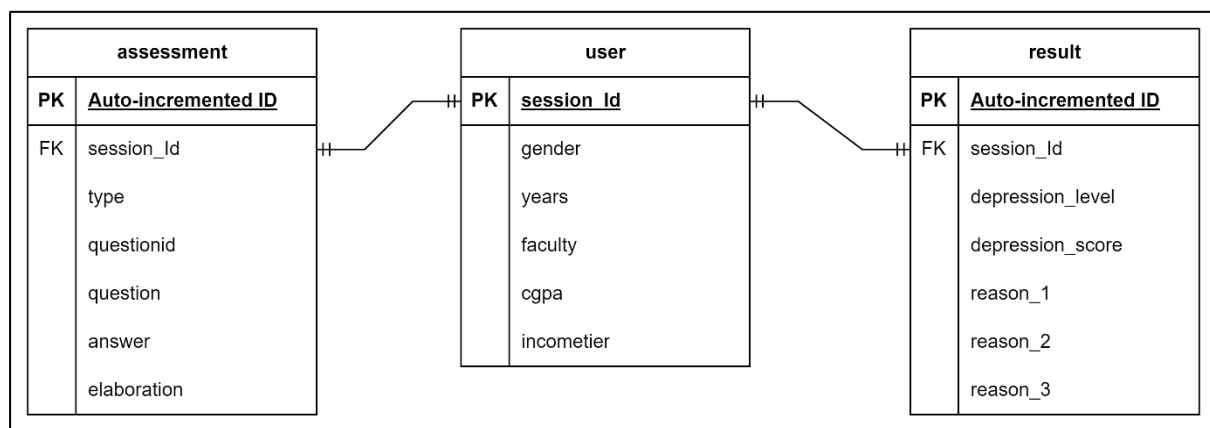


Figure 3.34: Entity Relationship Diagram of the proposed application

3.2.2.5 Data Dictionary

Table 3.3, Table 3.4 and Table 3.5 are the data dictionaries based on ERD from Figure3.35 that show cases the data needed and their usage.

Table 3.3: Data Dictionary for user entity

Field Name	Data Type	Constraint	Description	Example
session_Id	Text	Primary Key	Unique identifier for each session	1234_mdiidjddwd_d
gender	Text	Not Null	User's gender	Male, Female, Prefer not to say
years	Text	Not Null	User's year of study	Year 1, Year 2, Year 3, Year 4, Year 5
faculty	Text	Not Null	User's faculty	Faculty of Engineer, Faculty of Computer Science and Information Technology, etc
cgpa	Text	Not Null	User's academic performance	3.5 above, 3.5-3.0, 2.9-2.5, 2.4-2.0, below 2.0
incometier	Text	Not Null	User's income tier	T20, M40, B40, Not Sure

Table 3.4: Data Dictionary for assessment entity

Field Name	Data Type	Constraint	Description	Example
Auto-incremented ID	Integer	Primary Key	Unique Identifier for each input	1, 2, 3....etc
session_Id	Text	Foreign Key	Unique identifier for each session	1234_mdiiidjddwd_d
type	Text	Not Null	Question's type	PHQ, ASQ
questionid	Text	Not Null	Each question's identifier	1, 2
question	Text	Not Null	question	Feeling tire, or having little energy?
answer	Text	Not Null	User's answer	Several days
elaboration	Text	Not Null	User's optional elaborated text	I hate myself, I am very sad.

Table 3.5: Data Dictionary for result entity

Field Name	Data Type	Constraint	Description	Example
Auto-incremented ID	Integer	Primary Key	Unique Identifier for each result	1, 2, 3....etc
sessionid	Text	Foreign Key	Unique identifier for each session	1234_mdiidjddwd_d
depression_level	Text	Not Null	Results	Severely Depressed
depression_score	Double	Not Null	scoring metric	86.7%
reason_1	Text	Not Null	Top 1 contributing factors	Financial Struggles
reason_2	Text	Not Null	Top 3 contributing factors	Financial Struggles
reason_3	Text	Not Null	Top 3 contributing factors	Financial Struggles

3.2.2.6 Wireframe

Wireframe was drafted as well to serve as a blueprint and sketches on how the application work from user's point of view.

Homepage

Figure 3.35 shows the starting page of the application before initiating the assessment, this page includes a few descriptions of the application and disclaimer as to how this application on serve as a supplementary assessment and not officially diagnose and replace professional help.

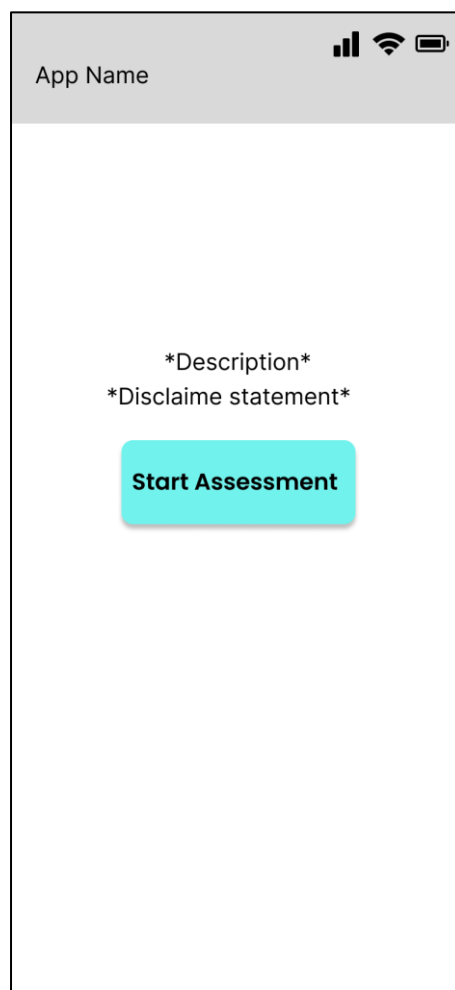


Figure 3.35: Wireframe of the homepage

Assessment page

Figure 3.36 is the assessment page of the application, user will be navigated here once they tap on ‘Start Assessment’ from homepage, where user can input their responses inside the text bubble below the question, then they can submit their responses by tapping on ‘Submit’.

The wireframe shows a mobile application interface for a 'Depression level assessment'. At the top, there is a header bar with 'App Name' on the left and status icons (signal, Wi-Fi, battery) on the right. Below the header, the title 'Depression level assessment' is centered. The main content area is titled 'Recently have you been...' and contains four questions. Questions 1 and 2 are multiple-choice with 'Yes' and 'No' options. Questions 3 and 4 are open-ended with text input fields. A 'Submit' button is located at the bottom right of the form.

App Name

Depression level assessment

Recently have you been...

Question 1:
question1

Yes ☐ No ☐

Question 2:
questions

Yes ☐ No ☐

Question 3:
question3

Question 4:
questions4

Submit

Figure 3.36: Wireframe of the assessment page

Result page

Figure 3.37 show the result page after the application have finish processing and come up with a result on the user's depression level based on the responses. Then, user can choose to download their results by tapping on 'Download' and retake the assessment whereby they will be navigated back to the assessment page by tapping on 'Retake Assessment'.

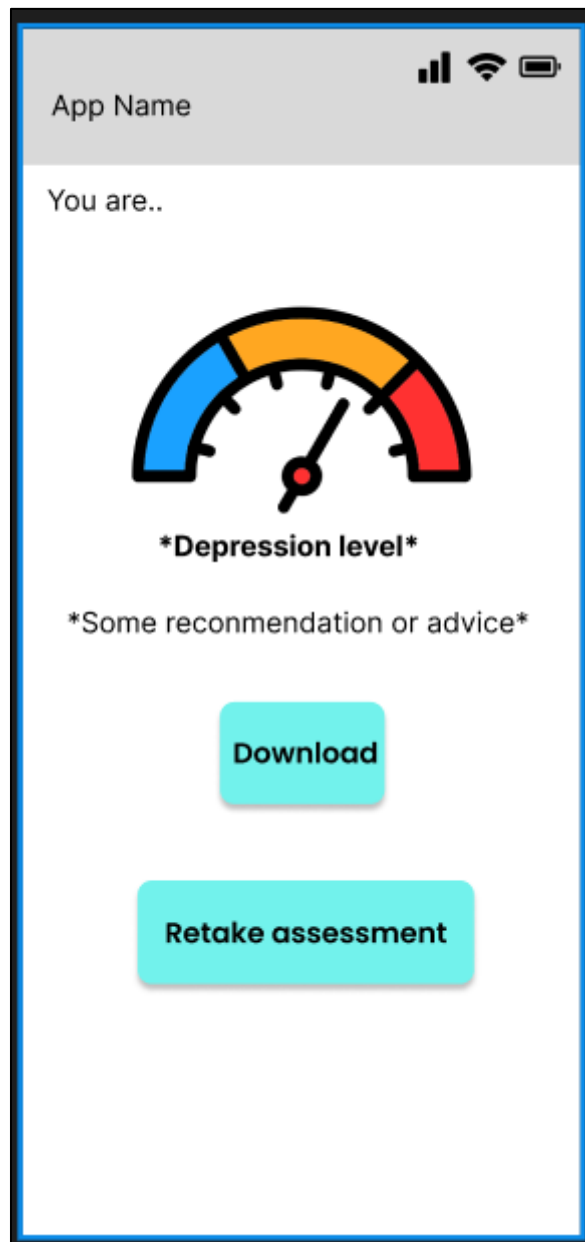


Figure 3.37: Wireframe of the result page

3.2.3 Application Implementation

Figure 3.38 shows the application implementation phase would take the longest time and most crucial part of the project as it involves training model and developing mobile application then integrated the trained model into mobile application. Thus, combining them to be the proposed application where it is capable of detecting depression level. Firstly, this project will crawl social media data from Reddit as reddit have several subreddits such as r/mentalhealth and r/depression that focuses solely on the topic, API such as Praw is required in order to crawl data from Reddit. Then, collected data will be labelled with respective text's depression level, labelling will include manual label half of the data and let a pretrained model such as Bidirectional encoder representations from transformers (BERT) to label the other half referencing from the manually labelled data thus together will be a pseudo-labelled data. Bert is used because of its ability to capture contextual relationship between words via bidirectional training, thus it is suitable for labelling the other half of the data to save more time. For context, reddit data will be crawled by using Jupyter notebook by leveraging on several libraries such as numpy and Pandas whereas BERT will be implemented by using python. Next, the labelled data will be fed to a classifier – logistic regression by using python so that it can understand the contexts of the responses to classify depression level. Although BERT might be a pretrained model but fine tuning it might be required should BERT does not perform as well as expected. Next, flutter will be utilised to develop the mobile application whereas FastAPI framework will be used to develop the API so that the mobile application can communicate with the model to determine depression level. Hence, by utilising these tools and framework, it is hoped that this proposed application will be developed without issue and work as intended. The implementation process is as illustrate as a pipeline in Figure 3.38. More will be discussed in the next chapter.

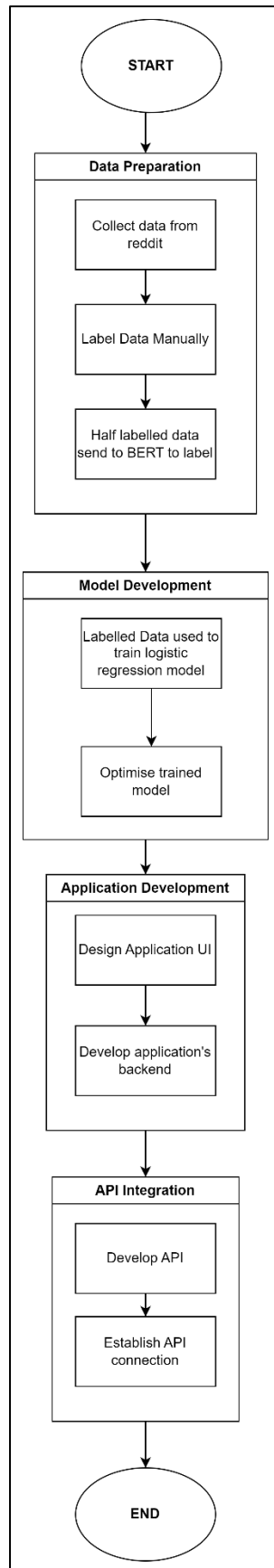


Figure 3.38: Pipeline for implementation process

3.2.4 Application Testing

After the proposed application is implemented, the testing phase will begin to test the functionalities of the application. The test will be carried out by using 2 mobile phones with 2 different OS, which are iOS and Android as these 2 is the main OS in most mobile devices now. The testing will test mobile phone to ensure the application will be able to work as intended for both OS. Then, the testing will also take the assessment to ensure the results given is accurate and logical. Testing is conducted so to ensure there's no issue as if there are bugs then there is a needed to go fix it as soon as possible. After addressing any issues identified during the initial testing phase, further rounds of testing will be conducted to ensure the stability and reliability of the application across both platforms. More will be discussed in the next chapter.

3.2.5 Application Deployment

Once testing is completed, next phase will commence where several users will be gathered to collect feedback on any usability concerns and necessary adjustments to improve the overall user experience. This will assist on getting feedback from other point of views and the effectiveness and usability of the application without bias. A google form will be sent out to get feedback on the application. Then, once everything is set and done and verified, the application can be deployed for anyone who would wish to evaluate their depression. More will be discussed in the next chapter.

3.2.6 Application Maintenance

After everything is said and done in the testing phase, then application might go into production and with production then there is a need to maintain the application to streamline user experience. However, there is no plan to put the application into production at the moment, therefore, more will be discussed in the future chapter.

3.3 Summary

This chapter highlights the methodologies applied to this project and how it the methodologies work well in this project. The chapter starts off with highlighting the adoption of Waterfall Model which is an SDLC method that works sequentially with each phase. The first phase explores the requirement of the project such as the hardware and software requirement to complete the project. Then, second phase dive into the application design that include several illustrations to showcase the functionalities and inner operation of the proposed application. Next, the third phase focus on the more practical and hands-on part of the project by highlighting the implementation and several tools that utilise to complete the development. Additionally, the fourth phase enter the testing phase to test the usability of the application followed by fifth phase which include user testing and deployment of the proposed application.

Chapter 4: Implementation & Testing

4.1 Introduction

This chapter will explore the implementation process of the proposed application which is known as MoodMate now. This chapter will include hardware specifications, highlighting devices used for development, then will dive into the implementation steps, methods and tools used for implementation and will be separated into 3 parts highlighting the main component of the application – Machine Learning model, database and system architecture.

Moreover, this chapter will also focus on the testing process conducted on the MoodMate application which will include several functionality testings such as unit testing, integration testing, functional testing, overall system testing and user acceptance testing to ensure the proposed application run as expected.

4.2 Hardware Specifications

Table 4.1 shows two hardware were used in implementation steps, which is a personal laptop for development and a mobile phone for deploying and application testing.

Table 4.1: Hardware Specification

Device	Purpose	Specifications
Personal Laptop	Development & Implementation	Dell Latitude 7390 (2018)
		Intel i5 core vPro 7 th Gen
		Windows 10
		20 GB RAM
Mobile phone	Application Deployment & Testing	Samsung Galaxy A13 5G
		Octa-core
		Android 14
		One UI version 6.1

4.3 Implementation

The implementation will explore three core components of the proposed application which consist of Machine Learning Model, database and the overall system architecture to showcase each technical and intricate details of the implementation process of the proposed application – MoodMate. Each of these components will be discussed in detail to highlight the technical processes and decision involve during development stage of the MoodMate Application. Therefore, the implementation aims to provide a comprehensive understanding of on the technologies utilized during this stage to achieve the project objectives.

