BEHAVIOR ANALYSIS FOR DEPRESSION DETECTION.

De Silva L. S. R

(IT18113914)

B.Sc. (Hons) Degree in Information Technology Specializing in Information Technology

Department of Information Technology

Sri Lanka institute of Information Technology
Sri Lanka

October 2021

BEHAVIOR ANALYSIS FOR DEPRESSION DETECTION.

De Silva L. S. R

(IT18113914)

The dissertation was submitted in partial fulfilment of the requirements for the B.Sc. Special Honors degree in Information Technology

Department of Information Technology

Sri Lanka institute of Information Technology
Sri Lanka

October 2021

DECLARATION

I declare that this is our own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant to Sri Lanka Institute of Information Technology, the nonexclusive right to reproduce and distribute my dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Name	Student ID	Signature
De Silva L. S. R	IT18113914	

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor: Date

[Dr. Pradeepa Samarasinghe]

Signature of the supervisor: Date

[Ms. Vijani Piyawardana]

Signature of the supervisor: Date

[Ms. Shalindi Pandithakoralage]

ABSTRACT

Mental wellness is essential for living a healthy and wealthy life. However, several factors and states decline the psychological wellness of an individual. One of the leading interferences to psychological health is depression. The main problem for increasing the number of depressed individuals is limited resources and support services. The study focused on addressing the above limitation using a mobile application for assessing the depression risk. The depression risk analysis considered public posts on social media. In addition, the proposed system implemented a chatbot to analyze the chatbot history. Natural Language Processing (NLP)and deep learning algorithms are employed to train classifiers. In addition, the proposed application is implemented using the mobile development technology flutter.

Keywords: Depression risk, FastText, social media posts, Chatbot, NLP

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my supervisor, Assistant Professor Pradeepa Samarasinghe, for her assistance in formulating the study objectives and methodology. Your insightful feedback motivated me to improve the quality of my work. I would also like to thank Ms. Shalindi Pandithakoralage, my external supervisor, for her invaluable assistance with the psychological component of my studies. In addition, I am grateful to Ms. Vijani Piyawardana, my co-supervisor, for assisting me in completing the research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Description
WHO	World Health Organization
SVM	Support vector Machine
VAD	Valence Arousal Dominance
KNN	K-Nearest Neighbor
NLTK	Natural Language Toolkit
LSTM	Long short-term memory
REST	REpresentational State Transfer
API	Application Programming Interface

1. INTRODUCTION

1.1. Background & Literature Survey

1.1.1. Background

Individual well-being and productive functioning of a community are founded based on mental health. It empowers the growth of human beings as well as the standard of living life. Moreover, the future well-being of the next generation requires a broad range of involvement of the emotionally and socially enhanced community. However, modern society has not been able to lead a healthy life due to the inability to identify that good life relies on mental wellness. Mental wellness is essential for living a healthy and wealthy life. Several factors and states decline the psychological wellness of an individual. One of the leading interferences to psychological health is depression. World Health Organization (WHO) stated that depressive conditions are affected over 300 million of the global population [1]. Further, it estimates as depression might be the leading psychological disorder by 2030 [2]. The main problem for increasing the number of depressed individuals is limited resources and support services. As mentioned in [3], Psychological and pharmacological treatments lacked resources in underdeveloped countries. Even 50% of depressed individuals do not receive treatments in developed countries due to limited or no support available with mental health disorders [4].

As an underdeveloped country, mental wellbeing is becoming an ongoing epidemic in the Sri Lankan community since the deficiency of expert assistance and community stigma limits mental care. Hence, depressed individuals are reluctant to get treated by engaging with mental care professionals. The treatment limitations arisen from social stigma can eliminate with social media behavior analysis for depression. Social media behavior can reveal extensive patterns that might be related to depressive disorder. An accurate analysis on social media may help to monitor early depression risk and get treated in advance. Although a medical examination indicates the general state of health of a patient, a specialist may use other aspects related to making a diagnosis of depression. Monitoring the early depression risk would be beneficial in reducing expensive and long-lasting treatment procedures.

1.1.2. Literature survey

Information on social networks has been considered in several studies [5 - 19]. Most of the studies focused on English-based linguistics [5 - 8], while few researchers considered Bangla [9], Chinese [10, 19], Thai [15], and Arabic [13] languages.

Previous studies were based on social media content to detect depression rather than identifying early depression signs. De Choudhury M et al. demonstrated a statistical model to estimate depression risk through the Twitter activities of the users. English-speaking Twitter users considered measuring and predicting depression in individuals. The study Proposed the SVM classifier using behavioral cues (linguistic styles, depressive language, ego network) to estimate the depression risk with an accuracy of approximately 70% [14]. Tsugawa et al. investigated a method to recognize depression using various features (frequencies of word usage, the ratio of positive/ negative affect words, number of users following, number of users followed, etc.) obtained from Twitter history activities [12]. The study extended the De Choudhury M et al. prediction framework to Japanese-speaking Twitter users [14]. Delahunty et al. developed a machine learning classifier to identify the depression level of the user by considering the chatbot conversation [18]. C. S. A. Raza et al. focused on developing a web application to analyze posts of Twitter users for detecting personal depression attitude using machine learning. The study used three different techniques (Naive Bayes Classifier technique, NLP techniques, Deep Learning technique) to analyze the depression risk by considering positive and negative tweets [17].

The study [6] used tweets to evaluate LSTM network-based depression prediction and intensity assessment. To examine the depressive condition, the study analysis acquired numerous features (User Level Online Behavior, n-gram, emotion, Topic). Moreover, online behavioral features, topical/event features, emotional features, valence arousal dominance (VAD) feature, user-level features, and depression-related n-Gram were some of the feature extraction approaches used in the study [6]. Despite the fact that the analysis reviewed a large number of features, the analysis has not taken into consideration the social network structure or the locations of the users. Moreover, the NLTK toolbox was employed in the study [6] to utilize preprocessing techniques.

Few studies examined the link between depression and social media activities. The effectiveness of using language and behavior data from social media to assess depression has been shown in these studies. Md. Rafiqul Islam et al. focused on analyzing depression through the Facebook activities of the users. The study observed the decision tree algorithm as the highest accuracy in emotional process and linguistic style comparing to other machine learning techniques (KNN, SVM, Ensemble). Facebook comments were considered in predicting depression among Facebook users [16]. Schwartz et al. studied a shortlist of words, topics, phrases to analyze depression. Further, the study focused on seasonal fluctuations of depression [11].

The study [9] proposed the LSTM Deep Recurrent (LSTM-RNN) model, which combines Recurrent neural network (RNN) with LSTM to predict depression using text data from Bangla tweets. All characters were removed from the analysis, with the exception of Bangla alphanumeric letters, spaces, and punctuations. The analysis [10] employed a Deep Neural Network (DNN) architecture, Multimodal Feature Fusion Network (MFFN), to detect depressed users on Sina Weibo by formulating the Weibo User Depression Detection Dataset (WU3D). The study used a pre-trained model called XLNet to extract the embedded word vectors. Furthermore, the research extracted the statical attributes of users' uploaded photos, tweets, and social behavior. Official accounts were filtered and non-text content was removed from the study to reduce bias and increase the model's training efficiency.

The study [15] developed an algorithm for the Thai language on Facebook using Neural Network (NN) and Natural Language Processing (NLP) approaches. Despite the fact that the analysis sample was limited, the model was more accurate (F1 score - 0.88). Few variables were converted to numerical values in the study [15], and several language-related features were translated into English. The system then segmented the words and classified them as parts of speech in order to analyze the sentiment. The study [5] used sentiment analysis techniques to determine the sentiment score for each tweet and categorize them as positive, neutral, or negative. The labeled tweets are sent through a machine learning algorithm, which allows the tweets to be classified into the appropriate categories. The chosen machine learning algorithms, Naive Bayes and

NBTree, were tested on two different sizes of tweet datasets to determine the algorithm's accuracy in categorizing depressive and non-depressive tweets. However, the endeavor is limited to text.

The goal of the study [13] was to use depression-related phrases in Arabic text to classify and predict depression signs. This research offered computational ways for using an Arabic online forum where people discuss and seek help on a variety of psychological issues. Initially, the study team collected data from the forum and classified it manually or automatically. For the prediction of sadness from posts, the study offered a supervised approach (machine-learning-based approach) and a semi-supervised technique (lexicon-based approach). Support vector machine, k-nearest neighbor, decision trees, ADA boost, random forest, and stochastic gradient descent are applied to create the proposed network. The usage of language in forum posts was studied using a variety of feature extraction classifiers and models. The best results were achieved with TF-IDF as the feature extraction model and SGD as the classifier.

The studies [7] and [8] focused on Bidirectional LSTM (BiLSTM) based depression analysis on the Reddit platform for evaluating English text data. The research examined the text from two independent datasets: CLEF eRisk 2017 and RSDD, respectively. The study [7] varies from [8] by only the uses of the XGBoost approach to balance the data. The CLEF eRisk 2017 corpus was used in the study [8], while the Reddit Self-reported Depression Diagnosis (RSDD) dataset was used in the study [7]. Moreover, the study [19] explored chats in the WeChat platform to detect prenatal depression using LSTMs. The study used the stabbing word segmentation tool for word segmentation. They coupled the HIT discontinued vocabulary with the stop word list from the Sichuan University machine intelligence lab. However, the study has not evaluated the performance of the LSTbased classifier. WeChat is a multi-purpose Chinese instant messaging platform that allows users to communicate with one another. Data signed by local doctors through hospitals and perinatal users with relevant agreements and informed consent were used in the study [21]. Personal information (user identity) was protected by privacy before using all of the sample data.

1.2. Research Gap

The previous studies in the domain of mental illnesses mainly focused on social media activities. Few studies explored depression analysis based on chatbot conversation, while the other researchers considered the social media content in analyzing depressive disorder features. The study of [18] focused on depressive disorder based on chatbot conversation, while both the studies in [14, 12] explored social media content-based depression analysis. Correspondingly, the researchers of [11, 16, 17] analyzed social media content in identifying depressive features. BiLSTM and XGBoost-based depression detection architecture were investigated in the work [7]. Similarly, BiLSTM was used in a study [8]. The studies evaluated the Reddit posts in order to diagnose depression.

The study [9] proposed LSTM -RNN classifier to predict depression using text data from Bangla tweets. A Deep Neural Network (DNN) architecture, Multimodal Feature Fusion Network (MFFN), was employed by the study [10] to detect depressed users on Sina Weibo by formulating the WU3D. The study [19] employed LSTM network to detect prenatal depression of conversations on the WeChat platform.

The study [15] developed an algorithm for analyzing the sentiment using Thai posts on Facebook. Further, the study [13] used sentiment analysis techniques to determine the sentiment score for each tweet and categorize them as positive, neutral, or negative. The study [13] was to use depression-related phrases in Arabic text to classify and predict depression signs. Similarly, the study [6] extracted several features (emotion, n-gram, Topic, Online Behavior, User Level) to analyze depressive disorder.

However, none of the studies focused on implementing an automated analysis in identifying depressive disorder using both the social media content and chatbot conversation. Besides, none of the previous studies focused on the probability of early depressive features based on social media content and chatbot conversation. The following Table 1.1 summarizes the limitations in previous studies.

Table 1. 1: Comparison between the previous studies

	[5, 6]	[7-14]	[15-17]	[18]	[19]	Proposed System
Social Media Content based Depression Analysis	✓	✓	✓	✗	✗	✓
Chatbot conversation-based Depression Analysis	✗	✗	✗	✓	✓	✓
sentiment analysis in the content	✓	✗	✓	✗	✓	✓
Probability of early depression features based on social media content	✗	✗	✗	✗	✗	✓
Probability of early depression features based on Chatbot conversation	✗	✗	✗	✗	✗	✓

A mobile application that identifies the symptoms of depression helps depressed individuals to have a broad view of their mental health status. "Happify" is a mobile application including effective tools and programs that helps the user to understand their feelings and thoughts. The science-based activities and games uplift the positivity of individuals. The application includes an AI coach to help individuals. Application is generating extensive mental health reports providing a synopsis of your emotional state. However, the Happify application does not include the mechanism to analyze the content, which leads to depression [20, 21].

The mobile application, "Wysa: Mental Health Support", offers a range of tools to manage stress and wellness. The Artificial Intelligent (AI) chatbot is the core feature that reacts and responds to the user with video, articles, and exercise suggestions based on the expressed emotions throughout the conversation. Although the feelings are analyzed based on the conversation, the app does not consider a depression-related analysis [22, 23].

Woebot is a fully automated agent for the conversation that design to manage depression and anxiety feelings. It helps people to manage feelings of depression and anxiety. Woebot offers guidance with interactive quizzes and videos based on

Cognitive Behavioral Therapy (CBT). However, Woebot is not cable of analyzing the content to identify the individuals who may lead to depression [24 - 27].

Mobile Application Youper is designed as a self-help AI-guided application to support individuals to improve their mental health. Youper consists of 4 main features: AI chat-bot, Emotional health Assessment, Mood logs, and journal logs. Although a comprehensive summary of mental health is provided to users, this is not considered the depression symptoms recognition [28 - 30]. The following Table 1.2 compare the existing mobile application with the proposed system.

Table 1. 2: Comparison of existing Mobile Applications for mental health

	Happify [20, 21]	Wysa [22, 23]	Woebot [24 - 27]	Youper [28– 30]	Proposed App
AI chatbot	✓	✓	✓	✓	✓
Depression risk analysis based on social media content	✗	✗	✗	✗	✓
Anlyze the conversation	✗	✓	✓	✗	✓
Sinhala content-based depression risk analysis	✗	✗	✗	✗	✓
Chat history-based depression risk analysis.	✗	✗	✗	✗	✓
Analyze positive thoughts.	✗	✗	✗	✗	✓
Comprehensive report Summary	✓	✗	✗	✓	✓

2. RESEARCH PROBLEM

Depressed individuals with self-awareness would receive effective therapy for mental health. A mobile application, which analyzes the social media behavior to identify early depressive disorder risk, may help the individual to have self-awareness on mental health. Generally, the existing mobile applications focused on self-monitoring of depressive signs by analyzing the user logged information on questionnaires. The analysis might be more biased since the data is providing the user. Few mobile applications include Chatbot to have the conversation with individuals. However, conversation content is not analyzing to recognize depressive risk. According to the above literature, an approach of automated analysis of depressive disorder by identifying early depression risk using social media is not yet researched in Sri Lanka.

Depression diagnosis shortcoming in the industry summarized as follow.

• Difficult to monitor individuals manually for two weeks.

• Lack the automated solution to identify early depression risk using social media platform.

• Lack the automated solution to analyze conversations to identify early depression risk.

• Social stigma hinders individuals for attending counseling sessions.

3. RESEARCH OBJECTIVES

The primary objective of the depressive behavior analysis is to analyze the signs that may lead to being a depressive person. The study focuses on a mobile application to identify behaviors that could be highly anticipated to contribute to depressive disorder.

3.1.1. Main Objective

The analysis mainly focuses on social media content analysis for the early risk identification of depressive disorder.

3.1.2. Specific Objectives

The social media content analysis for early risk identification of depressive disorder is divided into specific sub-objectives as follows.

- Build a database based on Social Media Content.
  - Initially, the social media content should be acquired and build a database to save the acquired social media content.

- Identify social media texting patterns based on the built database.
  - Social media texting pattern will be identified using the content in the built database.

- Build a classifier to model, abnormal social activities based on social media content.
  - A classifier will be built to identify abnormal social activities based on the social media content.

- Predict the probability of abnormal social activities towards depression with the designed model.
  - Probability of abnormal social activities towards depression will be predicted using the designed model.

- Design and implement ChatBot to initiate conversations, identify depressive thoughts based on conversations.
    - ChatBot will be designed to initiate conversation.
    - The conversation will be retrieved and analyze depressive thoughts.
    - Conversation with the ChatBot will predict the probability of abnormal thoughts towards depression.

Additionally, the following sub- objectives are completed with the mobile application.

- Integrate the model with the application.
    - The built model will be integrated with the mobile application with the help of Application Programing Interface (API).

- Implementing interfaces.
    - Frontend development will be focused on interface of the proposed system.

- Mobile Application development for social media analysis.
    - The implementation of mobile application will be considered in the mobile application development.

4. METHODOLOGY

4.1. Introduction

The approach used in this experiment is discussed in the following section. The component overview, commercialization elements of the product, tool & technologies, component design & implementation, and testing are the subsections.

The data acquisition, data analysis, model implementation, and mobile implementation subsections are separated in the component design and implementation. In the testing subsection, the study explores the frontend and backend test scenarios.