4.3.1 Machine Learning Model

The Machine Learning model in the proposed application are used to determine the level of depression of written input from user to contribute to the result which are the potential depression level and score. Therefore, this section will focus on the Machine Learning model's development and its integration to the application. The full development process includes multiple stages.

Dataset Collection

Raw text data was collected from Reddit, especially from mental health related subreddit such as r/suicidewatch, r/depression, r/mentalhealth and so on and approximately 5000 raw text data was collected. The collected data was then labelled manually based on 4 classifications: Not Depressed, Mildly Depressed, Depressed & Severely Depressed which is a standard depression phase for the user. Then, approximately 2000 data were manually labelled, equally classified across all 4 labels, which is 500 for each label. The labelled dataset was then pre-processed mostly to remove stop words so that the model can recognize the context of the sentence.

```
def clean_text(text):
    text = ftfy.fix_text(str(text)) # Ensure text is a string
    text = text.lower() # Convert to lowercase
    text = re.sub(r"http\S+|www\S+", "", text) # Remove URLs
    text = re.sub(r"@w+|#w+", "", text) # Remove hashtags and mentions
    text = re.sub(r"^\w\s", "", text) # Remove punctuations
    text = re.sub(r"d+", "", text) # Remove numbers
    text = re.sub(r"s+", " ", text).strip() # Remove extra spaces
    text = " ".join([lemmatizer.lemmatize(word) for word in word_tokenize(text) if word.lower() not in stop_words])

    return text
```

Figure 4.1: Snippet of stop words removal function

Figure 4.1 shows the functions to pre-process the data which include removal of symbols, punctuations, numbers and more.

```

# Load dataset
df = pd.read_csv("/content/drive/MyDrive/preprocessed3.csv")

# Distinguish between labeled and unlabeled data
df_labeled = df.dropna(subset=["label"]).copy()
df_unlabeled = df[df["label"].isna()].copy()

# Convert labels to numeric values
label_mapping = {"Not Depressed": 0, "Mildly Depressed": 1, "Depressed": 2, "Severely Depressed": 3}
df_labeled["label"] = df_labeled["label"].map(label_mapping)

# Split train and test datasets
train_texts, val_texts, train_labels, val_labels = train_test_split(
    df_labeled["text"].tolist(), df_labeled["label"].tolist(), test_size=0.2, random_state=42
)

# Load BERT Tokenizer
tokenizer = AutoTokenizer.from_pretrained("mental/mental-bert-base-uncased")

```

Figure 4.2: Snippet of pre-processed data set being used to train BERT model

Figure 4.2 shows that the pre-processed dataset as preprocessed3.csv were then loaded to be used to train the initial model which is a pretrained model specialise in detecting mental health related text, Mental BERT by Hugging Face (an AI focused company and community). The trained Mental BERT model will be used to determine the other unlabelled raw data text with their appropriate classification.

obsessed mathematics need help please li	Depressed
grieve relationship never problem somethir	Mildly Depressed
cope feel unbelievably sad boyfriend starte	Depressed
med dont like med im welltrubin anxiety im	Depressed
appointment tomorrow dont want tell every	Severely Depressed
fuck college everything related academic s	Severely Depressed
want stop medication ive taking lexapro qui	Depressed
life suck hate life life longer feel good hate l	Severely Depressed
feel sick stay home hate everything job care	Depressed
concept worst type suffering believing dese	Depressed
normal feel like wont make past certain age	Mildly Depressed
taking pill actually worth suffer intrusive thc	Depressed
control sudden locking fear always freeze f	Not Depressed
jealousy control control im year old im curr	Depressed
feel like killing option supposed go back col	Depressed
sertraline month feeling depressed anxious	Mildly Depressed
im going back school dont want teacher cla	Depressed
anyone feel shame coming home late drivir	Mildly Depressed
brewing misery many year doesnt end dont	Depressed

Figure 4.3: Snippet of labelled data using Mental BERT model

Figure 4.3 shows the result of the fully labelled dataset with each of the classification by the Mental BERT.

Machine Learning model training (Logistic Regression)

After obtaining the fully labelled dataset, then it can be used to train a more lightweight model which is the Logistic Regression model to avoid performance issue in determining depression level in the application since BERT is relatively heavier. However, Logistic Regression is a traditional Machine Learning model, thus it could not understand context of the text or natural language. Hence, the trained Mental BERT from previous stage will be used to convert each input into a meaningful number-based formatting (text embedding) that captures emotional and contextual details. This will allow the Logistic Regression model to make a more informed predictions based on the context and deeper understanding learnt by the trained Mental BERT.

```
#Load dataset
drive.mount('/content/drive')
df=pd.read_csv('/content/drive/My Drive/labeledx.csv')

#Convert label to numeric
custom_map = { 'Not Depressed': 0, 'Mildly Depressed': 1, 'Depressed': 2, 'Severely Depressed': 3}
df['encode_label'] = df['label'].map(custom_map)

#load Bert for embedding
tokenizer = AutoTokenizer.from_pretrained("/content/drive/My Drive/bert_modelM2")
bert_model = AutoModel.from_pretrained("/content/drive/My Drive/bert_modelM2").to(device)
bert_model.eval()

#define Bert embedding
def get_bert_embedding(text_list, batch_size=8):
    embedding = []
    for i in tqdm(range(0, len(text_list), batch_size)):
        batch = text_list[i:i+batch_size]
        encoded = tokenizer(batch, padding=True, truncation=True, max_length=256, return_tensors='pt').to(device)
        with torch.no_grad():
            outputs = bert_model(**encoded)
            mean_embedding = outputs.last_hidden_state.mean(dim=1).cpu().numpy()

        embedding.append(mean_embedding)
    return np.vstack(embedding)
```

Figure 4.4: Snippet of using trained Mental BERT as embedding

Figure 4.4 shows the trained Mental Bert model known as bert_modelM2 loaded as embedding.

```

#Reduce dimensionality of BERT embeddings using PCA
pca = PCA(n_components=600) # Reduce to 100 components (or experiment with other values)
X_reduced = pca.fit_transform(X)

#Train using Cross Validation
clf = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=1000, class_weight='balanced')
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
cv_scores = cross_val_score(clf, X_reduced, y, cv=skf, scoring='accuracy')

#Show accuracy for each fold and avg
print(f"Accuracy for each fold:", cv_scores)
print(f"Average accuracy:", np.mean(cv_scores))

#train model in general
clf.fit(X_reduced,y)
y_pred = clf.predict(X_reduced)
print("classification_Report:")
print(classification_report(y, y_pred))

```

Figure 4.5: Snippet of dimension reduction and validation

Figure 4.5 shows the training process also use Principal Component Analysis (PCA) to reduce dimension since BERT in general is a relatively heavy model. The figure also shows the evaluation method use cross validation to avoid overfitting since this method allow for a more balanced evaluation across different folds.

classification_Report:				
	precision	recall	f1-score	support
0.0	0.97	0.96	0.96	1299
1.0	0.82	0.96	0.89	512
2.0	0.97	0.88	0.92	1393
3.0	0.90	0.97	0.94	705
accuracy			0.93	3909
macro avg	0.92	0.94	0.93	3909
weighted avg	0.94	0.93	0.93	3909

Figure 4.6: Trained Model Performance Evaluation

Figure 4.6 shows the evaluation results of the trained Logistic Regression Model which achieved an overall accuracy of 93%, the macro average F1-score was 0.93 which indicates a

balanced performance across all four depression levels. These results proves that the model is effective in distinguishing between different levels of depression based on Text.

Model API Integration

When Model is completed and ready to be integrated, FastAPI is used to create a simple backend interface to receive user written input which in this case is the elaboration text in each question.

```
# FastAPI app
app = FastAPI()

# Request body format
class ElaborationInput(BaseModel):
    text: str

def get_bert_embedding(text):
    inputs = tokenizer(text, return_tensors="pt", truncation=True, padding=True, max_length=512)
    with torch.no_grad():
        outputs = bert_model(**inputs)
    mean_embedding = outputs.last_hidden_state.mean(dim=1).cpu().numpy() # Mean pooling
    return mean_embedding

@app.post("/predict_score")
def predict_score(input: ElaborationInput):
    embedding = get_bert_embedding(input.text)
    reduced = pca.transform(embedding)
    prediction = model.predict(reduced)
    return {"score": int(prediction[0])}
```

Figure 4.7: Snippet of API integration

Figure 4.7 show the API integration by receiving user input then processed it using the trained Mental BERT before making a prediction on depression score.

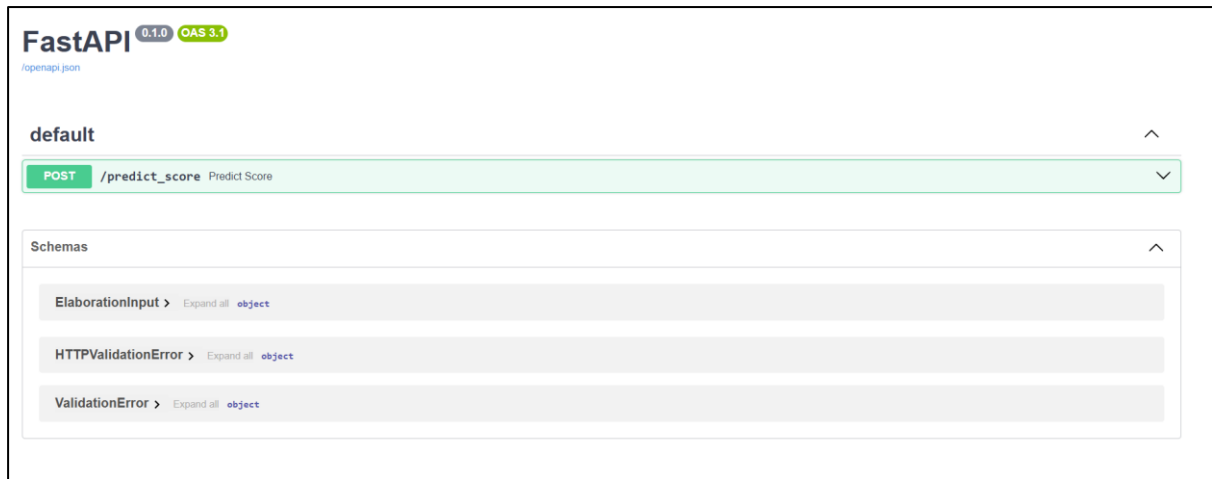


Figure 4.8: FastAPI endpoint

Figure 4.8 show the FastAPI endpoint which is a built-in API documentation interface by FastAPI. This page allows developers to test the endpoint by entering input directly from the interface and check the response in real time. Thus, in this project the main endpoint `/predict_score` is defined using a POST method that accept user's elaboration text and return depression score from 0 to 3.

4.3.2 Database

```
class DatabaseHelper {  
  Future _onCreate(Database db, int version) async {  
    // User Table  
    await db.execute('''  
      CREATE TABLE user (  
        session_id TEXT PRIMARY KEY,  
        gender TEXT,  
        years TEXT,  
        faculty TEXT,  
        cgpa TEXT,  
        incometier TEXT  
      )  
    ''');  
    // Assessment Table  
    await db.execute('''  
      CREATE TABLE assessment (  
        id INTEGER PRIMARY KEY AUTOINCREMENT,  
        session_id TEXT,  
        type TEXT,  
        questionid TEXT,  
        question TEXT,  
        answer TEXT,  
        elaboration TEXT,  
        FOREIGN KEY (session_id) REFERENCES user(session_id)  
      )  
    ''');  
    // Result Table  
    await db.execute('''  
      CREATE TABLE result (  
        id INTEGER PRIMARY KEY AUTOINCREMENT,  
        session_id TEXT,  
        depression_level TEXT,  
        depression_score double,  
        reason_1 TEXT,  
        reason_2 TEXT,  
        reason_3 TEXT,  
        FOREIGN KEY (session_id) REFERENCES user(session_id)  
      )  
    ''');  
  }  
}
```

Figure 4.9: Snippet of Database Table creation

The database in this project uses SQLite, which is a built-in database in Flutter that can store data locally on user's device, making it suitable for offline access. In this project, three tables were created which are User Table, Assessment Table and Result Table. Figure 4.9 shows how the tables with their respective attribute are created in the Flutter Dart code from the database from a helper function.

```

class DatabaseOperations {
    final dbHelper = DatabaseHelper();

    Future<void> insertUser({
        required String sessionId,
        required String gender,
        required String years,
        required String faculty,
        required String cgpa,
        required String incometier,
    }) async {
        final db = await dbHelper.database;

        print(
            '● Inserting: $sessionId, $gender, $years, $faculty, $cgpa, $incometier',
        );

        await db.insert('user', {
            'session_id': sessionId,
            'gender': gender,
            'years': years,
            'faculty': faculty,
            'cgpa': cgpa,
            'incometier': incometier,
        }, conflictAlgorithm: ConflictAlgorithm.replace);
    }
}

```

Figure 4.10: Snippet of Database Table creation

Figure 4.10 show the insertion on table, how when a user completes their input, it will trigger the insertion function which will access via the SQLite database then store the information into the appropriate table. Same approach is used for Assessment Table and Results Table in which generated results such as depression score and depression level will be inserted.

4.3.3 System Architecture

4.3.3.1 Splash Screen

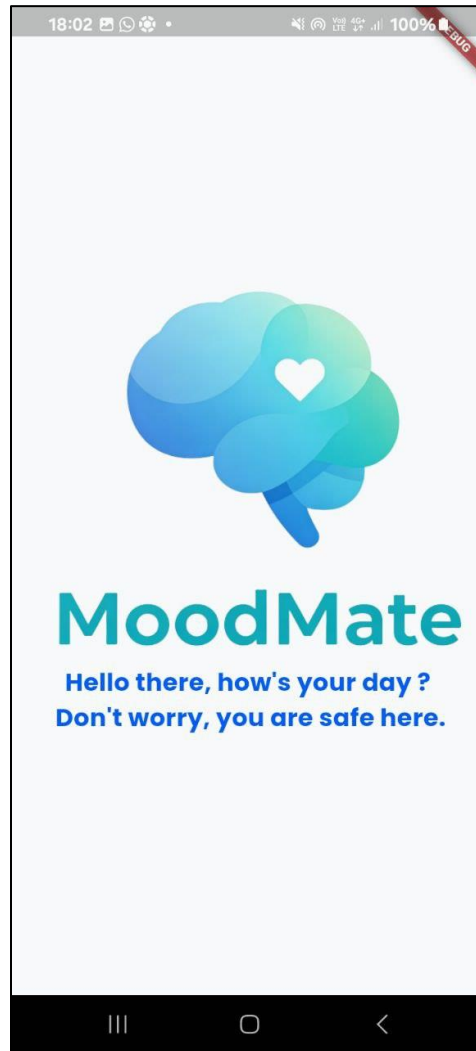


Figure 4.11: Splash Screen of MoodMate

This is the splash screen of the application, where it will only display for 5-10 seconds before entering homepage upon activating the application. The logo, name and welcoming message is as shown in Figure 4.11.

4.3.3.2 Home Screen

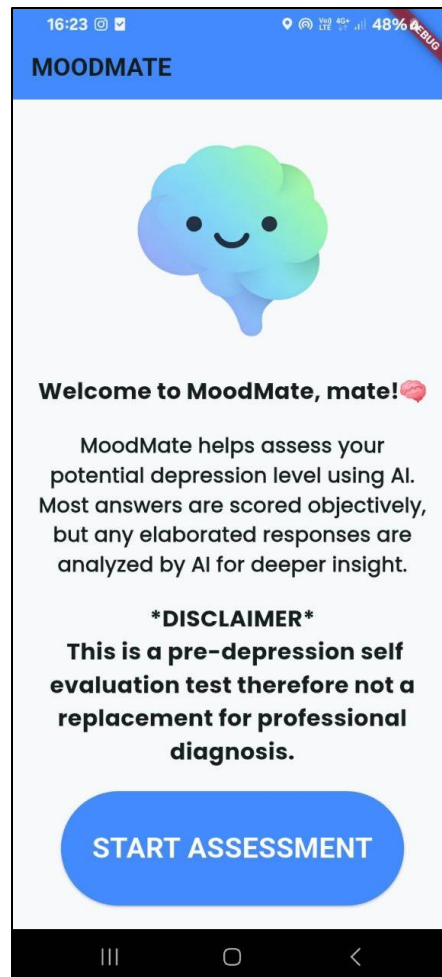


Figure 4.12: Home Screen of MoodMate

Figure 4.12 shows the home screen of MoodMate where a welcoming greeting, about the application and disclaimer. This is done to introduce the main use of MoodMate and also seek to inform user the limitation of the assessment. Then, below is a huge 'START ASSESSMENT' button where user will tap on to proceed to the assessment.

4.3.3.3 Test Screen

MoodMate's test screen consists of 3 parts which are demographic, Patient Health Questionnaire (PHQ-9) and Ask Suicide-Screening Questions (ASQ), which most will be useful in determining the potential level of depression and potential contributing factors for depression, that will be explained in detail.

Demographic Part

18:02 100% **MOODMATE**

1 Demographic Info

Gender

☐ Male

☐ Female

☐ Prefer not to say

Years of Study

☐ Year 1

☐ Year 2

☐ Year 3

☐ Year 4

☐ Year 5

Faculty

☐ Faculty of Economics and Business

☐ Faculty of Engineering

Figure 4.13: Demographic Test Screen 1 of MoodMate

18:02 100% 4G LTE

← MOODMATE

☐ Faculty or Built Enviroment

Academic Performance (CGPA)

☐ 3.5 above

☐ 3.5-3.0

☐ 2.9-2.5

☐ 2.4-2.0

☐ below 2.0

Income Tier

☐ T20

☐ M40

☐ B40

☐ Not Sure

Continue

2 PHQ-9 Assessment

Figure 4.14: Demographic Test Screen 2 of MoodMate

Figure 4.13 and Figure 4.14 show the first set of questions will be display in the assessment which is the demographic of the user, which consist of their gender, years of study, faculty, academic performance and income tier. This demographic is collected with the purpose of determining user's potential contributing factors to depressions.

PHQ-9 Part

18:02 100% **MOODMATE**

✓ Demographic Info

2 PHQ-9 Assessment

Little interest or pleasure in doing things?

☐ Not at all

☐ Several days

☐ More than half the days

☐ Nearly every day

Elaborate (Optional)

Feeling down, depressed, irritable, or hopeless?

☐ Not at all

☐ Several days

☐ More than half the days

Figure 4.15: PHQ-9 Part Screen 1 of MoodMate

18:03 100% **MOODMATE**

☐ Nearly every day

Elaborate (Optional)

Thoughts that you would be better off dead, or of hurting yourself in some way?

☐ Not at all

☐ Several days

☒ More than half the days

☐ Nearly every day

Elaborate (Optional)

Yes, i want to die, i hate myself

Continue Back

3 ASQ Assessment

Figure 4.16: PHQ-9 Part Screen 2 of MoodMate

Figure 4.15 and Figure 4.16 show that once user is done with demographic part, they will proceed to the PHQ-9 part where 9 questions will be asked to gather, to determine their potential level of depression. Moreover, each of the question will have an optional elaboration text bar where user can further elaborate on their situation regarding a certain related question. The elaborated text will be sent to a Machine Learning model to predict the score of their text to be added in the overall level of depression. Once they are done, they can proceed by tapping on 'Continue'.

ASQ Part

18:03 100% **MOODMATE**

✓ Demographic Info

✓ PHQ-9 Assessment

3 ASQ Assessment

In the past few weeks, have you wished you were dead?

☐ Yes

☐ No

Elaborate (Optional)

In the past few weeks, have you felt that you or your family would be better off if you were dead?

☐ Yes

☐ No

Elaborate (Optional)

Figure 4.17: ASQ Part Screen 1 of MoodMate

18:03 100% **MOODMATE**

☐ No

Elaborate (Optional)

Have you ever tried to kill yourself?

☒ Yes

☐ No

If yes when and how ?

Are you having thoughts of killing yourself right now?

☒ Yes

☐ No

If yes please describe

Submit Back

Figure 4.18: ASQ Part Screen 2 of MoodMate

Figure 4.17 and Figure 4.18 show that the final part of the assessment will consist of 5 questions from ASQ, which is related to suicidal question, and each ‘Yes’ answer will weigh more since this carries a more sensitive issue. Likewise, with PHQ-9 part, each ASQ question will also consist of optional elaboration where it will also send to the trained ML model to assess and add weights to overall. Once they are done, they will tap on ‘Submit’ to submit the assessment and get their result.

Incomplete Message

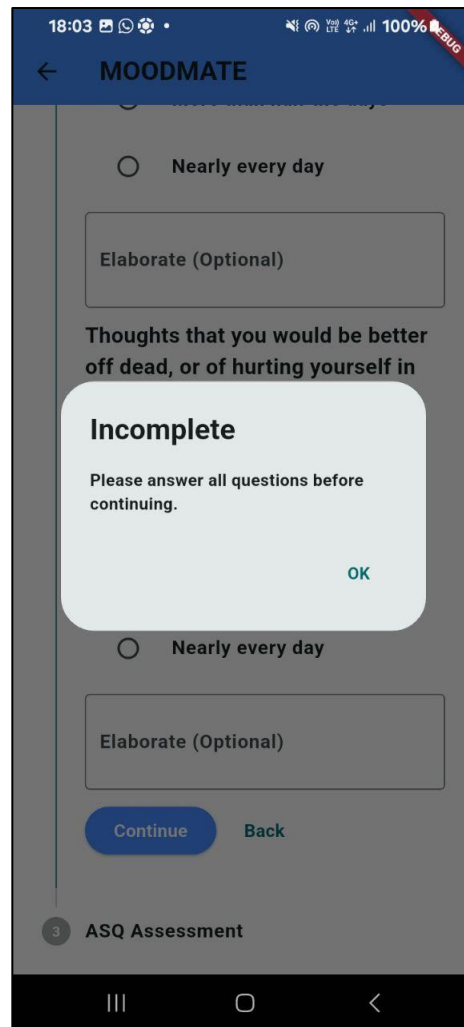


Figure 4.19: Incomplete Message

Figure 4.19 is the screen shown if the user overlooked or missed a question, a message will remind them to complete the assessment before proceeding.

4.3.3.4 Result Screen

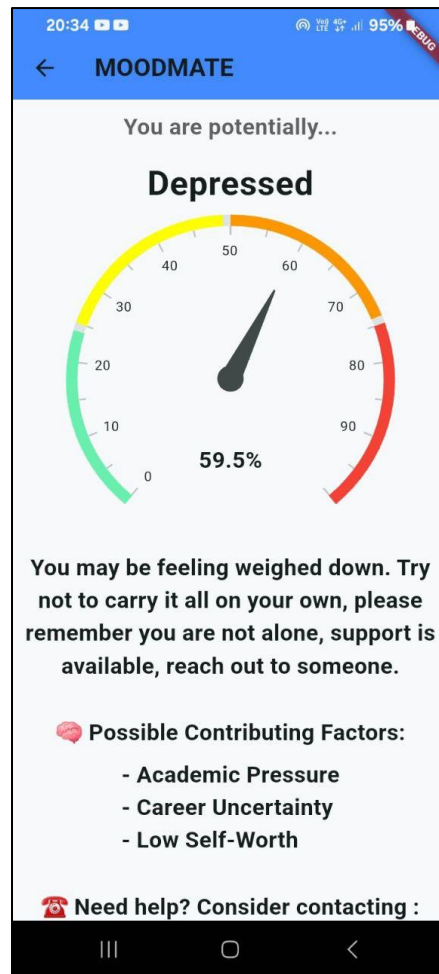


Figure 4.20: Result Screen of MoodMate

Figure 4.20 shows the result screen the result screen of MoodMate where it will show the potential depression level of the user based on their input and a visual gauge that will point based on the percentage of their level. Then, below the gauge is a message for user based on the percentage of depression and it will change depending on their percentage of depression.

Furthermore, the possible contributing factor is the potential factor for depression, where 3 factors will be shown and it will vary depending on the assessment.

Helpline Option



Figure 4.21: Helpline option in MoodMate result screen

Figure 4.21 shows the helpline options below possible contributing factors, which shows the university counselling unit's helpline and Kuching branch Befrienders helpline, which might could assist the user in need. User can directly contact the numbers by tapping on the contact number as highlighted in blue shown in Figure 4.21.

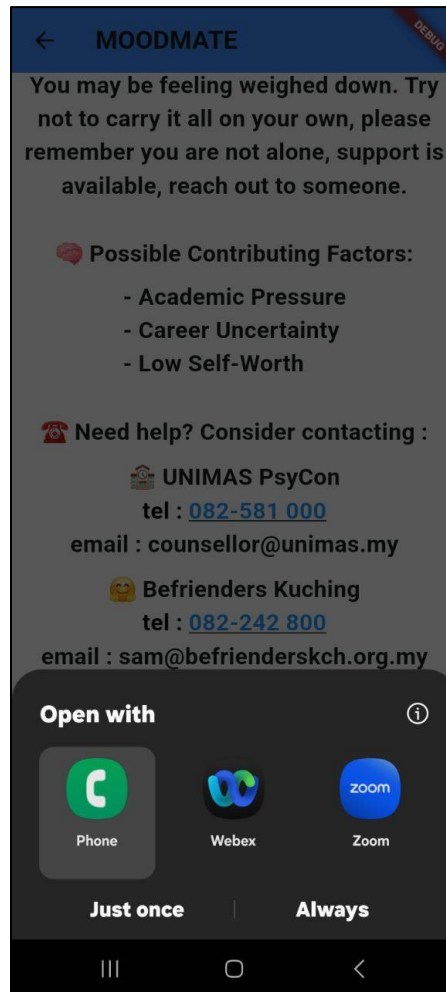


Figure 4.22: Contact options

Figure 4.22 show the application allowing user to choose the application to directly call the helplines once user tap on their respective contact numbers.

View Result Report & Retake Assessment

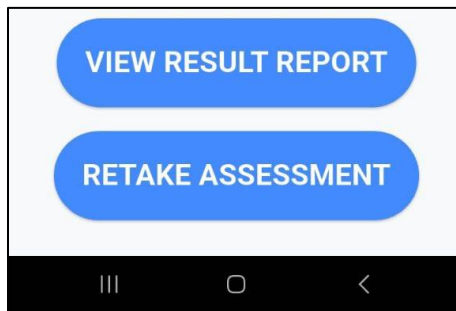


Figure 4.23: View result report and retake assessment button

From Figure 4.23, after the user are done with their result they can choose to view their result by tapping on the ‘View Result Report’ button to navigate them to a view report page and retake assessment will navigate the user back to test screen where they can attempt the assessment again.

4.3.3.4 View Result Report Screen

16:38 56% **MOODMATE**

Depression Assessment Report

Date: 2025-06-08 16:38:05

Demographic:

Gender	Years of Study	Faculty	Academic Performance (CGPA)	Income Tier
Female	Year 4	Faculty of Economics and Business	2.9-2.5	B40

Total Score: 40.54054054054054
Depression Level: Mildly Depressed
Potential reasons leading to depression:

- Academic Pressure
- Financial Struggles
- Low Self-Worth

Note: The result is for pre-depression evaluation purposes, therefore not a clinical diagnosis.

PHQ-9 Questions Breakdown:

Question	Answer
Little interest or pleasure in doing things?	Not at all
Elaboration	-
Feeling down, depressed, irritable, or hopeless?	Not at all
Elaboration	-
Trouble falling asleep, staying asleep, or sleeping too much?	Several days

Elaboration	-
Poor appetite, weight loss, or overeating?	More than half the days
Elaboration	-
Feeling tired, or having little energy?	More than half the days
Elaboration	-
Feeling bad about yourself - or feeling that you are a failure, or that you have let yourself or your family down?	More than half the days
Elaboration	-
Trouble concentrating on things like school work, reading, or watching TV?	Several
Elaboration	-

Download and Share icons

Figure 4.24: Result report page

As shown in Figure 4.24, user will be able to view and read their report thoroughly before deciding whether to download for record purposes or share to others. The two icons below allow user to download and share their report.

Share Icon

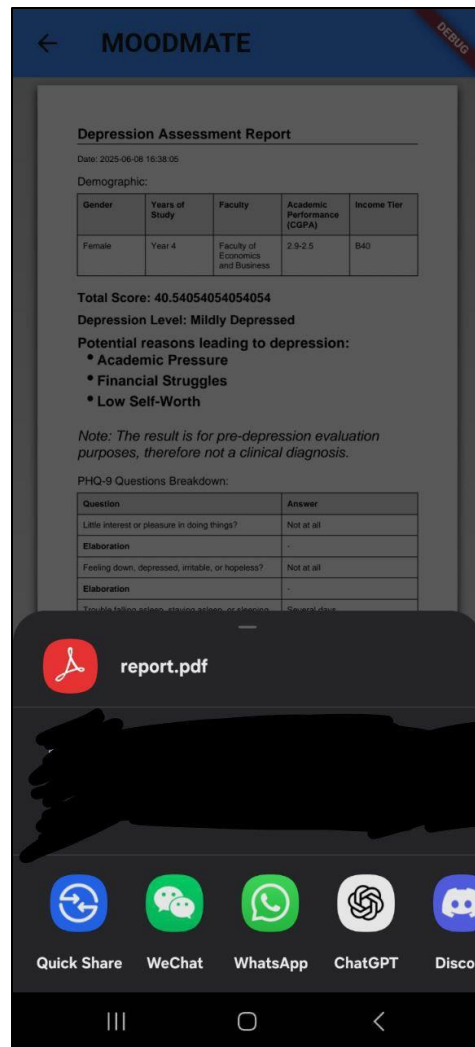


Figure 4.25: Share report

Figure 4.25 will be shown when user tap on the share icon they will be able to share their report as report.pdf to anyone with the standard mobile application sharing interface.

Download Icon



Figure 4.26: Download folder in device

Once it is downloaded, it will be in user's device and naming of the file will be based on the time of the device as shown in Figure 4.26, so that they may keep multiple copy for future reference, rather than overwriting old one.