4.2. Component Overview

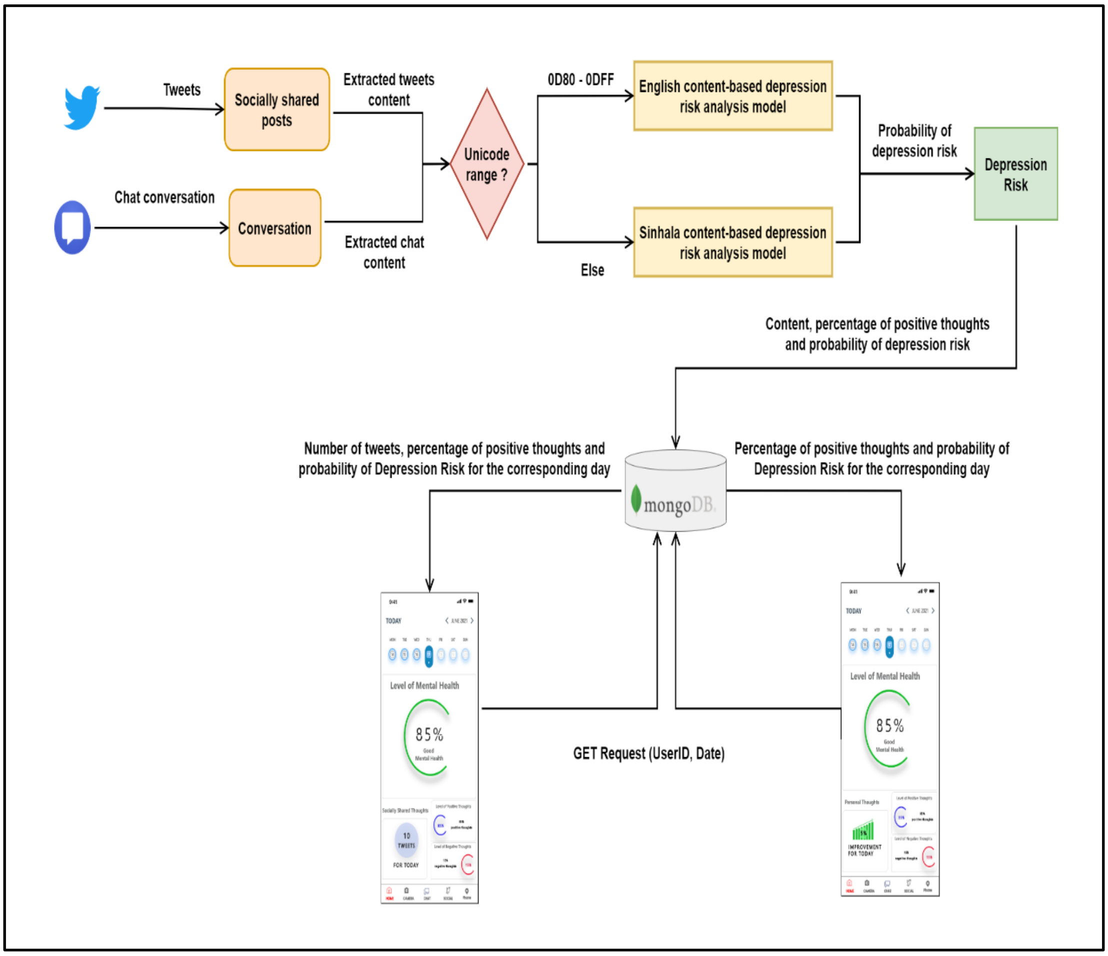


Figure 2. 1: Component overview

The study focused on the socially and personally shared thoughts to identify the depressive risk of an individual. As illustrated in Figure 2. 1, public Twitter posts and chat conversations should be input into the system by accessing the Twitter platform or Chat history to initiate the procedure. The content will be extracted from the given Twitter posts and chat history to feed to the classifiers. As the next step, the analysis will check for Unicode range on the retrieved content. English content will be input to the English content-based depression risk analyzer. Further, the Sinhala content will feed to the Sinhala analyzer while the Unicode range is identified as Sinhala.

The output probability of depressive risk for English or Sinhala content considers as the probability of depressive risk. The percentage of positive thoughts and depression risk values will save in the MongoDB. REST API will connect with the mobile application to access the data points. Once the data points are accessed, the detailed summary will display on the end-user application.

4.3. Commercialization Aspects of the Product

The mental health care providers can use the content-based depression risk analyzer as the initial level identification for depression risk. Hence, the mental health care providers can motivate to use the application by promoting the application through online mental health communities and forums. The health care provider can encourage to suggest the mobile application for their client while in the counseling sessions.

The younger generation has better knowledge of modern technologies and is active on social media platforms. Hence, the application can promote using social media platforms. Moreover, the groups on social media platforms can use to promote the mobile application. The senior people can be motivated to use the mobile application through the younger generation. Although the senior citizens have less knowledge of modern technologies, the application is designed by considering all aspects of the abilities of individuals.

4.4. Tools and Technologies

The tools, technologies, and libraries on the system implementation are outlined as follows. The tools and technologies used in the model implementation are explored in Table 2. 1, and the applied tools and technologies in the mobile application are explained in Table 2. 2.

Table 2. 1: Technologies for model implementation

Technology	Description
Flutter	Flutter UI software development kit will use for Frontend development.
Visual Studio Code	Freeware source-code editor used for implementation of mobile application.
MongoDB	Document-oriented, cross-platform, and source-available capabilities are included in this NoSQL database software.
http package	This package is used to connect the API with the mobile application.
WebView	The WebView is plugin which provides WebView widgets.
Shared Preferences	This package is used to store tweets.
Google Cloud	The service was deployed using the google cloud, a collection of cloud-based computer services.
Postman	A platform for validating APIs.

Table 2. 2: Technologies for mobile implementation

Technology	**Description**
Anaconda Environment	all the packages require to implement the model will be managed by the Anaconda environment. Packages can be installed, upgraded downgraded easily.
NLTK	Natural Learning Processing Toolkit to build python programs.
Python Programming Language	The model will be implemented using high-level, object-oriented, and generic purpose language, Python.
PyTorch	Open-source library, PyTorch will use to train the model.
MarianMT Transformers	A pre-defined model that uses to convert Russian phrases to English.
FastText	The classifiers were trained by employing the fastText network.
Glove word vector	English words are converted into vectors using this vectorization approach.
Sinhalese Vector Model	Sinhala words are converted into vectors using this vectorization approach.
FastAPI	A python web framework uses to implement RESTful APIs.

5. IMPLEMENTATION AND TESTING

5.1. Component Design & Implementation

5.1.1. Data Acquisition

This section outlines the procedure of data acquisition for the content-based depressive behavior analysis. The study acquired the data from Kazakhstan research for analyzing depressive risk [31]. The Kazakhstan study gathered Depressive Posts from VKontakte's social network's public accounts in Commonwealth of Independent States countries. Initially, the research team of [31] considered the most commonly used keywords to indicate a depressive state. VK.api was employed to collect the depressive and non-depressive posts. The team was able to source 64 039 depressive-related posts. It comprises 32 018 depressive posts and 32 021 non-depressive posts (Figure 3. 1) classified by licensed psychologists, as detailed in [31]. Note that the depressive content is denoted as 1, and 0 is denoted as non-depressive content.

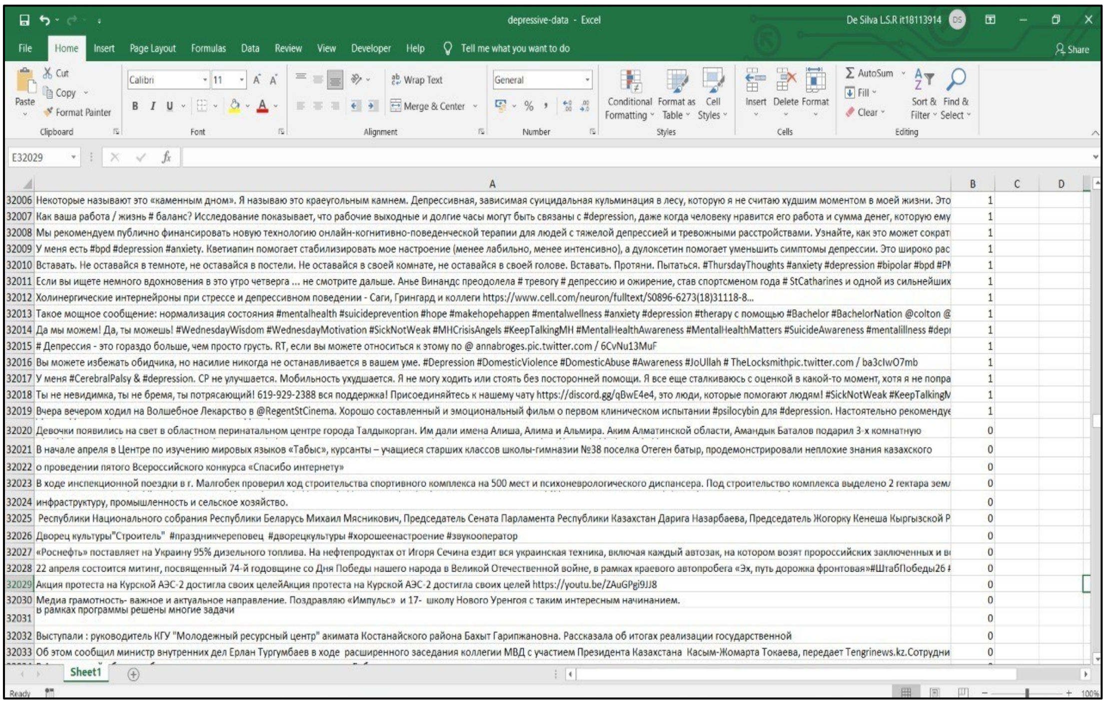
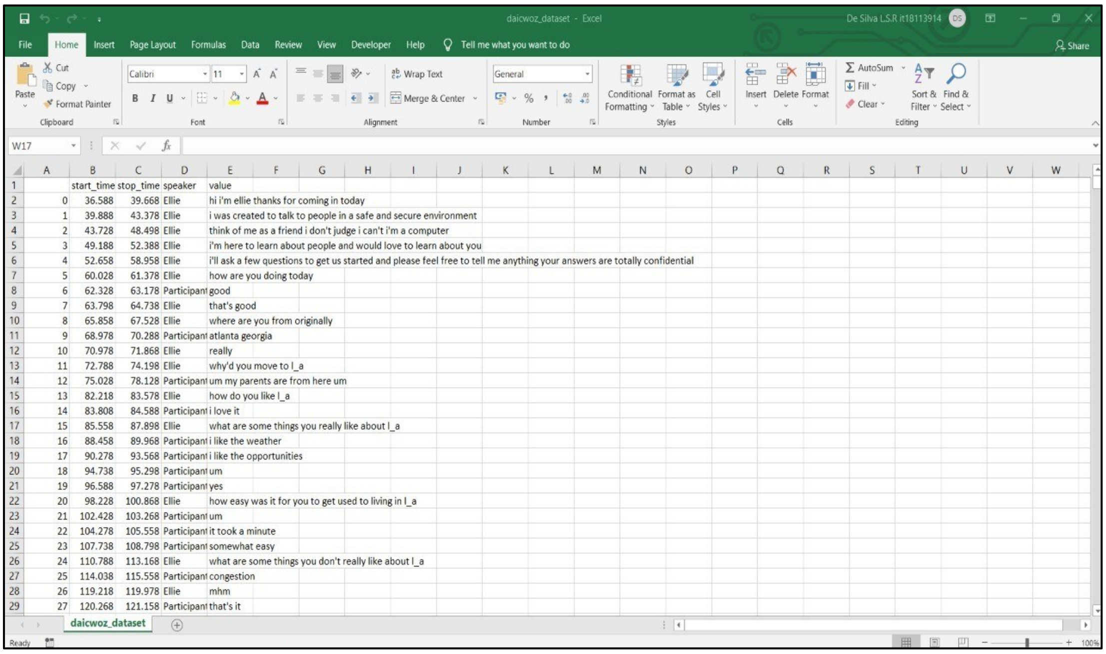