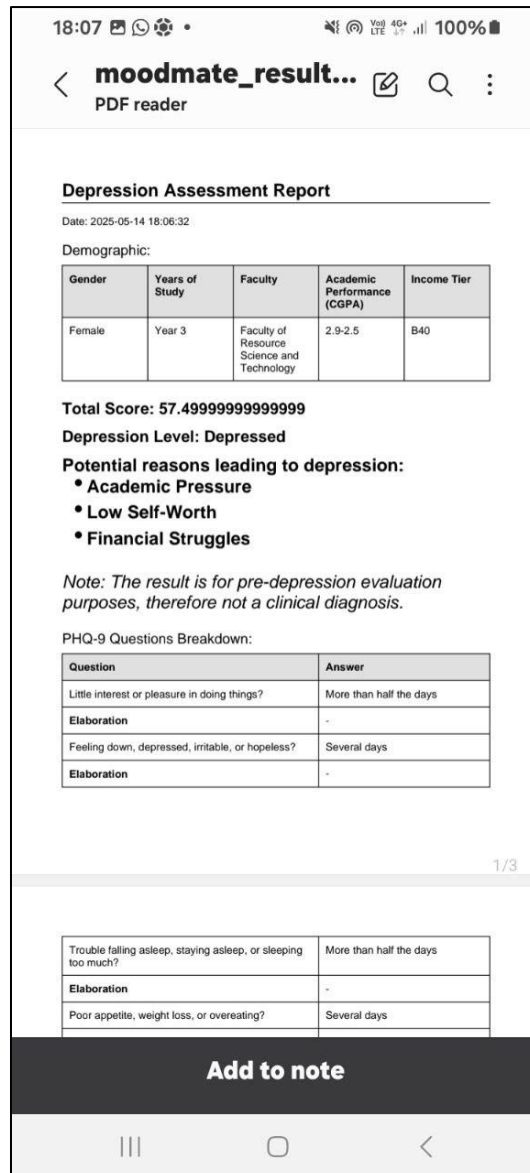


Figure 4.27: MoodMate report in PDF 1

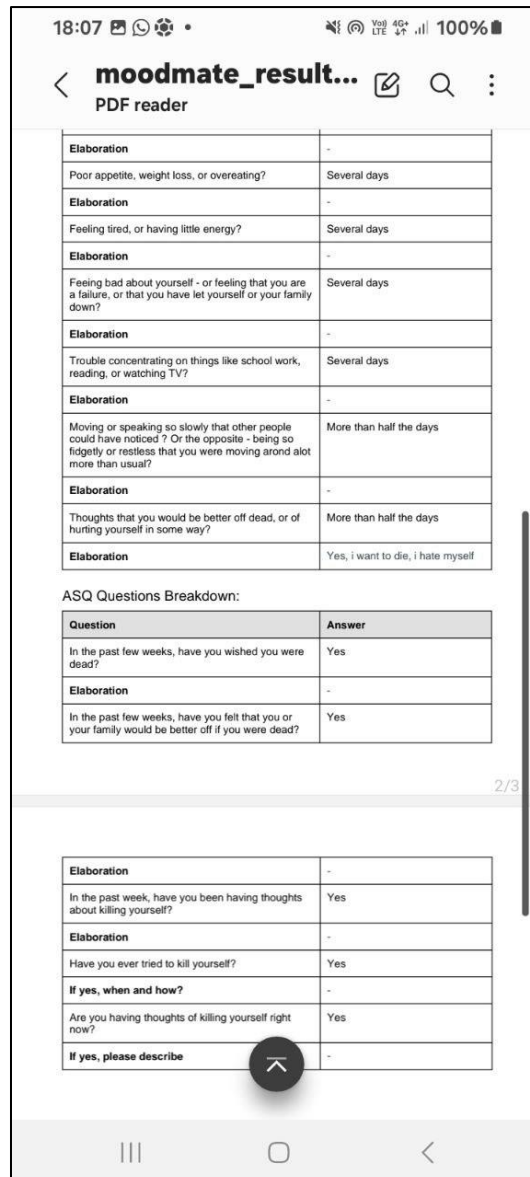


Figure 4.28: MoodMate report in PDF 2

Figure 4.27 and Figure 4.28 show the downloaded PDF report, which shows all the answered questions from assessments and potential level of depression and potential contributing factors. This record may be useful for record purpose and evaluation purposes by clinical professionals.

4.4 Application Testing

The testing stage plays a significant role in ensuring the functionality and usability of the MoodMate application so that it could perform as expected and achieve the objectives of the project. This section of the chapter will outline several testing approaches such as unit testing, integration testing, functional testing, system testing and user acceptance testing.

4.4.1 Unit Testing

Unit testing is conducted to ensure each component of the proposed application run and work as intended, thus, several test cases were applied during the unit testing phase as shown in Table 4.2, Table 4.3 and Table 4.4.

Table 4.2: Unit Testing 1 of the proposed application

Test Title:		Depression score and depression level calculation			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
UT01_01	Verify PHQ & ASQ scoring return “Not	1. Tap on “START ASSESSMENT”.	-Depression Level: Not Depressed	-Depression Level: Not Depressed	Pass

	depressed” with minimal responses	2. Select all “Not at all” in PHQ section & “No” on ASQ Section. 3. Tap on “Submit”.	-Depression Score: 0.0%	-Depression Score: 0.0%	
UT01_02	Verify PHQ & ASQ scoring return “Severely depressed” with Maximum responses	1. Tap on “START ASSESSMENT”. 2. Select all “Nearly Every day” in PHQ section & “Yes” on ASQ Section. 3. Tap on “Submit”.	-Depression Level: Severely Depressed -Depression Score: 100.0%	-Depression Level: Severely Depressed -Depression Score: 100.0%	Pass
UT01_03	Verify PHQ & ASQ scoring with Mixed responses that return appropriate result	1. Tap on “START ASSESSMENT”. 2. In PHQ, select first two questions “Not At all”. Proceeding two questions with “Several Days”. Next two with “More than half of the days” Last three	-Depression Level: Depressed -Depression Score: 56.8%	-Depression Level: Depressed -Depression Score: 56.8%	Pass

		questions with “Nearly every day”. 3. In ASQ alternate between “Yes” and “No” starting from “Yes”. 4. Tap on “Submit”.			
UT01_04	Verify elaboration on both PHQ & ASQ affects results	1. Tap on “START ASSESSMENT”. 2. Select all “Not at all” in PHQ section & “No” on ASQ Section. 3. Input several depressive sentences in elaboration such as “I want to die”. 4. Tap on “Submit”.	-Depression Score > 0.0%	-Depression Score > 0.0%	Pass

Table 4.3: Unit Testing 2 of the proposed application

Test Title:		Rule-based contributing factors to depression			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
UT02_01	Verify demographic affects top contributing factors	1. Tap on “START ASSESSMENT”. 2. Select “B40” in income tier in the demographic part of assessment. 3. Complete the rest of the assessment. 3. Tap on “Submit”.	“Financial Struggles” as the first contributing factors.	“Financial Struggles” as the first contributing factors.	Pass
UT02_02	Verify elaboration keywords affects top contributing factors	1. Tap on “START ASSESSMENT”. 2. Input keywords in elaboration that indicate academic pressure	“Academic Pressure” as the first contributing factors.	“Academic Pressure” as the first contributing factors.	Pass

		such as “exam”, “fail”, “assignment” and so on. 3. Complete the assessment. 4. Tap on “Submit”.			
--	--	--	--	--	--

Table 4.4: Unit Testing 3 of the proposed application

Test Title:		User Interface logic			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
UT03_01	Verify the application does not allow user to proceed before completing the assessment.	1. Tap on “START ASSESSMENT”. 2. Try to proceed without finishing each part of the assessment.	An Incomplete pop-up message will inform user and stop the application from proceeding.	An Incomplete pop-up message will inform user and stop the application from proceeding.	Pass

4.4.2 Integrations Testing

Integration testing is conducted to verify that the component of MoodMate application work together well with other components which in this case include verifying the insertion and retrieval of data via SQLite and the Machine Learning model integration via FastAPI work as intended with the application. Integration testing and test cases are as shown in Table 4.5.

Table 4.5: Integration Testing of the proposed application

Test Title:		SQLite & FastAPI Integration			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
IT01_01	Verify the data is passed and inserted correctly to their respective tables	1. Tap on “START ASSESSMENT”. 2. Finish the assessment and submit. 3. Use debugprint to check if data is stored.	Data is stored correctly and accurately.	Data is stored correctly and accurately.	Pass

IT01_02	Verify the Machine Learning model is integrated correctly via FastAPI	1. Manually Connect to FastAPI via Command Prompt terminal. 2. Open FastAPI endpoint link on both mobile and computer. 3. Tap on “START ASSESSMENT”. 4. Select all “Not at all” in PHQ section & “No” on ASQ Section. 5. Input several depressive sentences in elaboration such as “I want to die”. 6. Tap on “Submit”.	-Able to open FastAPI endpoint without any issue. -Depression Score > 0.0%	-Able to open FastAPI endpoint without any issue. -Depression Score > 0.0%	Pass
---------	---	--	---	---	------

4.4.3 Functional Testing

Functional testing is also conducted to ensure that the feature and the flow of the application perform accordingly as this type of testing focuses more on functionalities from user's point of view, thus this testing will include all interactions in the MoodMate application to verify it behave as expected. Several functional tests and test cases were tested as shown in Table 4.6 and Table 4.7.

Table 4.6: Functional Testing 1 of the proposed application

Test Title:		Assessment Flow			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
FT01_01	Verify application can start assessment	1. Tap on “START ASSESSMENT”.	Navigate to assessment screen upon tapping.	Navigate to assessment screen upon tapping.	Pass
FT01_02	Verify assessment questions are separated with three parts and are able to go back and forth	1. Tap on “START ASSESSMENT”. 2. Assessment screen contains demographic parts, PHQ part & ASQ part.	-Assessment screens show demographic, PHQ and ASQ questions.	-Assessment screens show demographic, PHQ and ASQ questions.	Pass

		3. Able to go back and forth by tapping on the stepper of each part.	-Stepper can be tapped on to a specific part of the assessment.	-Stepper can be tapped on to a specific part of the assessment.	
FT01_03	Verify the application does not allow user to proceed before completing the assessment.	1. Tap on “START ASSESSMENT”. 2. Try to proceed without finishing the assessment.	Show incomplete pop-up message to inform user to complete the assessment.	Show incomplete pop-up message to inform user to complete the assessment.	Pass
FT01_04	Verify application can navigate to result screen upon completing assessment	1. Tap on “START ASSESSMENT”. 2. Complete assessment. 3. Tap on “Submit”.	Navigate to result screen with the correct results.	Navigate to result screen with the correct results.	Pass

Table 4.7: Functional Testing 2 of the proposed application

Test Title:		Results Screen			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
FT02_01	Verify application can display result accordingly	1. Tap on “START ASSESSMENT”. 2. Complete assessment. 3. Tap on “Submit”.	Result screen is as expected with depression level, score, top contributing factors and two buttons which are retake assessment and view PDF report.	Result screen is as expected with depression level, score, top contributing factors and two buttons which are retake assessment and view PDF report.	Pass
FT02_02	Verify application can redirect to device’s contact list to contact helplines.	1. On result screen, tap both blue font contact number for UNIMAS PsyCon & Befrienders Kuching.	Application is able to redirect to device’s contact list or other relevant application.	Application is able to redirect to device’s contact list or other relevant application.	Pass

FT02_03	Verify application can generate accurate report based on assessment and results.	1. On result screen, tap on “View Result Report”.	Application is able to generate and show PDF report with the accurate results and selected answers from assessment.	Application is able to generate and show PDF report with the accurate results and selected answers from assessment.	Pass
FT02_04	Verify PDF report can be downloaded	1. On result screen, tap on “View Result Report”. 2. Tap on download icon button on view report page.	Application is able to download the same accurate PDF report into device.	Application is able to download the same accurate PDF report into device.	Pass
FT02_05	Verify PDF report can be shared	1. On result screen, tap on “View Result Report”. 2. Tap on share icon button on view report page.	Application is able to share the same accurate PDF report to anyone in the contact list.	Application is able to share the same accurate PDF report to anyone in the contact list.	Pass

FT02_06	Verify user can retake assessment after completing.	1. On result screen, tap on “Retake Assessment”.	Application navigates back to new assessment page.	Application navigates back to new assessment page.	Pass
---------	---	--	--	--	------

4.4.4 System Testing

After validating individual units, integrated modules and some specific functionalities, system testing was conducted to evaluate the overall behaviour of MoodMate application to ensure all the components such as user interface, backend logic, scoring mechanism and PDF report handling work together seamlessly to provide a smooth user experience. Testing and test cases are as shown in Table 4.8.

Table 4.8: System Testing of the proposed application

Test Title:		Overall System Testing			
Test ID	Test Case	Test Procedure	Expected result	Actual result	Status (Pass/Fail)
ST01_01	Verify application can work as intended.	1. Tap on “START ASSESSMENT”.	Result screen is as expected with depression level, score,	Result screen is as expected with depression level, score,	Pass

		2. Complete assessment with some elaboration to make use of the Machine Learning model. 3. Tap on “Submit”. 4. Check if data is being stored with debugprint.	top contributing factors and two buttons which are retake assessment and view PDF report. Data is stored in the relevant table.	top contributing factors and two buttons which are retake assessment and view PDF report. Data is stored in the relevant table.	
ST01_02	Verify application can generate, view, print and share PDF report	1. Tap on “START ASSESSMENT”. 2. Complete assessment with some elaboration to make use of the Machine Learning model. 3. Tap on “Submit”. 4. On result screen, tap on “View Result Report”.	-PDF report generated with the accurate user’s input and the displayed results -Generated PDF report is able to view.	-PDF report generated with the accurate user’s input and the displayed results -Generated PDF report is able to view.	Pass

			-Generated PDF report is able to download to device. -Generated PDF report is able to share.	-Generated PDF report is able to download to device. -Generated PDF report is able to share.	
ST01_03	Verify user can retake assessment after completing.	1. Tap on “START ASSESSMENT”. 2. Complete assessment with some elaboration to make use of the Machine Learning model. 3. Tap on “Submit”. 4. On result screen, tap on “Retake Assessment”.	Application navigates back to new assessment page and is able to start and repeat the same process and store different input appropriately as	Application navigates back to new assessment page and is able to start and repeat the same process and store different input appropriately as	Pass

		5. Repeat step 2-3	different input from previous assessment.	different input from previous assessment.	
--	--	---------------------------	--	--	--

4.4.5 User Acceptance Test

After all the functionalities tests are verified, a User Acceptance Test (UAT) is conducted to evaluate the MoodMate application from end-user's perspective to ensure that it meets the user expectations. Total of twenty respondents were selected to participate in the UAT which will cover 8 aspects of the application – usability, clarity, performance, results, trust in accuracy, emotional impact, overall impression and open feedback. Each of these aspects will be covered in each question respectively and will be analysed to understand the overall expectation of the proposed application. Moreover, an additional part regarding expert will also be added in this section to justify development's designs after consulting domain expert.

4.4.5.1 Usability of the application

This question uses Likert Scale from one to five with:

One - Not easy at all

Five – Very easy

Figure 4.29 shows that every respondent agree that the application is easy to use and navigate. This indicates that the application has a user-friendly interface and provides a simple and yet intuitive user experience, making it easy for user to understand what actions to take at every steps.