Figure 3. 1: Depressive and non-depressive posts in Russian

Moreover, the study gathered a conversational content dataset (Figure 3. 2) from the DAIC-WOZ database. This database is part of a larger corpus, the Distress Analysis Interview Corpus (DAIC) [32]. Clinical interviews for the diagnosis of emotional distress illnesses as anxiety, post-traumatic stress disorder, and depression are included in this database. The database contains recordings of interviews done by Ellie; an animated virtual interviewer operated by a human interviewer in a separate room [32]. The database comprises 189 sessions of recorded interviews with lengths ranging from 7 to 33 minutes. The transcript of the interview is included in each session.



	start_time	stop_time	speaker	value
0	36.588	39.668	Ellie	hi i'm ellie thanks for coming in today
1	39.888	43.378	Ellie	i was created to talk to people in a safe and secure environment
2	43.728	48.498	Ellie	think of me as a friend i don't judge i can't i'm a computer
3	49.188	52.388	Ellie	i'm here to learn about people and would love to learn about you
4	52.658	58.958	Ellie	i'll ask a few questions to get us started and please feel free to tell me anything your answers are totally confidential
5	60.028	61.378	Ellie	how are you doing today
6	62.328	63.178	Participant	good
7	63.798	64.738	Ellie	that's good
8	65.858	67.528	Ellie	where are you from originally
9	68.978	70.288	Participant	atlanta georgia
10	70.978	71.868	Ellie	really
11	72.788	74.198	Ellie	why'd you move to l_a
12	75.028	78.128	Participant	um my parents are from here um
13	82.218	83.578	Ellie	how do you like l_a
14	83.808	84.588	Participant	i love it
15	85.558	87.898	Ellie	what are some things you really like about l_a
16	88.458	89.968	Participant	i like the weather
17	90.278	93.568	Participant	i like the opportunities
18	94.738	95.298	Participant	um
19	96.588	97.278	Participant	yes
20	98.228	100.868	Ellie	how easy was it for you to get used to living in l_a
21	102.428	103.268	Participant	um
22	104.278	105.558	Participant	it took a minute
23	107.738	108.798	Participant	somewhat easy
24	110.788	113.168	Ellie	what are some things you don't really like about l_a
25	114.038	115.558	Participant	congestion
26	119.218	119.978	Ellie	mhm
27	120.268	121.158	Participant	that's it

Figure 3. 2: Sample chat conversation

5.1.2. Data Analysis

The English-based analysis was required to translate the Russian dataset to English as the initial step for implementing a content-based depressive risk analysis classifier. The study has applied a pre-defined model MarianMT Transformers to translate the Russian content to English (Figure 3. 3). The word embedding process utilized the GloVe Vector model on translated English content. Stanford University developed the GloVe Vector Model for word Embeddings and Text Classification [33].

Content-based depressive risk analyzer employed the NLP technique, word vectorization, to preprocess the content. Word Vectorization, also known as Word Embeddings, is an NLP technique for mapping words or phrases from a lexicon to a corresponding vector of real numbers, which can then be used to derive word predictions and semantics [34].

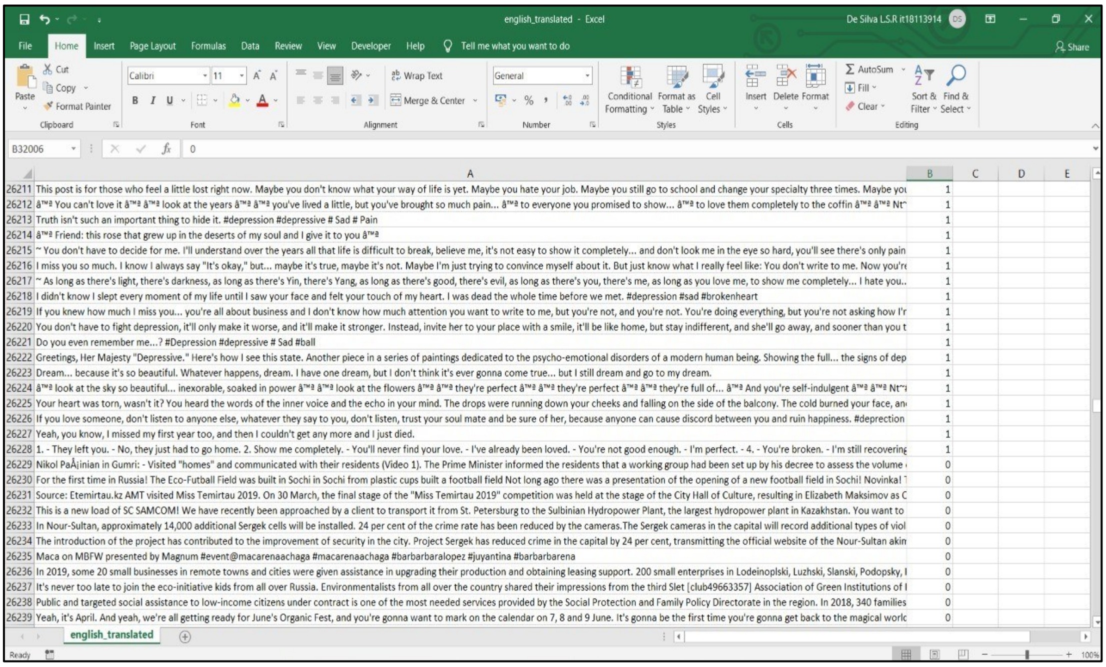


Figure 3. 3: Depressive and non-depressive posts in English

Similarly, The Sinhala-based analysis was required to translate the Russian dataset to Sinhala. The study has employed Google Translator for converting the Russian dataset to Sinhala (Figure 3. 4). The word embedding process utilized the Sinhalese Vector Model, developed by Facebook's AI Research lab, on translated Sinhala content [35].

Figure 3. 4: Depressive and non-depressive posts in Sinhala

5.1.3. Model Implementation

The analyzer for content-based early depression risk consists of two separate classifiers for English and Sinhala. Initially, the classifiers have trained on the machine learning algorithm, Support Vector Machines (SVM). The SVM classifier for English could achieve 94% test accuracy, while 84% test accuracy has obtained with the Sinhala content. However, the study employed deep learning algorithms to review the classifier performance by considering the classical machine learning approach as the baseline model.

The content-based classifiers for English and Sinhala employed the pre-trained model FastText. FastText is a Library for word Embeddings and Text Classification [36]. The implemented classifiers (Figure 3. 5) consist of three layers. The first layer, the embedding layer, is applied to estimate the word embedding for each word in the given content. Word embedding is a process of transforming words into numbers [34]. The technique maps the similarities and semantics of each word in the phrase. The second layer, the liner layer, estimates the average value for the whole word embedding. The last layer is the average pooling 2D layer. It classifies the text by utilizing the output of the liner layer.

```python
import torch.nn as nn
import torch.nn.functional as F

class FastText(nn.Module):
    def __init__(self, vocab_size, embedding_dim, output_dim, pad_idx):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding_idx=pad_idx)
        self.fc = nn.Linear(embedding_dim, output_dim)

    def forward(self, text):
        embedded = self.embedding(text)
        embedded = embedded.permute(1, 0, 2)
        pooled = F.avg_pool2d(embedded, (embedded.shape[1], 1)).squeeze(1)
        return self.fc(pooled)
```

Figure 3. 5: Define the classifier

To compute the probability distribution over the classes, the model used sigmoid as the activation function. The study used the sigmoid as the activation function since the analysis involves a binary classification problem. Adam Optimizer was used to construct the models. Note that the classifier input is text.

The chatbot was implemented using the Raza framework. Rasa is an Open-Source Conversational AI to build contextual AI Assistants and Chatbots [37]. The components of the Raza framework define as intent, action, entity, and stories. The entity uses to extract information. Entities are logically organized blocks of records that can be taken from a message of the user. Intent (Figure 3. 6) defines the possible inputs of the user, and the flow is defined using stories (Figure 3. 7).

```
nlu:
  - intent: greet
    examples: |
      - hey
      - hello
      - hi
      - hello there
      - good morning
      - good evening
      - moin
      - hey there
      - let's go
      - hey dude
      - goodmorning
      - goodevening
      - good afternoon

  - intent: goodbye
    examples: |
      - good afternoon
      - cu
      - good by
      - cee you later
      - good night
      - bye
      - goodbye
```

Figure 3. 6: Defined Intent

```
stories:

- story: happy path
  steps:
  - intent: greet
  - action: utter_greet
  - intent: mood_happy
  - action: utter_happy

- story: sad path 1
  steps:
  - intent: greet
  - action: utter_greet
  - intent: mood_unhappy
  - action: utter_cheer_up
  - action: utter_did_that_help
  - intent: affirm
  - action: utter_happy

- story: sad path 2
  steps:
  - intent: greet
  - action: utter_greet
  - intent: mood_unhappy
  - action: utter_cheer_up
  - action: utter_did_that_help
```

Figure 3. 7: Defined stories

the responses (Figure 3. 8) are denoted as action.

```yaml
rules:

- rule: Say goodbye anytime the user says goodbye
  steps:
  - intent: goodbye
  - action: utter_goodbye

- rule: Say 'I am a bot' anytime the user challenges
  steps:
  - intent: bot_challenge
  - action: utter_iamabot
```

Figure 3. 8: Defined actions

As illustrated in Figure 3. 9, user message is fed to the defined flow in the Rasa framework. The Rasa NLU in the framework then identifies the corresponding intent from the intent catalog and the related entities. Once the corresponding user intent is identified, the subsequent appropriate action will be performed by the Rasa stack to respond to the user.

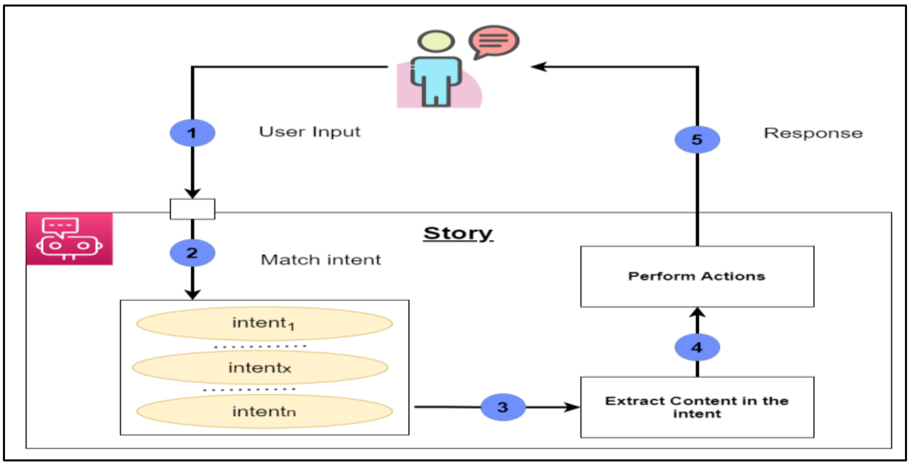


Figure 3. 9: Flow of the Chatbot process

The API endpoints will be used to acquire the predicted values. The study employed the FastAPI for implementing the RESTful API [38]. The POST method (Figure 3. 10) is used to create the REST API Endpoint for saving the percentage of positive thoughts and the probability of depression risk. The classifier will determine the likelihood of depressive risk based on the sentiment in the content once the content is sent through the API. In addition, the system analyzes and saves the improvement percentage of personal thoughts by comparing the depression risk value on the previous day.

```
@router.post("/")
async def get_depression(depression: Depression, db: AsyncIOMotorClient = Depends(get_database)):
```

Figure 3. 10: POST method to save values

Furthermore, the GET (Figure 3. 11) method is used to get the data for the extended summary endpoint. To get the data points via the built REST API endpoint, the response is represented as a JSON (Figure 3. 12) object.

```
@router.get("/{sender_id}")
async def get_chat_score(sender_id: str, db: AsyncIOMotorClient = Depends(get_database)):
    scores = await calculate_chat_depression(sender_id, db)
    return await build_response(scores)
```

Figure 3. 11: GET method to retrieve values

```
    await save_chat(chats, db)
    chats_json = jsonable_encoder(chats, exclude={"chats": {"__all__": {"id"}}})["chats"]
    return await build_response(chats_json)
```

Figure 3. 12: Save chat history

Content-based depression risk analyzer service is hosted on the Google cloud platform. The REST API is implemented to access the deployed service. The service is executed on a virtual machine with four virtual CPUs and 32 GB of memory (Figure 3. 13).

Machine type
n2-highmem-4 (4 vCPUs, 32 GB memory)

Figure 3. 13: Type of the virtual machine

Ubuntu is the operating system image (Figure 3. 14) utilized in the virtual computer with size of 50 GB.

Boot disk

Name	Image	Size (GB)	Device name	Type	Encryption	Mode	When deleti
ml-instance	ubuntu-2004-focal-v20210927	50	ml-instance	Balanced persistent disk	Google managed	Boot, read/write	Delete disk

Figure 3. 14: Details of the instance

5.1.4. Mobile Implementation

The flutter-based mobile implementation approach used in the study is described in this section. The content-based depression risk analyzer utilizes the tweet content and chats conversation from a mobile phone. The Twitter developer account is used to access the tweets for a given user account. WebView in flutter is applied to connect the flutter application and Twitter platform. The Twitter developer account (Figure 3.15) is granting access to extract public posts.

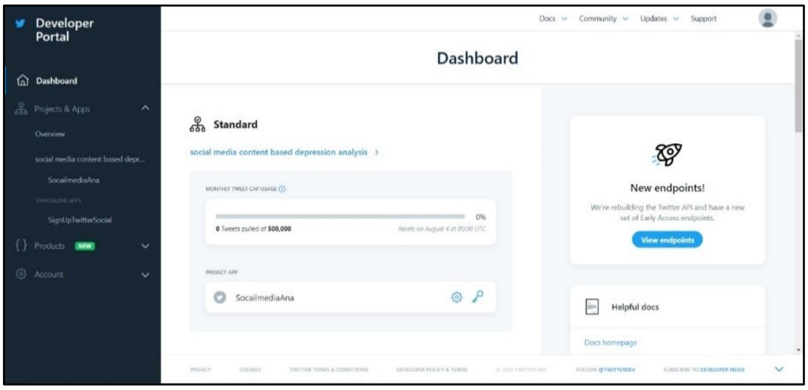


Figure 3. 15: Twitter developer account

In addition, the study implemented a chatbot to initiate the conversation with the end-user. The conversation is managed from the backend. Further, the analysis obtains the chats conversation with the implemented chatbot to identify the depressive risk of individuals. The depression risk is calculated from the backend. However, the conversation history is accessed from REST API. The mobile application is responsible to display (Figure 3. 16) the continued conversation with the chatbot.

```
itemBuilder: (context, index) => _msgs[index]["by"] == 1
    ? _buildBotMessage(_size, index)
    : _buildUserMessage(_size, index),
```

Figure 3. 16: Implementation of chatbot continuation

The API request is initiated once the user is authenticated and public posts are extracted from the user account. The shared preferences flutter package is applied to store the public posts. Once the procedure of assessing the depressive risk for a given content, the user interface will display an extensive summary, including the percentage of positive thoughts (Figure 3. 17) and probability of depressive risk (Figure 3. 18).

```
Text(
  '${(double.parse(data["presentage"].toString()) * 100).toInt()}%',
  style: TextStyle(
    fontSize: 48,
  ), // TextStyle
), // Text
```

Figure 3. 17: Implementation of displaying the positive thoughts percentage

```
'${(double.parse(data["positive"].toString()) * 100).toInt()}%',
style: TextStyle(
  fontSize: 10,
  color: Color(0xff2A23EB),
), // TextStyle
```

Figure 3. 18: Implementation of displaying the depression risk probability

Further, the detailed summary includes the number of tweets (Figure 3. 19) posted with the day.

```
Text(
  '${data["tweets"]}',
  style: TextStyle(
    fontSize: 20,
    fontWeight: FontWeight.bold,
  ), // TextStyle
), // Text
```

Figure 3. 19: Implementation of displaying the number of tweets

The extensive summary for conversation with the chatbot is included the improvement percentage (Figure 3. 20) of personal thoughts by comparing the depression risk value on the previous day.

```
color: int.parse(data["improvement"].toString())
            .sign ==
        -1
    ? Colors.red
    : Colors.green,
```

Figure 3. 20: Display improvement percentage of personal thoughts

5.2. Testing

5.2.1. Backend test cases

The following Table 3. 1 explains the test cases for backend development.