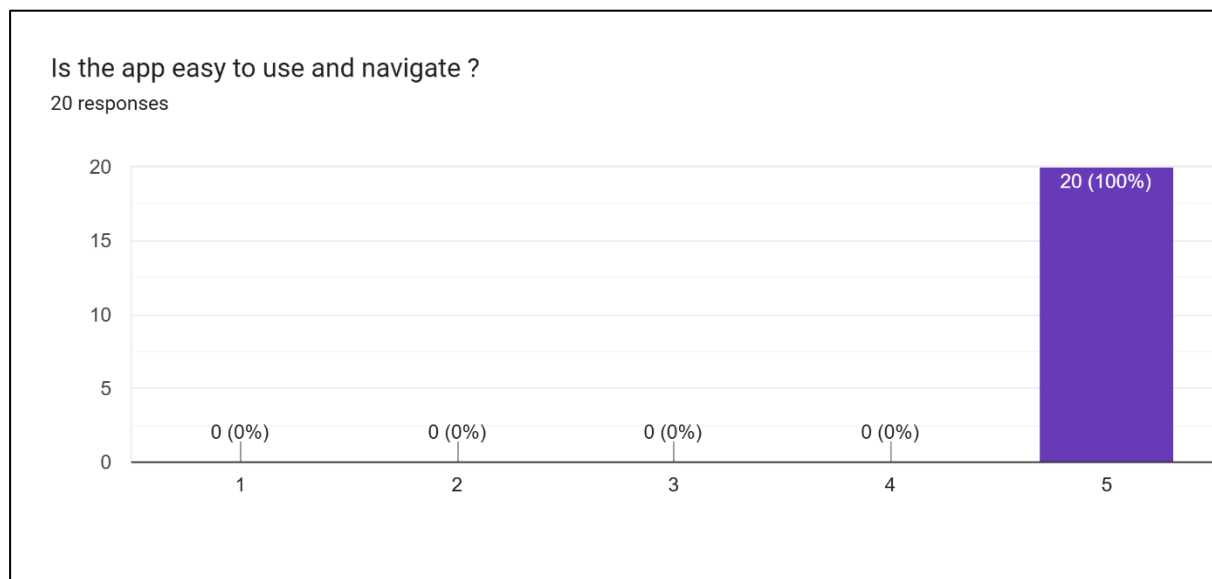


Figure 4.29: Usability UAT question

4.4.5.2 Clarity of the application

This question uses Likert Scale from one to five with:

One - Not at all

Five – Very easy to understand

Figure 4.30 shows that almost all respondents think the questions asked in the MoodMate application such as the demographics part, PHQ and ASQ part are easy to understand. However, there is one respondent (5%) that still think it is generally easy to understand but there is room for improvement like making it prettier rather than generic digital form design.

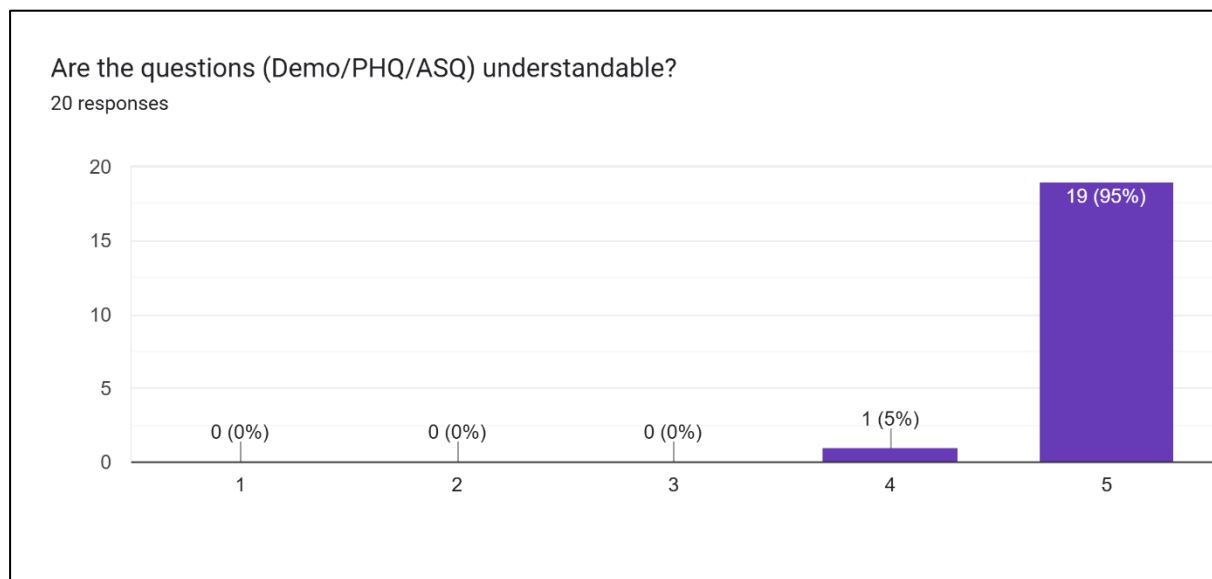


Figure 4.30: Clarity UAT question

4.4.5.3 Performance of the application

Figure 4.31 shows that all respondents think the applications does not lag or crash which indicates that there are no performance issues with the MoodMate application thus far. Therefore, this indicates that the application is stable and responsive during usage and suggest that there are no issues in regards with complex architecture affecting the performance, especially with the involvement of Machine Learning model.

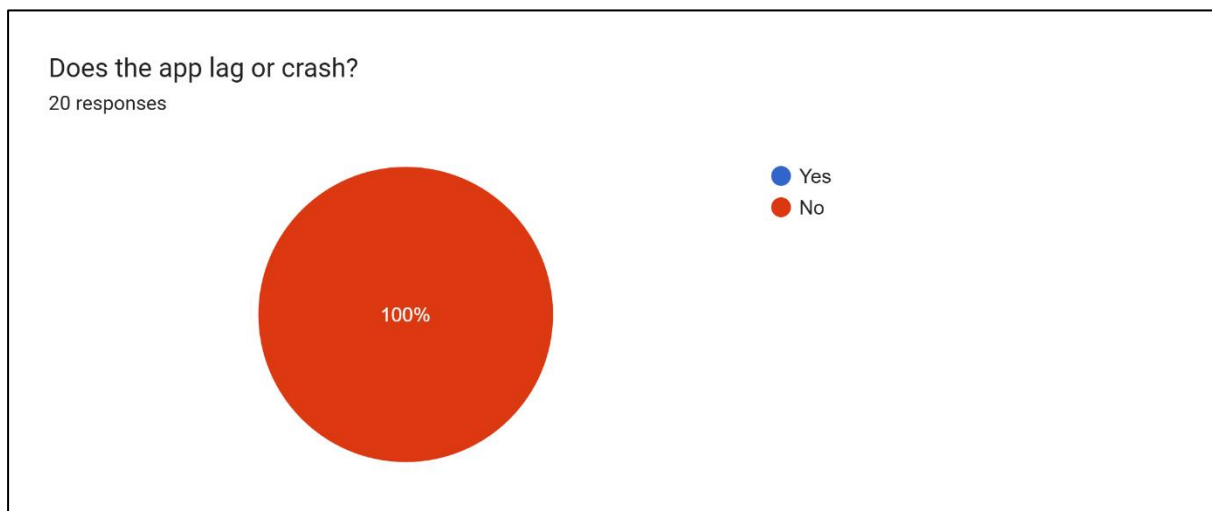


Figure 4.31: Performance UAT question

4.4.5.4 Result of the application

This question uses Likert Scale from one to five with:

One - Not at all

Five – Very clear

Figure 4.32 shows that almost all respondents think that the output of the application such as depression score, depression level and factors are clear. However, there is one respondent (5%) that think the output is clear, but it can be better, such as improving the UI design of the result screen making it even more visually appealing and emotionally appropriate for users dealing with depressions. The feedback by that respondent include using calming visuals and layout that indicate empathy and support.

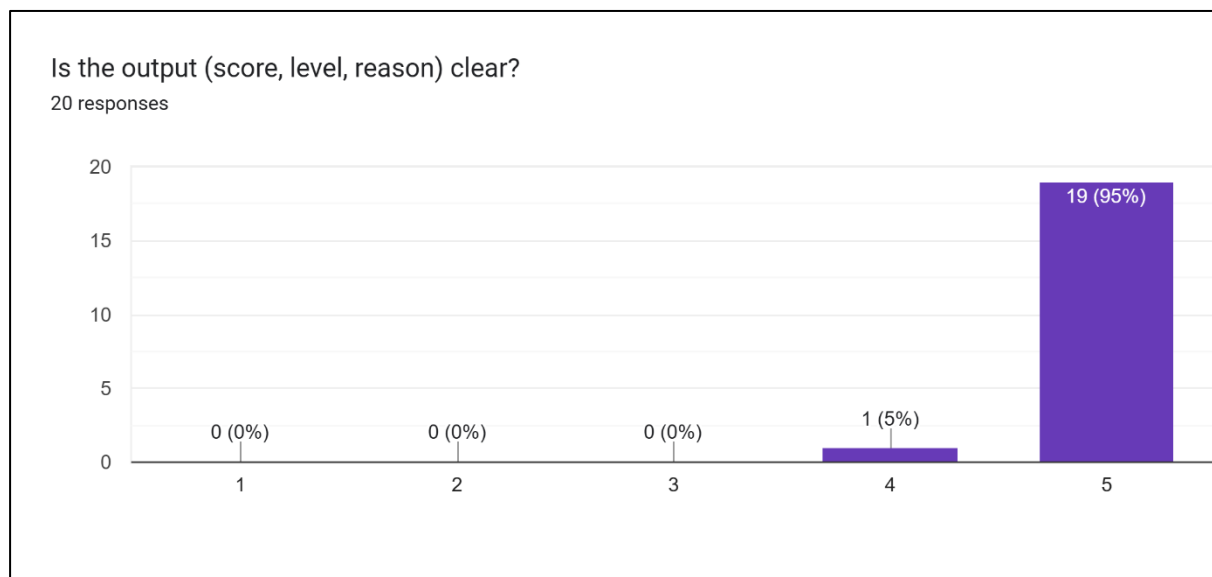


Figure 4.32: Result UAT question

4.4.5.5 Trust in accuracy of the application

This question uses Likert Scale from one to five with:

One - Not at all

Five – Very accurate

Figure 4.33 shows that majority of the respondents trust in the accuracy of the results by the application, which is 70% of the respondents completely trust and think the results by the application are accurate. However, there are six respondents (30%) while still believe the results are accurate but think that it is slightly inaccurate in some parts, especially the top potential factor contributing to depression. While they do think the potential factors are relatable but not all of them agree that it is completely accurate which is expected because it is a rule-based factor instead of an intelligent system. Nonetheless, these respondents don't have much issue with the depression score since it is from a clinically verified PHQ toolkit, so they do not have qualms with it, even with the addition of elaboration by Machine Learning model.

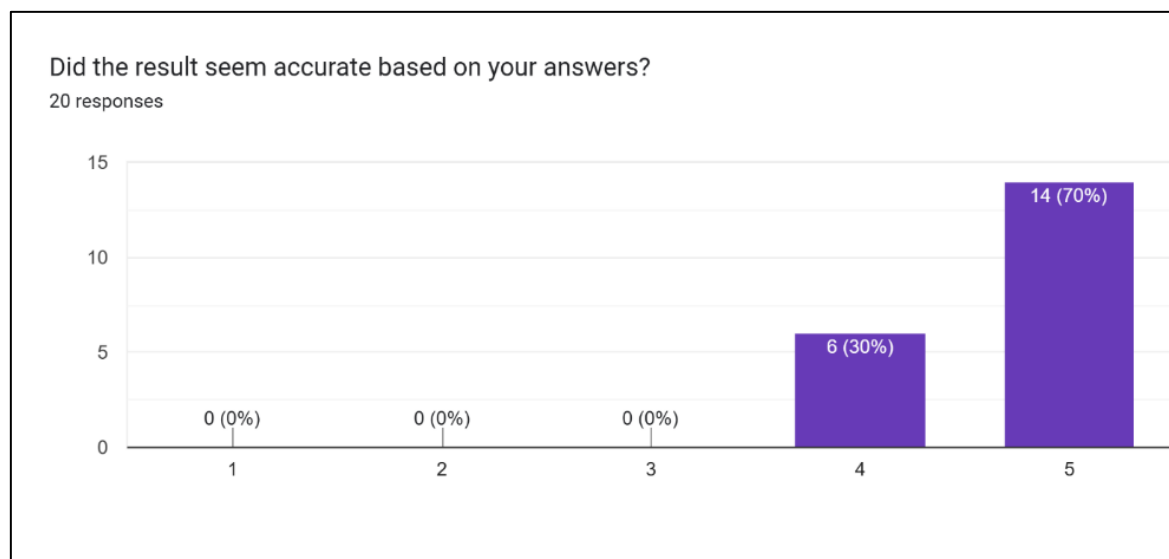


Figure 4.33: Trust in accuracy UAT question

4.4.5.6 Emotional Impact of the application

This question uses Likert Scale from one to five with:

One - Not supportive at all

Five – Very supportive

Figure 4.34 shows that almost all respondents think the message in result screen is very supportive and not judgemental at all, with eighteen respondents (90%). While there are two respondents (10%) that also think the message in result screen is supportive without judgement, but it can be better like making the message sounds even more human and supportive to support their emotions. Moreover, one of them also suggested adding tips for people who are in dire depressive state.

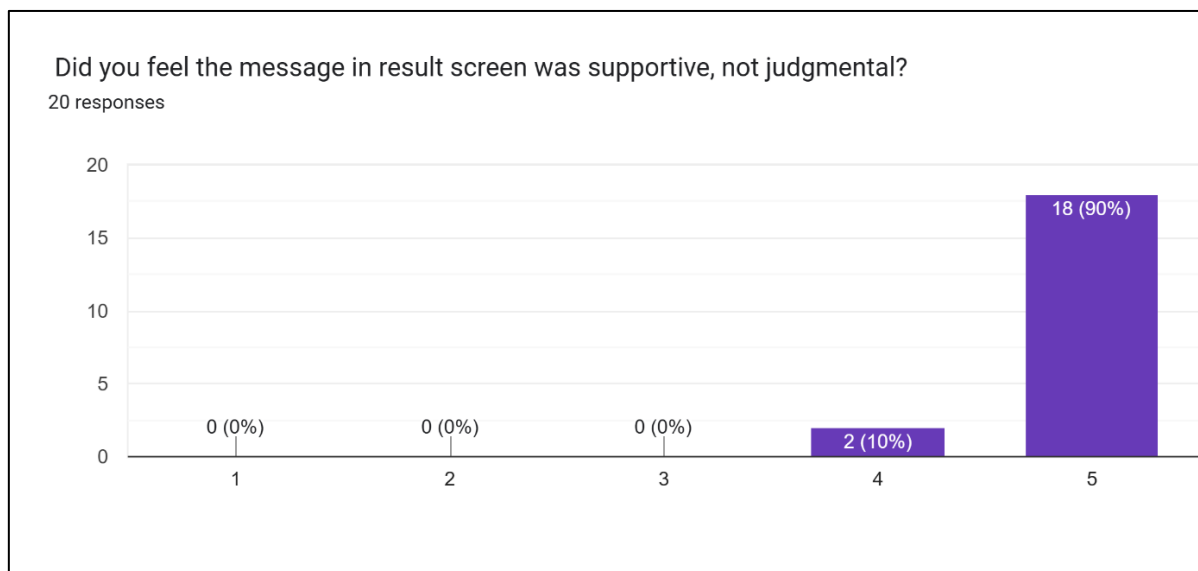


Figure 4.34: Emotional impact UAT question

4.4.5.7 Overall impression of the application

Figure 4.35 shows that majority of the respondents would trust and recommend the apps with fourteen respondents (70%) would trust and recommend the application whereas six respondents (30%) are unsure and chose “Maybe”. The hesitant respondents are unsure because they think the application can be further polished, particularly to improve the top factor accuracy and make the application to be more emotionally supportive in terms of designs and wording. Moreover, another notable reason for the doubt is because it could be improved by adding clinical professional’s endorsement or maybe add some features to include professionals’ involvement like inform them of the students with high depression level but at the end, they still think the application work as intended without needing any huge change or any severe issues. Therefore, these suggestions only reflect the desire for a more polished user experience, rather than concerns over core functionality and reliability of the application.