Table 3. 1: Test cases for backend development

Test case ID	Test scenario	Test steps	Test Data	Expected Result	Actual result	Status
T001	Validate depressive risk of a depressed phrase using the English content-based classifier.	1. Select phrase. 2. Input phrase to English content-based classifier	I found that with depression, one of the most important things you could realize is that you're not alone.	High depression risk	High depression risk score: 0.77 High Risk of Depression	Pass
T002	Validate depressive risk of a depressed phrase using the Sinhala content-based classifier.	1. Select phrase. 2. Input phrase to English content-based classifier	මොන බයිලා කිවුවත් සමහර අයට අලුත් අය ලැබුණ ගමන් පරණ අපිව ලොකු කරදරයක් වෙනවා. අත්දැකීමෙන් දන්නවා.	High depression risk	High depression risk score: 0.52 High Risk of Depression	Pass
T003	Validate response of the chatbot for depressive phrase.	1. Initialize chatbot. 2. Continue chat with chatbot	Feeling so depressed today	Corresponding response	Glad for sharing that whit me, being honest about your feeling is a big step.	Pass

T004	Validate depressive risk of a non-depressed phrase using the English content-based classifier.	1. Select phrase. 2. Input phrase to English content-based classifier	I'm gonna sell the kits all the questions to the bass!	Low depression risk	Low depression risk score: 0.06 Low Risk of depression	Pass
T005	Validate depressive risk of a non-depressed phrase using the Sinhala content-based classifier.	1. Select phrase. 2. Input phrase to English content-based classifier	මහ මුහුදට පැණි දැම්මට මුහුදෙ ලුණු රස වෙනස් වෙන්නෙ නෑ වගේ සමහරු වෙනුවෙන් අපි මොන තරම් කැප කිරීම් කළත් එයාලට ඒක වටින්නෙ නෑ	Low depression risk	Low depression risk score: 0.32 Less Risk of depression	Pass
T006	Validate response of the chatbot for non-depressive phrase.	1. Initialize chatbot. 2. Continue chat with chatbot	Today is an awesome day I met my friends	Corresponding response	glad to hear it	Pass
T007	Initialize chatbot	1. Navigate to the chatbot interface.	-	Hi, I'm Smart Bot thanks for coming today.	Hi, I'm Smart Bot thanks for coming today.	Pass

5.2.2. Frontend test cases

The following table 3. 2 explains the test cases for frontend development.

Table 3. 2: Test cases for frontend development

Test case ID	Test scenario	Test steps	Test Data	Expected result	Actual result	Status
T001	Access Twitter platform.	1. Navigate to the Twitter login interface 2. Login to Twitter account.	Login credentials	Successfully login to Twitter account.	Successfully login to Twitter account	Pass
T002	Continue chat conversation.	1. Continue chat with chatbot using the chat interface.	how are you doing today?	Responses from chatbot	“Great”	Pass
T002	Check social thoughts summary for Selected date.	1. Navigate to summary interface. 2. select date	Previous Date – 2021-10-10	Display summary for Selected date. (Depression Risk, number of posts for day)	Extensive summary	Pass
T004	Check personal thoughts summary for Selected date.	1. Navigate to summary interface. 2. select date	Previous Date – 2021-10-10	Display summary for Selected date. (Depression Risk, improvement percentage)	Extensive summary	Pass
T005	Display current details in the home screen	1. Navigate to home screen	-	Display details in home screen	Summarized details in home screen.	Pass

6. RESULTS & DISCUSSION

6.1. Results

The test results and performance of classifiers are discussed in the next section. The section is divided into test findings and performance of the English content-based classifier, Sinhala content-based classifier, and chatbot implementation.

6.1.1. English content-based classifier

Although the study trained the SVM on content, the analysis could achieve 94% for the English-based classifier. The study employed a pre-trained deep learning classifier, FastText, to enhance the classifier performance. The trained classifier achieved 96% test accuracy with the 0.16 test loss (Figure 4. 1) upon English content.

```
Test Loss: 0.160 | Test Acc: 96.71%
```

Figure 4. 1: Accuracy of the English content-based classifier

Classification report is one of the performance evaluation metrics [39]. The performance is evaluated based on four metrics: precision, recall, F1 score, and support. As illustrates in the classification report (Figure 4. 2), the classifier based on English content has obtained a 0.96 precision value for low-risk (class 0), while the high-risk (class 1) achieved 0.98 value on the precision metric. The classifier obtained better value (0.97) for F1 score on low-risk (class 0) and high-risk (class 1).

	precision	recall	f1-score	support
0.0	0.96	0.98	0.97	3767
1.0	0.98	0.96	0.97	4316
accuracy			0.97	8083
macro avg	0.97	0.97	0.97	8083
weighted avg	0.97	0.97	0.97	8083

Figure 4. 2: Classification report of English content-based classifier

The ROC curve represents the graphical interpretation of the classifier performance [40]. The analysis was used to interpret the performance in the graphical mode as the ROC curve is compatible with binary classification. The ROC curve for the English content-based classifier (Figure 4. 3) was 0.99, which can consider as the perfect classifier.

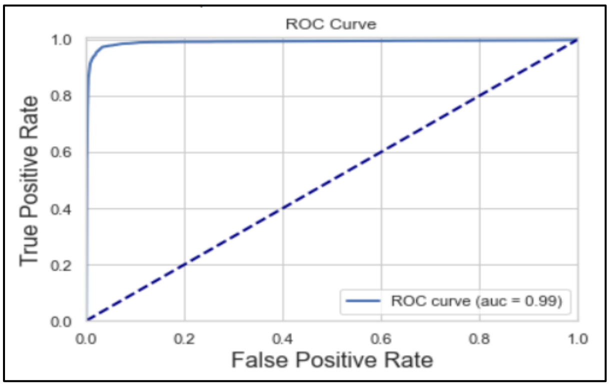


Figure 4. 3: ROC curve of English content-based classifier

English content-based prediction (Figure 4. 4) is evaluated on high-risk phase and low-risk phase in English. The result indicates that the low-risk phrase has obtained a low depression risk (4%). Further, the high-risk phase indicates a higher depressive risk (100%).

```
I'm gonna sell the kits all the questions to the bass!
        score: 0.04
        Low Risk of depression
--------------------
I'm writing this for the first time, and I'll be glad if anyone can help me or at least just talk.
        score: 1.0
        High Risk of Depression
--------------------
```

Figure 4. 4: Output of the English content-based classifier

6.1.2. Sinhala content-based classifier

Although the study trained the SVM on content, the analysis could achieve 84% for the Sinhala-based classifier. The study employed a pre-trained deep learning classifier, FastText, to enhance the classifier performance. The trained classifier achieved 95% test accuracy with the 1.01 test loss (Figure 4. 5) upon Sinhala content.

```
Test Loss: 1.011 | Test Acc: 94.89%
```

Figure 4. 5: Accuracy of the Sinhala content-based classifier

The confusion matrix summarizes the performances of the classifier [41]. According to the confusion matrix (Figure 4. 6) matrix for the Sinhala classifier, data points of 4910 are correctly categorized as low risk of depression, and data points of 4613 are correctly categorized as high risk of depression. The analysis considered 5086 data points for low-risk depression and 4960 data points for high-risk depression in the test phase.

```
Confusion Matrix
[[4910  176]
 [ 347 4613]]
```

Figure 4. 6: Confusion matrix of Sinhala content-based classifier

The ROC curve for the Sinhala content-based classifier (Figure 4. 7) was 0.98. Although the Sinhala classifier could not outperform the English classifier, the Sinhala classifier can consider as a perfect classifier.