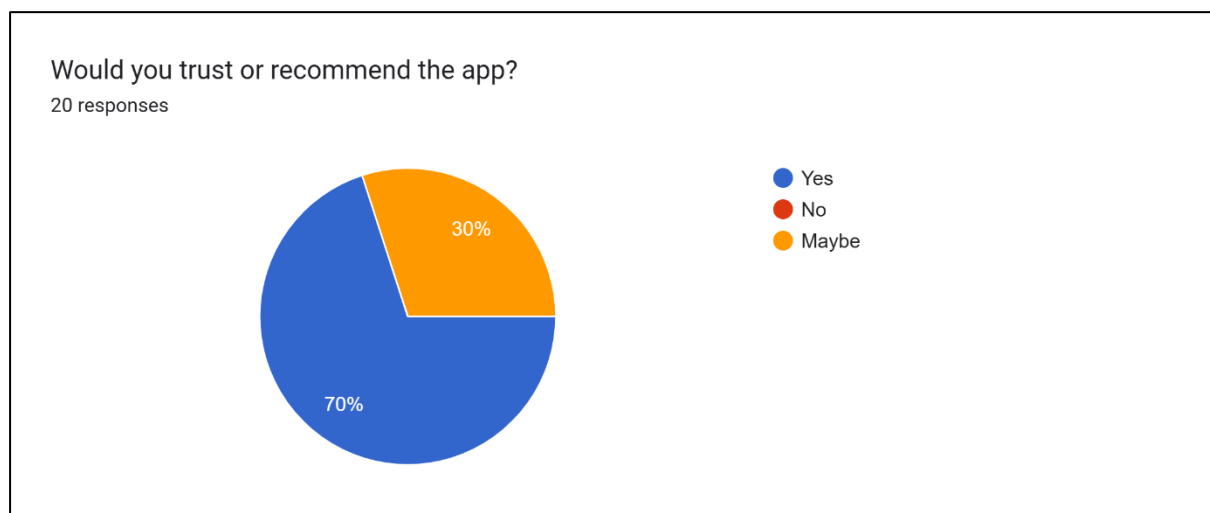
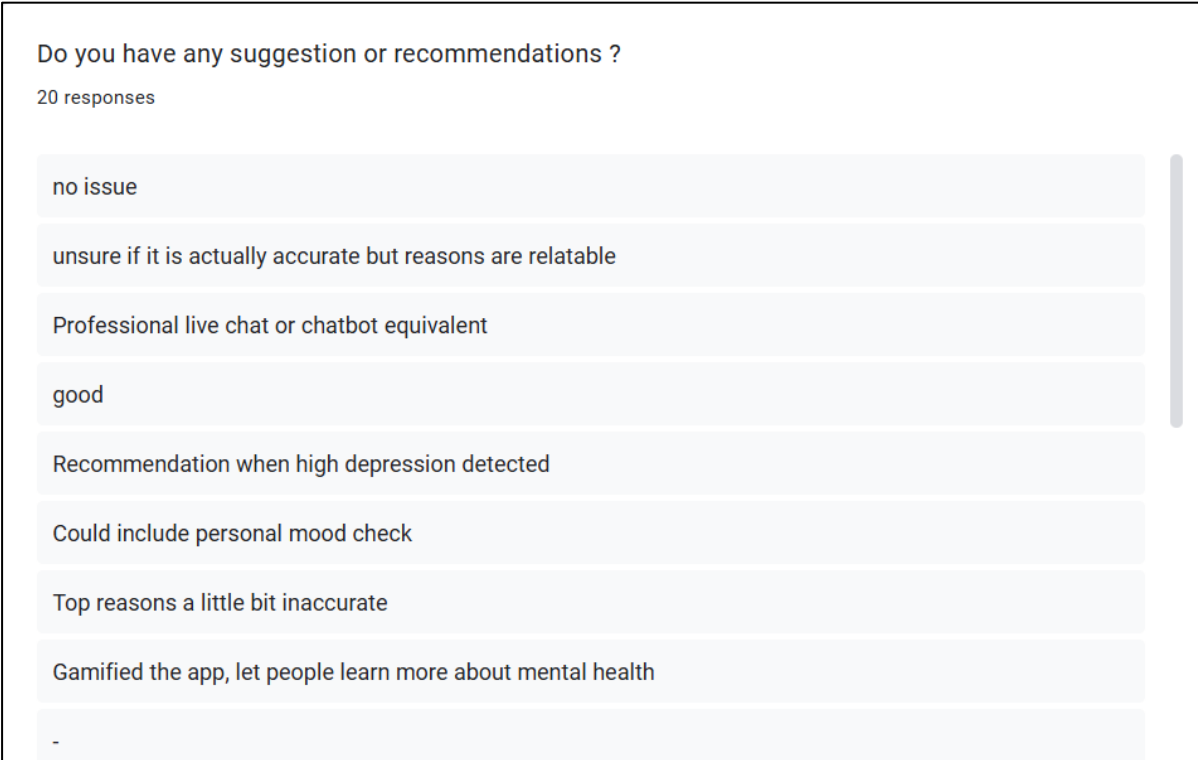


Figure 4.35: Overall Impression UAT question

4.4.5.8 Open Feedback of the application

Figure 4.36, Figure 4.37 and Figure 4.38 shows the open feedback from respondents who have tested the MoodMate applications. While some of them have no further comments or suggestions for MoodMate applications but some of them gave valuable recommendations which could be implemented for future work. Some notable recommendations are gamified the application making it more about learning about mental health, chatbot, professional live chat and mood tracking system. There are also some that are similar from feedback earlier which is the top contributing factors accuracy and tips for improving mental health.



Do you have any suggestion or recommendations ?

20 responses

- no issue
- unsure if it is actually accurate but reasons are relatable
- Professional live chat or chatbot equivalent
- good
- Recommendation when high depression detected
- Could include personal mood check
- Top reasons a little bit inaccurate
- Gamified the app, let people learn more about mental health
-

Figure 4.36: Overall feedback 1 UAT question



A screenshot of a scrollable list of feedback responses. The list contains nine items, each on a separate line. The items are: 'unsure', 'all good', 'Was expecting chatbot when AI was mentioned', 'seperate suicidal risk with depression level', 'add feature that can connect the result to counselors', 'mood tracking feature', 'no', 'ways to reduce depression level', and 'Maybe can add suicide helpline'. A vertical scrollbar is visible on the right side of the list.

- unsure
- all good
- Was expecting chatbot when AI was mentioned
- seperate suicidal risk with depression level
- add feature that can connect the result to counselors
- mood tracking feature
- no
- ways to reduce depression level
- Maybe can add suicide helpline

Figure 4.37: Overall feedback 2 UAT question



A screenshot of a scrollable list of feedback responses. The list contains two items: 'share tips to improve mental fortitude' and 'nothing'. A vertical scrollbar is visible on the right side of the list.

- share tips to improve mental fortitude
- nothing

Figure 4.38: Overall feedback 3 UAT question

4.4.5.9 Domain Expert

A domain expert from UNIMAS's unit counselling was interviewed to get input on how the application approach users should. The main purpose of this interview is to gather information related to depression, especially approach used to assess an individual's depression level. After the interview, the domain expert states that the Patient Health Questionnaire-9 (PHQ-9) questionnaire is a verified psychological toolkit that can be implemented to the application. Furthermore, the initial plan of using elaboration only in the application were changed to PHQ-9 with the addition of optional elaboration as the expert claim that too many elaborations will potentially overwhelm the patients, especially patients with actual depressive symptoms. Therefore, the development decisions were changed after the interview with the expert, from elaboration only assessment to PHQ-9 with optional elaborations.

On top of that, the domain expert also suggested the usage of Ask Suicide-Screening Questions (ASQ) which as the name states, a suicidal ideations toolkit assessment to further supports the application's assessment. Thus, the final development decision of using both PHQ-9 and ASQ with the optional elaborations on each of those questions to assess individual's potential depression level. For more details and proof, may refer to Appendix D.

4.5 Summary

This chapter highlights both the implementation and the testing phase of the proposed application which is the MoodMate application. The chapter start with determining the devices used for development which in this project include a personal laptop for development and a personal android mobile phone for deployment and testing. Then, the implementation section focuses on process of developing the three primary components of the application which is the Machine learning Model, database and the system architecture of the application itself, by combining them together at the end to be MoodMate, the proposed application of this project.

Furthermore, this chapter dive into testing phase where fives types of tests were conducted – unit testing, integration testing, functional testing, system testing and User Acceptance Test (UAT). The testing phase start with unit testing that highlights each component individually of the application and the result of the test were all positive with all unit passed every test cases. Integration testing was conducted secondly to test if the other component of the system able to communicate with the application such as the SQLite local database and Machine Learning model integration via FastAPI. The results of were positive as the system passed all integration test cases.

Moreover, functional testing was conducted using test cases based on typical user flow scenarios in which the application performed as expected and passed all the test cases. Finally, system testing was conducted to test the full end-to-end process from user's point of view to test the overall performance of the MoodMate application, and the application passed all test cases without any issues.

After all the functionality tests were completed, twenty respondents were chosen to test MoodMate applications and fill out their feedback on a Google Form based on eight aspects of

the UAT – usability, clarity, performance, result, trust in accuracy, emotional impact, overall impression and open feedback. Overall, the feedback from users is mostly positive without any major technical issue. While some users suggested minor improvement in design and emotional tone, the application is generally well-received and considered functional and user-friendly from its intended purpose and objective of the project. The chapter also focuses on the final development decision after the consultation from a domain expert, which involve changing initial plan from elaboration only assessment to integration of PHQ and ASQ with the inclusion of optional elaboration.

Chapter 5: Conclusion & Future work

5.1 Introduction

This chapter will focus on the closing of the project and will highlight achievements of objectives, the project limitation and future work to dive into the potential enhancement of the application, then ultimately conclude the project. The goal of this chapter is to provide an overview of the project's outcomes and evaluate its current capabilities, limitations and potential to further refined and expanded to better support pre-depression self-evaluation assessment. Moreover, this chapter will delve into the contribution of this project and conclusion.

5.2 Achievement of Objectives

This section of the chapter is to ensure that the proposed application – MoodMate achieved the project objectives, thus achievement of the application is shown in Table 5.1 below.

Table 5.1: Achievement of Project Objective of the MoodMate application

Objective	Achievement
This project aims to raise user awareness on their depression's levels which can be achieve by analysing user's text input and displaying depression levels depending on the input.	Achieved through the development of MoodMate, an application that evaluate user's mental condition using PHQ and ASQ with additional elaboration options for each question in assessment. The calculated output clearly present user's potential depression level and depression score based on assessment.
To enables early detection on their mental health by identifying early signs or symptoms of depression.	Achieved by combining structured assessment with demographics, PHQ and ASQ with elaboration option in assessment analysed via Machine Learning model. On top of that, a rule-based system was implemented to identify and display top potential factors for depression, informing users of possible warning signs based on

	their demographics and keywords found in their elaborated response.
To develop and implement a tool that is capable of assessing depression level with the help of machine learning model, serving as a functional solution for early self-assessment, by providing users with potential depression score and contributing factors to their depressive state.	Achieved with the completion of MoodMate Application as a mental health tools that allows for self-assessment and utilization of Machine Learning model to support the evaluation of depression level, by displaying user's potential depression level and top three contributing factors to their mental state.

According to Table 5.1, the three objectives of the projects were achieved with the development of MoodMate applications, which allows users to assess their potential depression level and score using PHQ and ASQ with additional optional elaboration. Then, it also provides early signs of potential factor contributing to depression with the rule-based system based on user's demographic and keywords. Finally, this application serves as a functional mental health tool for early self-evaluation that utilize a machine learning model when needed.

5.3 Project Limitation

While this project has its benefits and achieved its objectives, but it is without a doubt it has its drawback and limitation as well. Identifying these limitations is important to provide a realistic view of the application's capabilities and highlight areas for future work with further improvements and enhancements. The limitations stem from several reasons which include resource constraints, design choices and feasibilities of project within the project timeline. Despite overall success of the development of MoodMate applications, several limitations were identified:

1. Limited Accuracy of Rule-Based Factorings

The potential contributing factor to depression is currently determined using a rule-based that relies on user's demographics and keywords matching from elaborated text, which is not an intelligent system as it only provides factors based on static rules instead of dynamic factoring. Hence, this undermined the accuracy of user's actual factor contributing to their mental crisis and some testers also felt that while it is relatable but not completely accurate.

2. Lack of Machine Learning Model Adaptability

It is without a doubt MoodMate application relies on a trained Machine Learning model, particularly in the elaboration section of each PHQ and ASQ questions which is ensured to be able to accurately determine potential depression level during development stage. However, due to resource constraints, the model does not support self-learning based on every new inputted data. Hence, the model is unable to fully adapt to evolving language patterns and improve dynamically.

3. Limited Scope of Assessment

The depression detection is focused solely on assessment method which include PHQ and ASQ with short elaborations, but it does not cover other psychological factors such as behavioural patterns and environmental triggers which could offer a more comprehensive understanding of mental health.

4. Lack of Emotional Support Features

While the application can accurately determine potential depression level and depression score, but it does not have features that offers emotional support such as healthy coping strategy, support resources or guided interventions which are often essential in mental health related tools.

All in all, while these limitations are not severely or critical, but it could help frame the scope and open opportunities for future development and enhancement of the MoodmMate application.

5.4 Future works

While the current version of MoodMate meets the core objectives of the project but future enhancements can help make the application smarter, more adaptive and scalable because these improvements could focus on refining prediction system, expand functionalities and incorporate real-world support system to enhance user experience. These enhancement for future work includes:

1. Enhance Rule-Based Factoring to Intelligent System

The current rule-based system while it is accurate to some extent, but it is only limited to its rule, therefore, this could be replaced with a more intelligent system that are able to determine user's possible contributing factors to depression. This can be done by using an association technique such as Association Rule Mining that are able to discover pattern between demographics factors, PHQ, ASQ and elaborated input with depression factors.

2. Make the Machine Learning Model Adaptive

The current Machine Learning model is used to analysed elaboration text, while it can make depression level prediction accurate, but it is not able to adapt to new data, hence, for future work, the project can enhance the adaptability of render it able to learn and process new text pattern and data. This can make the model re-train user's input every time the MoodMate application is used, keeping the model up to date and future-proof.

3. Admin Analytics Tools - Dashboard

The MoodMate in future could introduce an admin-end user interface that provide access to authorized personnel to aggregate analytics for early intervention, this system can include features such as statistic overview of depression level trends based on demographics and early-warning sign by flagging users with high depression levels. This administrative analytics tool could provide a general view of user depressive trend, depression level distribution, commonly flagged keywords and other relevant metrics to support decision-making.