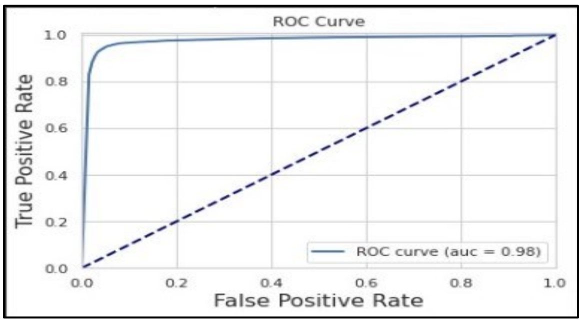


Figure 4. 7: ROC curve of Sinhala content-based classifier

Sinhala content-based prediction (Figure 4. 8) is evaluated on high-risk phase and low-risk phase in Sinhala. The result indicates that the low-risk phrase has obtained a low depression risk (0%). Further, the high-risk phase indicates a higher depressive risk (100%).

```
මට සියදිවි නසා ගැනීමට අවශ්‍යයි
        score: 1.0
        High Risk of Depression
--------------------
අගමැතිතුමාගෙ උපදෙස් පරිදි වැඩි වූ තෙල් මිල අඩු කරන ලදි කොටස කවදද පෙන්වන්නෙ
        score: 0.0
        Less Risk of depression
--------------------
```

Figure 4. 8: Output of the Sinhala content-based classifier

6.1.3. Chatbot

The performance of the implemented chatbot is indicated in the following Figure 4. 9. Although the analysis employed the Rasa framework, the chatbot should properly design to continue the chat flow. The test accuracy of 0.96 was achieved on chat flow implementation. Note that the evaluation is based on the action level of the chatbot. Further, the chat flow implementation obtained a better value (0.96) for the F1 score.

```
[[16  0  0  0  0  0  0]
 [ 0  3  0  0  0  0  0]
 [ 0  0  3  0  0  0  0]
 [ 0  0  0  4  0  0  0]
 [ 0  0  0  0  5  0  0]
 [ 0  0  0  0  0  3  0]
 [ 0  0  0  0  0  0  1]]
```

Figure 4. 9: Confusion matrix of implemented chatbot

The following Figure 4. 10 indicates the confusion matrix for chat flow implementation.

```
2021-07-04 11:26:20 INFO     rasa.core.test  - Evaluation Results on ACTION level:
2021-07-04 11:26:20 INFO     rasa.core.test  -  Correct:          33 / 35
2021-07-04 11:26:20 INFO     rasa.core.test  -  F1-Score:         0.961
2021-07-04 11:26:20 INFO     rasa.core.test  -  Precision:        0.961
2021-07-04 11:26:20 INFO     rasa.core.test  -  Accuracy:         0.961
2021-07-04 11:26:20 INFO     rasa.core.test  -  In-data fraction: 0.886
2021-07-04 11:26:20 INFO     rasa.utils.plotting  - Confusion matrix, without normalization:
```

Figure 4. 10: Classification report of implemented chatbot

A sample chat conversation is indicated in Figure 4. 11.

```
2021-07-04 15:48:02 INFO     root  - Rasa server is up and running.
Bot loaded. Type a message and press enter (use '/stop' to exit):
Your input ->  hii
Hi, I'm ellie thanks for coming in today.
 I was created to talk to people in a safe and secure environment. Think of me as a friend i don't judge i can't i'm a computer i'm here to learn about people and would love to learn a
bout you. i'll ask a few questions to get us started and please feel free to tell me anything your answers are totally confidential.
 how are you doing today?
Your input ->  feeling bad
Here is something to cheer you up:
Image: https://i.imgur.com/nGF1K8f.jpg
Did that help you?
Your input ->  somewhat
Great, carry on!
```

Figure 4. 11: Sample chat flow

6.2. Research Findings

The study employed an SVM classifier on English content as the initial step of identifying the depression risk. The SVM classifier performed better with obtaining 94% test accuracy. The classifier based on SVM was able to achieve higher test accuracy. However, the study mainly focused on exploring a higher performance since the analysis is a health-related classification. Hence, the study applied pre-defined fastText considering machine learning as the baseline model. Ultimately, the fastText classifier could outperform the SVM. The network obtained 96% test accuracy based on English content.

Further, the study applied an SVM classifier on Sinhala content. The SVM classifier could achieve 84% test accuracy. The analysis forwarded with a deep learning approach even though the SVM classifier obtained a higher performance since the study was ultimately focused on exploring a higher accuracy. The study applied fastText by considering machine learning as the baseline model. The classifier could outperform the SVM classifier with 95% test accuracy.

Moreover, the study focused on chatbot implementation to provide a platform for the end-user of the mobile application facilitating the share of personal thought with a mental health care-related intelligent bot. The chat flow implementation could achieve 0.96 test accuracy. Further, the chat flow implementation obtained a better value (0.96) for the F1 score.

The findings of this study can be summarized as follows.

- The English content-based classifier obtained high accuracy (96%) in identifying the depressive risk.
- Chat conversations can utilize to identify depressive risk.
- The Sinhala content-based classifier obtained high accuracy (95%) in identifying the depressive risk.
- FastText can be utilized for content-based health-related classification.

6.3. Discussion

The study primarily evaluated depression risk based on content in English and Sinhala. Despite the machine learning algorithm SVM has built on highly correlated parameters, the study could achieve 84% test accuracy for Sinhala analysis. However, the analysis based on English content could achieve higher accuracy (94%). The study was ultimately focused on exploring a higher accuracy. As a result, we investigated the deep learning algorithms, using the machine learning approach as our baseline model. accommodated

The deep learning approach has awarded remarkable accuracy in the English (96%) and Sinhala (95%) classifiers. The classifiers were implemented by employing fastText, which utilizes fewer resources for high performance. Even though the classifiers trained on a considerable amount of data points, the analysis could find classified data points in the Russian language. The study had to transform Russian content into English and Sinhala.

Moreover, the study required developer accounts of social media platforms. However, the social media platforms limit to grant access to developer accounts. Facebook, WhatsApp, and Instagram need a working system to grant access to developer accounts. Hence, the study was not able to extend to other social networks.

The limitations of this study are summarized as follows.

- Access limitation on social media developer accounts is limited to extend the study to other social networks.
- The analysis could only find the classified data points in the Russian language.

7. CONCLUSION

The study focused on a mobile-based depression analyzer to address the limitation of limited access to access to treatment. The study implemented a classifier that analyzes content in English and Sinhala for assessing depressive disorder risk. The analysis employed a pre-trained classifier, fastText, and NLP techniques to train the classifier. The analysis trained the English content-based classifier, which was able to achieve 96% accuracy. Further, the study trained the Sinhala content-based classifier, which was able to achieve 95% accuracy. Moreover, the study implemented a chatbot to analyze the chatbot history.

REFERENCES

[1] Q. Liu, H. He, J. Yang, X. Feng, F. Zhao, and J. Lyu, “Changes in the global burden of depression from 1990 to 2017: Findings from the Global Burden of Disease study,” *Journal of Psychiatric Research*, vol. 126, pp. 134–140, 2020.

[2] B. Vimaleswaran and G. S. Ratnayake, "E - Therapy Improvement Monitoring Platform for Depression using Facial Emotion Detection of Youth," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, 2021, pp. 950-955, doi: 10.1109/ICICV50876.2021.9388447.

[3] Y. S. Balhara, N. Anwar, and P. Kuppili, “Depression and physical noncommunicable diseases: The need for an integrated approach,” *WHO South East Asia J. Public Health*, vol. 6, no. 1, p. 12, 2017.

[4] World Health Organization, “‘Depression: let’s talk’ says WHO, as depression tops list of causes of ill health,” *World Health Organization*. [Online]. Available: https://www.who.int/news-room/headlines/30-03-2017--depression-let-s-talk-says-who-as-depression-tops-list-of-causes-of-ill-health. [Accessed: 01-Oct-2021].

[5] K. A. Govindasamy and N. Palanichamy, "Depression Detection Using Machine Learning Techniques on Twitter Data," *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2021, pp. 960-966, doi: 10.1109/ICICCS51141.2021.9432203.

[6] S. Ghosh and T. Anwar, "Depression Intensity Estimation via Social Media: A Deep Learning Approach," in IEEE Transactions on Computational Social Systems, doi: 10.1109/TCSS.2021.3084154.

[7] a Deep Learning Approach for Depression Detection in Imbalanced Data," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2018, pp. 1624-1627, doi: 10.1109/BIBM.2018.8621230.

[8] F. M. Shah et al., "Early Depression Detection from Social Network Using Deep Learning Techniques," 2020 IEEE Region 10 Symposium (TENSYMP), 2020, pp. 823-826, doi: 10.1109/TENSYMP50017.2020.9231008.

[9] A. H. Uddin, D. Bapery and A. S. M. Arif, "Depression Analysis from Social Media Data in Bangla Language using Long Short Term Memory (LSTM) Recurrent Neural Network Technique," *2019 International Conference on*

Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), 2019, pp. 1-4, doi: 10.1109/IC4ME247184.2019.9036528.

[10] Y. Wang, Z. Wang, C. Li, Y. Zhang and H. Wang, "A Multimodal Feature Fusion-Based Method for Individual Depression Detection on Sina Weibo," *2020 IEEE 39th International Performance Computing and Communications Conference (IPCCC)*, 2020, pp. 1-8, doi: 10.1109/IPCCC50635.2020.9391501.

[11] H. A. Schwartz *et al.*, “Towards assessing changes in degree of depression through Facebook,” in *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, 2014.