4. Professional Referral System

The application could also include feature that connect users with certified counsellors or hotline to bridge the gap between awareness and actions. Therefore, with permission, high-risk users can be flagged for a professional mental health evaluation. Additionally, the application can integrate in-app chat with professional and system that enable users to book session with available mental health professionals with push notifications and reminders used as encouragement for follow-up professionals' assessments and healthy coping strategies.

5. Online Deployment and Scalability

The application could be extended to an online or cloud-based hosting platform to enable wider accessibility beyond its initial form. By deploying it to official app stores and integrating to cloud-based service can enable the tool to support seamless access across devices and regular model updates.

5.5 Contribution

The development of the MoodMate application contributes meaningfully to the awareness of mental health via technology by providing a free-to-use tool for early depression test. The pre-depression self-evaluation assessment combine both verified psychological toolkit such as PHQ and ASQ with optional elaboration analysed using Machine Learning model to predict potential depression level for user's awareness of their own mental wellbeing. Furthermore, the potential contributing factors to depression through a rule-based system further enhance the credibility and help user gain more insights into their emotional state. Overall, the application also demonstrates that a low-resource mental health tools can be developed for individual use that bridge the gap between self-assessment and awareness, especially for individuals who may not have immediate access to mental health support.

5.6 Conclusion

In conclusion, the MoodMate application successfully meets all the project's objectives by offering a practical and functional tool for user to assess their mental health, particularly their depression level and score which increases their awareness of their mental wellbeing. With the integration of Machine Learning model via FastAPI, the application is able to analyse user's elaboration of each PHQ and ASQ questions to contribute to overall depression level based on their assessment provide insightful feedback to users. Additionally, the rule-based factoring further enhance user understanding by suggesting potential contributing factors based on their response are able to help them manage their lifestyle. Overall, MoodMate demonstrates how technology can be effectively utilized to support early mental health awareness, especially for individuals for who lack the resources for professional help, hence this project highlights the importance of digital health solutions in promoting mental wellbeing and set direction for future development in making mental health support more proactive, personalised and inclusive.

References

- Chung, J., & Teo, J.. (2022). Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges. *Applied Computational Intelligence and Soft Computing*. DOI : <https://doi.org/10.1155/2022/9970363>
- Haque, MDR., Rubya, S.. (2023). An Overview of Chatbot-Based Mobile Mental Health Apps: Insights From App Description and User Reviews. *JMIR Mhealth Uhealth* 2023;11:e44838 doi: 10.2196/44838
- Jain, P., Ram, S. K., & Vichare, A.. (2022). Depression and Suicide Analysis Using Machine Learning and NLP. *Journal of Physics: Conference Series*. 2161 (2022) 012034
doi:10.1088/1742-6596/2161/1/012034
- Khan, S. M.. (2023). Waterfall Model Used in Software Development
Reference: Software Requirements Engineering Waterfall Model. *ResearchGate*
DOI:10.13140/RG.2.2.29580.69764
- Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B., Berry, J. T., & Mokdad, A. H. (2009). The PHQ-8 as a measure of current depression in the general population. *Journal of affective disorders*, 114(1-3), 163–173.
<https://doi.org/10.1016/j.jad.2008.06.026>
- Tadesse, M. M., Lin, H., Xu, B., & Yang, L.. (2019). Detection of Depression-Related Posts in Reddit Social Media Forum. *IEEE Access*. vol. 7, pp. 44883-44893, 2019, doi: 10.1109/ACCESS.2019.2909180.

M. Matlala, M.L. Maponya, C.K. Chigome and J.C. Meyer. (2018). Overview of mental health: a public health priority. *SA Pharmaceutical Journal*. Vol. 85, No. 6.

Muhammed Radzi Abu Hassan & Rabindra Abeyasinghe. (2024). Transforming Workplaces: The Crucial Push for Mental Health Inclusivity in Malaysia. *World Health Organization(WHO)*.

<https://www.who.int/malaysia/news/commentaries/detail/transforming-workplaces--the-crucial-push-for-mental-health-inclusivity-in-malaysia>

National Health Service(NHS). (n. d.). Causes - Depression in adults. <https://www.nhs.uk/mental-health/conditions/depression-in-adults/causes/>

National Institute of Mental Health. (n.d). Depression. <https://www.nimh.nih.gov/health/topics/depression>

Nepal, S., Pillai, A., Wang, W., Griffin, T., Collins, A. C., Heinz, M., Lekkas, D., Mirjafari, S., Nemesure, M., Price, G., Jacobson, N., Campbell, A.. (2024). MoodCapture: Depression Detection using In-the-Wild Smartphone Images. *In Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, Article 996, 1–18. DOI: <https://doi.org/10.1145/3613904.3642680>

Rendyk. (2024). A Guide to Automated Deep/Machine Learning for Natural Language Processing: Text Prediction. *Analytics Vidya*. <https://www.analyticsvidhya.com/blog/2021/11/a-guide-to-automated-deep-machine-learning-for-natural-language-processing-text-prediction/>

Richter, T.; Fishbain, B., Richter-Levin, G., Okon-Singer, H. (2021). Machine Learning-Based Behavioral Diagnostic Tools for Depression: Advances, Challenges, and Future Directions. *J. Pers. Med.* 2021, *11*, 957. <https://doi.org/10.3390/jpm11100957>

Shaker, R., Ibrahim, N., & Abdennadher, S., Detecting Depressive Symptoms: Activity Tracking and Chatbot Intervention. (2024). *IEEE 12th International Conference on Serious Games and Applications for Health (SeGAH)*, Funchal, Portugal, 2024, pp. 1-8, doi: 10.1109/SeGAH61285.2024.10639580.

Tabassum, A. & Patil, R. R..(2020). A Survey on Text Pre-Processing & Feature Extraction Techniques in Natural Language Processing. *International Research Journal of Engineering and Technology (IRJET)*. Volume: 07 Issue: 06. <https://www.academia.edu/download/64643112/IRJET-V7I6913.pdf>

World Health Organization(WHO). (8 June 2022). Mental disorders. <https://www.who.int/news-room/fact-sheets/detail/mental-disorders>

World Health Organization(WHO).(31 March 2023). Depressive disorder (depression). <https://www.who.int/news-room/fact-sheets/detail/depression>

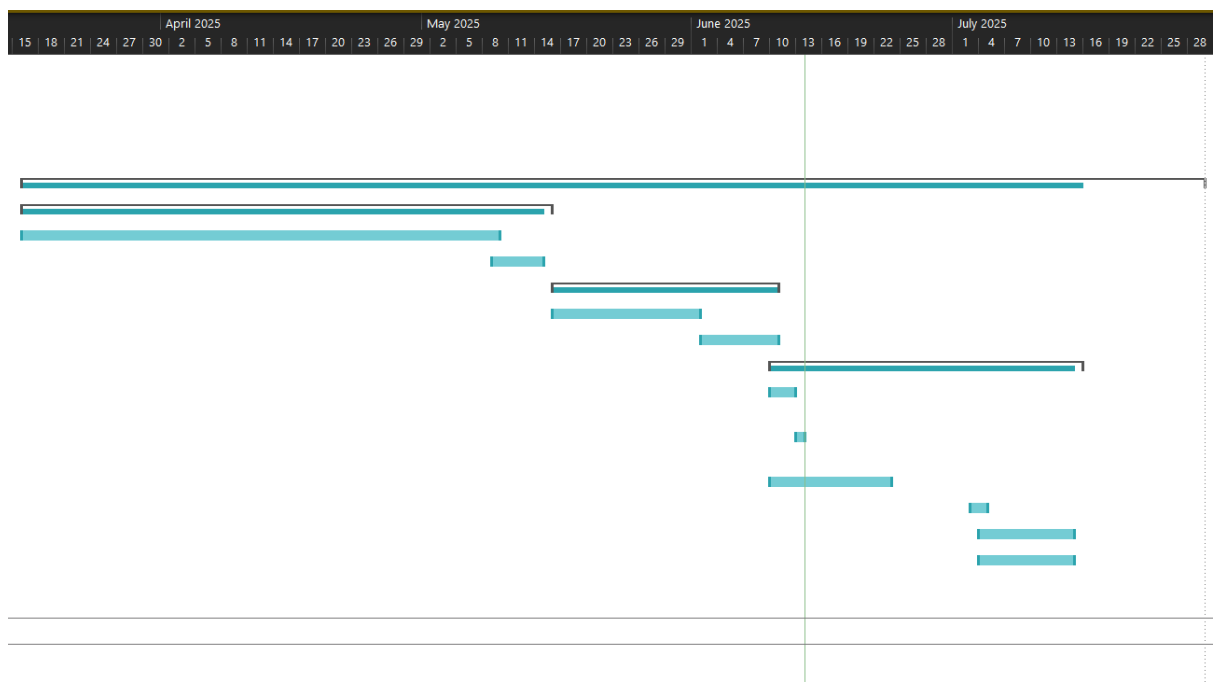
Zhou, Z. H. (2021). Machine Learning. *Springer Nature*.
https://books.google.com.my/books?hl=en&lr=&id=ctM-EAAAQBAJ&oi=fnd&pg=PR6&dq=machine+learning+&ots=o_LjZ9Tz_n&sig=vO5GPqRzlSdvRqJb99h9g3ZZqgM#v=onepage&q=machine%20learning&f=false

Appendix A

Project Gantt Chart

WBS	Task Mode	Task Name	Duration	Start	Finish
1		Final Year Project 1	98 days?	Mon 7/10/24	Wed 19/2/25
1.1		Identify project title and supervisor	10 days	Mon 7/10/24	Fri 18/10/24
1.2		FYP brief proposal	2 days?	Fri 18/10/24	Sun 20/10/24
1.2.1		Brief proposal submission	1 day	Sun 20/10/24	Sun 20/10/24
1.3		FYP full proposal	20 days	Sun 20/10/24	Thu 14/11/24
1.3.1		FYP full proposal submission	1 day	Thu 14/11/24	Thu 14/11/24
1.4		Chapter 1	5 days	Thu 14/11/24	Wed 20/11/24
1.4.1		Chapter 1 submission	1 day	Wed 20/11/24	Wed 20/11/24
1.5		Chapter 2	18 days	Wed 20/11/24	Fri 13/12/24
1.5.1		Chapter 2 submission	1 day	Fri 13/12/24	Fri 13/12/24
1.6		Chapter 3	26 days	Sat 14/12/24	Fri 17/1/25
1.6.1		Survey Creation	9 days	Wed 1/1/25	Mon 13/1/25
1.6.2		Chapter 3 submission	26 days	Fri 13/12/24	Fri 17/1/25
1.7		FYP 1 submission	29 days?	Fri 10/1/25	Wed 19/2/25
1.7.1		FYP 1 Report submission	0 days	Sat 11/1/25	Sat 11/1/25
1.7.2		FYP 1 Paper submission	0 days	Fri 10/1/25	Fri 10/1/25
1.7.3		FYP 1 Presentation submission	0 days	Fri 10/1/25	Fri 10/1/25
1.7.4		FYP 1 submission	7 days	Fri 10/1/25	Sun 19/1/25
1.7.5		Supervisor and Examiner evaluation	7 days	Sun 19/1/25	Sat 25/1/25
1.7.6		Ammenmant and Modification period	17 days	Sun 19/1/25	Mon 10/2/25
1.7.7		FYP 1 report final submission	1 day	Wed 19/2/25	Wed 19/2/25
2		Final Year Project 2	98 days?	Mon 17/3/25	Wed 30/7/25
2.1		Chapter 4	56 days?	Mon 17/3/25	Sat 31/5/25
2.1.1		Development	44 days	Mon 17/3/25	Thu 15/5/25

2.1		Chapter 4	45 days?	Sun 16/3/25	Thu 15/5/25
2.1.1		Development	41 days	Sun 16/3/25	Fri 9/5/25
2.1.2		Chapter 4 submission	4 days	Fri 9/5/25	Wed 14/5/25
2.2		Chapter 5	18 days?	Fri 16/5/25	Tue 10/6/25
2.2.1		Development touch up	12 days	Fri 16/5/25	Sun 1/6/25
2.2.2		Chapter 5 submission	7 days	Mon 2/6/25	Tue 10/6/25
2.3		FYP 2 submission	26 days	Tue 10/6/25	Tue 15/7/25
2.3.1		FYP 2 Report submission (draft)	3 days	Tue 10/6/25	Thu 12/6/25
2.3.2		FYP 2 Paper submission (draft)	1 day	Fri 13/6/25	Fri 13/6/25
2.3.3		FYP 2 report final submission	10 days	Tue 10/6/25	Mon 23/6/25
2.3.4		FYP Symposium	2 days	Thu 3/7/25	Fri 4/7/25
2.3.5		Supervisor and Examiner evaluatic	7 days	Fri 4/7/25	Mon 14/7/25
2.3.6		Ammenmant and Modification period	7 days	Fri 4/7/25	Mon 14/7/25



Appendix B

Google Form survey

Section 1 of 6

Depression Detection application via Artificial Intelligence (AI) (FYP 1 questionnaire)

B *I* U  

Hello and welcome, My name is Dwayne Chan King Chiu (79242) - a University of Sarawak, Malaysia (UNIMAS) final year student in Faculty of Computer Science and Information Technology (FCSIT) in Information System Program pursuing my Final Year Project (FYP) which is an application capable of detecting depression via Artificial Interlligence (AI) using text-based questionnaire approach.

The survey will be divided into 4 sections:

- Section A: Demographic Information
- Section B: Current Mental Health Awareness
- Section C: View on Depression Detection via Artificial Intelligence(AI)
- Section D: Preferences for the Application's Features

This survey aims to gather feedback to understand user preferences, expectations, and concerns about an AI-based depression detection mobile application. Your participation is highly appreciated and you will only need 3-5 minutes to complete this survey. Thank you in advance as this will be a great help to my FYP.

Should you have any inquire, feel free me to contact me via 79242@siswa.unimas.my

Section 2 of 6

Section A: Demographic Information

This section is to gather respondent's demographic information without going into too much detail in case of any privacy concerns.

Gender *

☐ Male

☐ Female

Age *

- ☐ Below 18
- ☐ 18 -21
- ☐ 22 - 30
- ☐ 31 - 40
- ☐ 41 - 50
- ☐ 51 - 60
- ☐ Above 60

Highest education level (completed) *

- ☐ SPM
- ☐ Pre-University (Diploma / Foundation / Matriculation / STPM / A-Level / STAM / UEC)e
- ☐ Bachelor's Degree
- ☐ Master's Degree
- ☐ Doctor of Philosophy (PhD)
- ☐ Other...

Occupation Status *

- ☐ Student
- ☐ Employed
- ☐ Unemployed
- ☐ Retired
- ☐ Other...

Section 3 of 6

Section B: Current Mental Health Awareness



This section aim to gather respondent's Mental Health Awareness, specifically depression.

How familiar are you with the symptoms of depression? *

	1	2	3	4	5	
Very Unfamiliar	☐	☐	☐	☐	☐	Very Familiar

Where do you usually get your information about mental health and depression *

- ☐ Social Media
- ☐ Friends/Family
- ☐ Websites
- ☐ Healthcare Professional
- ☐ Books
- ☐ Course/Classes
- ☐ Other...

Have you ever sought professional help or counseling for mental health concerns? *

- ☐ Yes
- ☐ No

How confident are you in identifying signs of depression in yourself or others? *

	1	2	3	4	5	
Not confident at all	☐	☐	☐	☐	☐	Very confident

Section 4 of 6

Section C: View on Depression Detection via Artificial Intelligence(AI)



This section aim to gather respondents opinion on detecting depression via the use of AI.

Additional Note: This application only aim to act as a supplementary assessment for those who have no access to mental health assessment and DOES NOT aim to replace professional help.

How comfortable are you with the idea of using AI to detect depression? *

	1	2	3	4	5	
Not comfortable at all	☐	☐	☐	☐	☐	Very Comfortable

Do you believe AI can accurately assess mental health, such as detecting depression? *

- ☐ Yes
- ☐ No
- ☐ Unsure

Why ? (Continue from previous question) *

Long-answer text

How important do you think privacy and data security are when using an AI application for depression detection? *

	1	2	3	4	5	
Not important at all	☐	☐	☐	☐	☐	Very important

Would you be willing to share personal data (e.g., mood, sleep patterns, activities) for more accurate depression detection? *

☐ Yes

☐ No

☐ Maybe

How likely are you to use an AI-based depression detection app if it were available? *

1 2 3 4 5

Not likely ☐ ☐ ☐ ☐ ☐ Very likely

What concerns do you have about the accuracy of AI in detecting depression? *

Long-answer text

Section 5 of 6

Section D: Preference for the Application's feature

This section aim to gather respondent's preference on the application's feature

Additional Note: The assessment would be text-based questionnaire.

Would you prefer the app to provide recommendations (recommendation or motivation) *

☐ Yes

☐ No

☐ Other...

What other features would make this app more useful for you? *

Long-answer text

Section 6 of 6

Thank you very much for your time.



Additional Note: This application only aim to act as a supplementary assessment for those who have no access to mental health assessment and DOES NOT aim to replace professional help

Feedback obtained via the Google Form

Timestamp	Gender	Age	Highest ec	Occupatic	How famil	Where do	Have you e	How confi	How serio	How often	Do you thi	What sour	How conf	Do you bel	Why ? (Co	How impo	Would you	How likely	What con	Would you	What other features would make this app more useful for you?			
2025/01/	Male	22-30	Pre-Univer	Student	4	Websites; No		3	5	4	No	Verified wi	4	Unsure	It is 5050	3	Yes	4	Might give	Yes	-	Offline	Without ai	3
2025/01/	Male	22-30	Bachelor's	Student	5	Social Mec	No	5	1	3	Yes	Healthcar	4	No	Because A	5	Yes	5	It may cau	Yes	Simple gat	Either	With acco	5
2025/01/	Male	22-30	Pre-Univer	Student	4	Friends/Fr	No	3	5	3	No	Health We	3	Unsure	Using AI tc	5	Maybe	4	I'm worrie	Yes	Maybe ad	Either	With acco	5
2025/01/	Female	22-30	Pre-Univer	Student	3	Social Mec	No	3	5	2	Yes	Informatic	4	Yes	Because A	5	Yes	4	Wrongly d	Yes	An appoin	Either	Without ai	5
2025/01/	Female	22-30	Pre-Univer	Student	5	Social Mec	Yes	5	5	3	Yes	talk	5	Yes	AI is the ar	5	Yes	5	not sure	Yes	warning si	Either	Without ai	5
2025/01/	Male	22-30	Pre-Univer	Student	5	Social Mec	No	5	5	2	No	Academic	5	Yes	AI can anal	5	Maybe	5	Context ur	Yes	User-Frien	Offline	Without ai	5
2025/01/	Male	22-30	Pre-Univer	Student	4	Social Mec	No	3	5	1	No	Research	4	Yes	can narrow	5	Maybe	4	that its no	Yes	activities	Either	Without ai	4
2025/01/	Female	22-30	Pre-Univer	Student	5	Social Mec	Yes	3	5	3	No	DSM-5 (di	4	Unsure	AI can be li	4	Yes	4	Might be ir	Yes	Provide su	Either	Without ai	5
2025/01/	Male	22-30	Pre-Univer	Student	2	Social Mec	No	2	3	3	No	No	2	No	Since hurr	5	Yes	4	It is not ac	No	no	Either	With acco	5
2025/01/	Male	22-30	Pre-Univer	Student	4	Social Mec	No	3	5	4	Yes	KKM Webs	4	Unsure	Based on	5	Yes	4	The sympt	Yes	Mini notes	Offline	With acco	5
2025/01/	Female	22-30	Pre-Univer	Student	4	Social Mec	No	4	5	1	No	Scientific	3	No	Depressio	5	Maybe	3	Since AI d	Yes	Sharing pr	Online	With acco	5
2025/01/	Male	22-30	Pre-Univer	Student	3	Social Mec	No	2	5	2	No	From Trair	4	Yes	With vario	5	Yes	5	No concer	Yes	Burnout d	Online	With acco	5
2025/01/	Female	18-21	Bachelor's	Student	4	Social Mec	Yes	2	5	2	Yes	Mental he	2	No	AI cant ob	5	Yes	2	Lack of hu	Yes	Live chat v	Online	Without ai	5
2025/01/	Female	22-30	Pre-Univer	Student	4	Social Mec	No	4	5	1	Yes	Licensed p	4	No	never try	4	Yes	4	false resul	Yes	privacy coi	Online	With acco	3
2025/01/	Male	18-21	Pre-Univer	Student	5	Social Mec	Yes	5	4	4	No	Journal art	4	Yes	AI can det	5	Yes	4	Confident	Yes	AI licenc	Either	With acco	5
2025/01/	Male	18-21	Bachelor's	Student	2	Social Mec	No	3	5	4	No	school coi	4	Yes	AI can rapi	2	Yes	2	Although i	Yes	If it can be	Online	With acco	1
2025/01/	Female	22-30	Bachelor's	Student	3	Social Mec	No	4	5	3	No	professor	4	Yes	Because A	5	Yes	5	Data priva	Yes	Beautiful i	Either	With acco	5
2025/01/	Male	22-30	Pre-Univer	Student	5	Social Mec	No	5	5	2	No	Governme	4	Unsure	because it	5	Yes	4	AI might n	Yes	Maybe a fr	Either	Without ai	5
2025/01/	Male	22-30	Pre-Univer	Student	3	Social Mec	Yes	4	5	3	No	Certified p	3	Unsure	With our b	5	Maybe	3	Personal i	Yes	Information that	sepr	With acco	5
2025/01/	Male	22-30	Pre-Univer	Student	3	Social Mec	No	2	3	1	No	Professor	3	Unsure	Still not fa	4	Maybe	4	As mentio	Yes	Unsure		Without ai	4

Appendix C

UAT Google Form survey

MoodMate User Acceptance Test

Hello and welcome, this google form will be given to respondents who have tested MoodMate. The sole purpose of this google form is only to get users' feedback on MoodMate based on the User Acceptance Test (UAT) format which will showcase each of these component in each question in order:

- Usability
- Clarity
- Performance
- Result Screen
- Trust in Accuracy
- Emotional Impact
- Overall Impression
- Open Feedback

Then, feedback will be collected for analysis purposes.

dwaynechan123@gmail.com [Switch accounts](#)

 Not shared

* Indicates required question

Is the app easy to use and navigate ? *

	1	2	3	4	5	
Not easy	☐	☐	☐	☐	☐	Very Easy

Are the questions (Demo/PHQ/ASQ) understandable? *

Not at all 1 2 3 4 5 Very

☐ ☐ ☐ ☐ ☐

Does the app lag or crash? *

☐ Yes
☐ No

Is the output (score, level, reason) clear? *

Not clear at all 1 2 3 4 5 Very clear

☐ ☐ ☐ ☐ ☐

Did the result seem accurate based on your answers? *

Not at all 1 2 3 4 5 Very accurate

☐ ☐ ☐ ☐ ☐

Did you feel the message in result screen was supportive, not judgmental? *

1 2 3 4 5

Not supportive at all ☐ ☐ ☐ ☐ ☐ Very supportive

Would you trust or recommend the app? *

☐ Yes

☐ No

☐ Maybe

Do you have any suggestion or recommendations ? *

Your answer _____

Submit Clear form

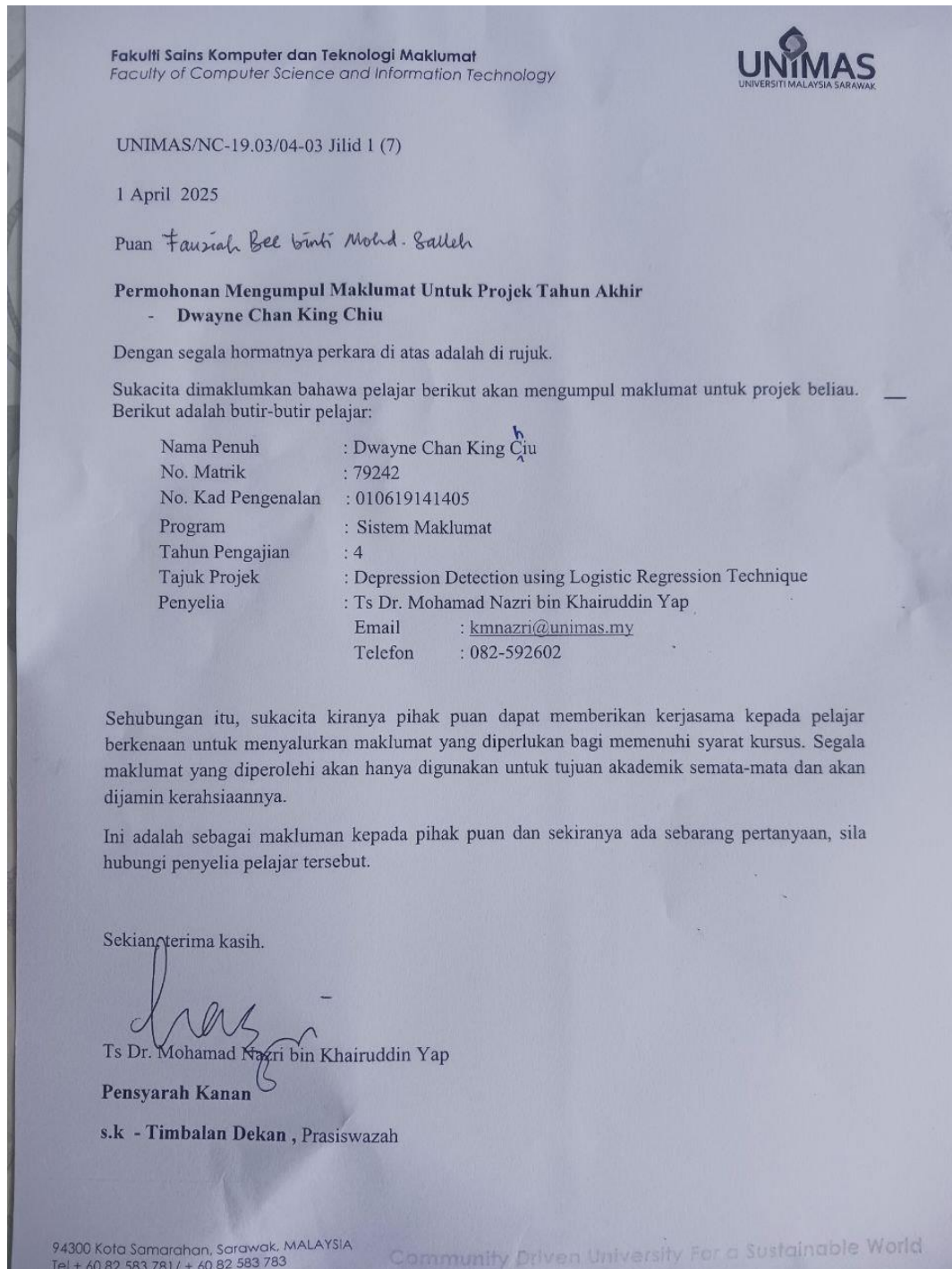
Collected data in excel form

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Timestamp	Is the app useful?	Are the questions helpful?	Does the app provide accurate results?	Is the output clear?	Did the results match your expectations?	Did you feel the message was supportive, not judgmental?	Would you trust or recommend the app?	Do you have any suggestion or recommendations ?					
2	2025/06/1	5	5	No	5	5	5	Yes	Maybe can add suicide helpline					
3	2025/06/1	5	5	No	5	5	5	Yes	add feature that can connect the result to counselors					
4	2025/06/1	5	5	No	5	4	5	Maybe	-					
5	2025/06/1	5	5	No	5	5	5	Yes	all good					
6	2025/06/1	5	4	No	5	4	5	Maybe	seperate suicidal risk with depression level					
7	2025/06/1	5	5	No	5	4	5	Yes	Top reasons a little bit inaccurate					
8	2025/06/1	5	5	No	5	5	5	Yes	no issue					
9	2025/06/1	5	5	No	5	5	4	Yes	Could include personal mood check					
10	2025/06/1	5	5	No	5	5	5	Yes	Recommendation when high depression detected					
11	2025/06/1	5	5	No	5	5	5	Maybe	Professional live chat or chatbot equivalent					
12	2025/06/1	5	5	No	5	5	5	Yes	Gamified the app, let people learn more about mental health					
13	2025/06/1	5	5	No	5	5	5	Yes	share tips to improve mental fortitude					
14	2025/06/1	5	5	No	4	4	4	Maybe	unsure					
15	2025/06/1	5	5	No	5	5	5	Maybe	Was expecting chatbot when AI was mentioned					
16	2025/06/1	5	5	No	5	5	5	Yes	no					
17	2025/06/1	5	5	No	5	4	5	Maybe	nothing					
18	2025/06/1	5	5	No	5	5	5	Yes	ways to reduce depression level					
19	2025/06/1	5	5	No	5	4	5	Yes	unsure if it is actually accurate but reasons are relatable					
20	2025/06/1	5	5	No	5	5	5	Yes	mood tracking feature					
21	2025/06/1	5	5	No	5	5	5	Yes	good					
22														

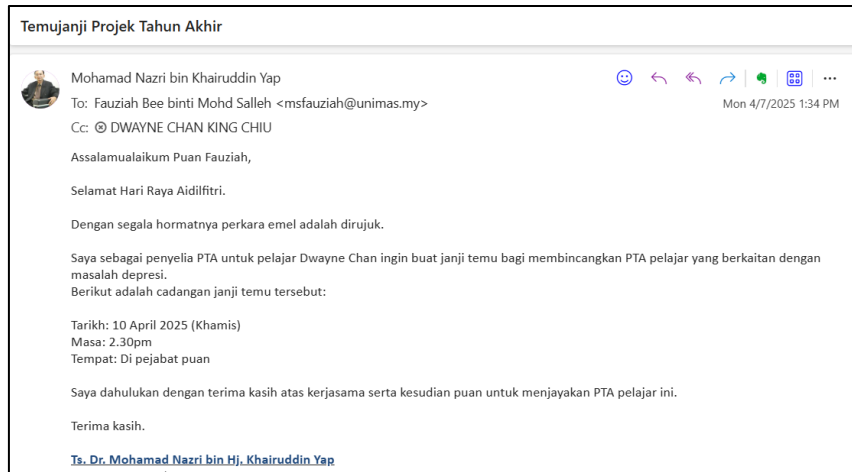
Appendix D

Domain expert (Puan Fauziah from UNIMAS counseling unit) interview materials

Official invitation letter



Email Request



Whatapps Communications