[12] S. Tsugawa, Y. Kikuchi, F. Kishino, K. Nakajima, Y. Itoh, and H. Ohsaki, “Recognizing depression from twitter activity,” in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI ’15*, 2015.

[13] N. S. Alghamdi, H. A. Hosni Mahmoud, A. Abraham, S. A. Alanazi and L. García-Hernández, "Predicting Depression Symptoms in an Arabic Psychological Forum," in *IEEE Access*, vol. 8, pp. 57317-57334, 2020, doi: 10.1109/ACCESS.2020.2981834.

[14] M. de Choudhury, M. Gamon, S. Counts and E. Horvitz, "Predicting Depression via Social Media," *Seventh Int. AAAI Conf.* Weblogs Soc., 01 July 2013.

[15] K. Katchapakirin, K. Wongpatikaseree, P. Yomaboot and Y. Kaewpitakkun, "Facebook Social Media for Depression Detection in the Thai Community," *2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 2018, pp. 1-6, doi: 10.1109/JCSSE.2018.8457362.

[16] M. R. Islam, M. A. Kabir, A. Ahmed, A. R. M. Kamal, H. Wang and A. Ulhaq, "Depression detection from social network data using machine learning techniques," *Health Information Science and Systems*, vol. 6, no. 1, 2018.

[17] C. S. A. Razak, M. A. Zulkarnain, S. H. A. Hamid, N. B. Anuar, M. Z. Jali, and H. Meon, “Tweep: A system development to detect depression in twitter

posts," in *Lecture Notes in Electrical Engineering*, Singapore: Springer Singapore, 2020, pp. 543–552.

[18] F. Delahunty, I. D. Wood and M. Arcan, "First insights on a passive major depressive disorder prediction system with incorporated conversational chatbot," in 26th AIAI Irish Conference on Artificial Intelligence and Cognitive Science, 2018.

[19] Y. Chen, B. Zhou, W. Zhang, W. Gong and G. Sun, "Sentiment Analysis Based on Deep Learning and Its Application in Screening for Perinatal Depression," 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC), 2018, pp. 451-456, doi: 10.1109/DSC.2018.00073.

[20] "Happify: Science-based activities and games," *Happify.com*. [Online]. Available: https://my.happify.com/. [Accessed: 11-Oct-2021].

[21] "Happify App Review," *Choosingtherapy.com*. [Online]. Available: https://www.choosingtherapy.com/happify-app-review/. [Accessed: 11-Oct-2021].

[22] "Wysa: anxiety, depression & sleep therapy chatbot," *Google.com*. [Online]. Available: https://play.google.com/store/apps/details?id=bot.touchkin&hl=en&gl=US. [Accessed: 11-Oct-2021].

[23] A. Beltran, "Wysa: Mental Health Support," *Commonsensemedia.org*, 08-Jul-2019. [Online]. Available: https://www.commonsensemedia.org/app-reviews/wysa-mental-health-support. [Accessed: 11-Oct-2021].

[24] "Relational agent for mental health," *Woebothealth.com*, 08-Dec-2020. [Online]. Available: https://woebothealth.com/. [Accessed: 11-Oct-2021].

[25] "Woebot: Your Self-Care Expert," *Apple.com*. [Online]. Available: https://apps.apple.com/us/app/woebot-your-self-care-expert/id1305375832. [Accessed: 11-Oct-2021].

[26] "Woebot: Your Self-Care Expert," *Google.com*. [Online]. Available: https://play.google.com/store/apps/details?id=com.woebot&hl=en&gl=US. [Accessed: 11-Oct-2021].

[27] E. Brodwin, "I spent 2 weeks texting a bot about my anxiety — and found it to be surprisingly helpful," *Business Insider*, 30-Jan-2018.

[28] "Terms of Use - Youper," *Youper.ai*, 10-Jun-2021. [Online]. Available: https://www.youper.ai/terms-of-use. [Accessed: 11-Oct-2021].

[29] "Youper mental health AI app review," *Onemindpsyberguide.org*, 16-Aug-2018. [Online]. Available: https://onemindpsyberguide.org/apps/youper-app-review/. [Accessed: 11-Oct-2021].

[30] C. Shu, "Youper, a chatbot that helps users navigate their emotions, raises $3 million in seed funding," *TechCrunch*, 18-Jun-2019.

[31] S. Narynov, D. Mukhtarkhanuly, and B. Omarov, "Dataset of depressive posts in Russian language collected from social media," Data Brief, vol. 29, no. 105195, p. 105195, 2020.

[32] J. Gratch et al., "The Distress Analysis Interview Corpus of human and computer interviews," in Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), 2014, pp. 3123–3128.

[33] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 2014

[34] Prabhu, "Understanding NLP Word Embeddings — Text Vectorization," *Towards Data Science*, 11-Nov-2019. [Online]. Available: https://towardsdatascience.com/understanding-nlp-word-embeddings-text-vectorization-1a23744f7223. [Accessed: 05-Oct-2021].

[35] "Word vectors for 157 languages," Fasttext.cc. [Online]. Available: https://fasttext.cc/docs/en/crawl-vectors.html. [Accessed: 05-Jul-2021].

[36] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," in Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, 2017.

[37] "Introduction to Rasa Open Source," *Rasa.com*. [Online]. Available: https://rasa.com/docs/rasa/. [Accessed: 06-Oct-2021].

[38] "FastAPI," *Tiangolo.com*. [Online]. Available: https://fastapi.tiangolo.com/. [Accessed: 11-Oct-2021].

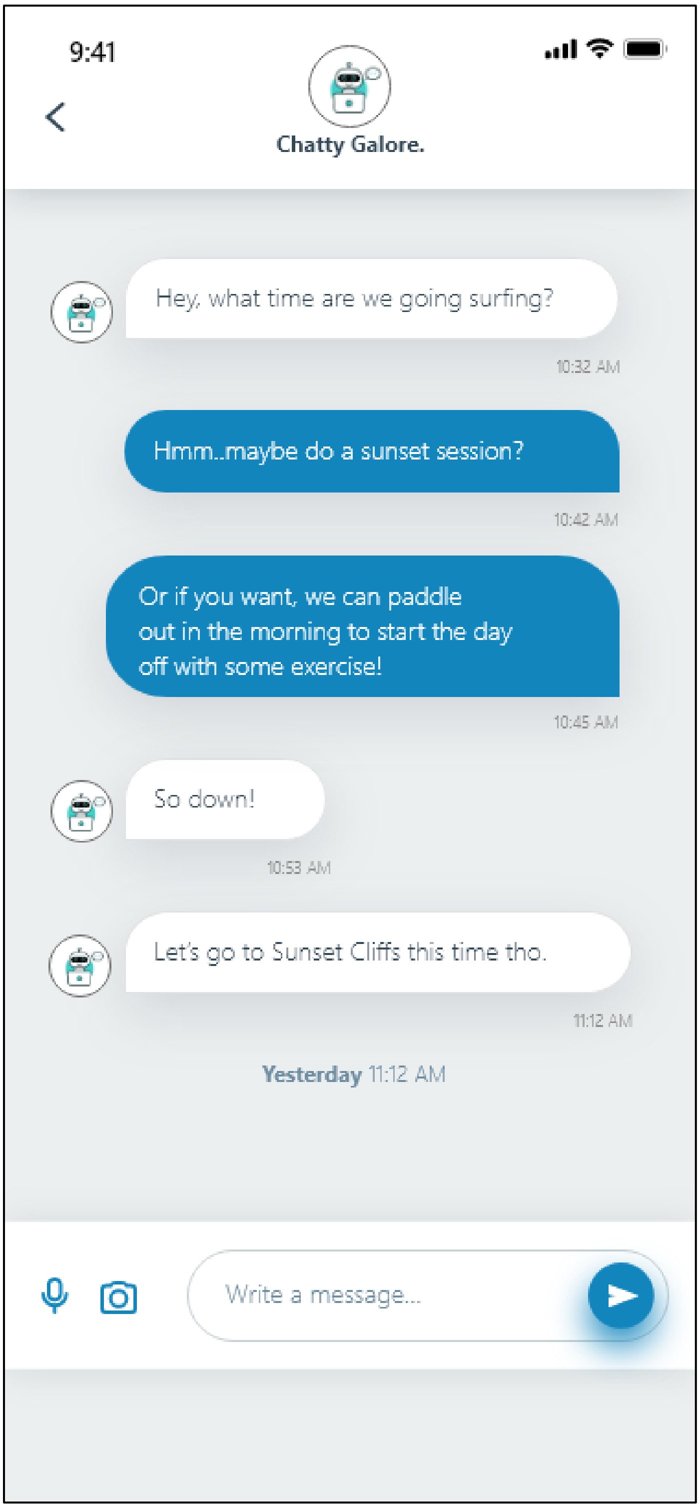
[39] A. Kharwal, "Classification report in machine learning," *Thecleverprogrammer.com*, 07-Jul-2021. [Online]. Available:

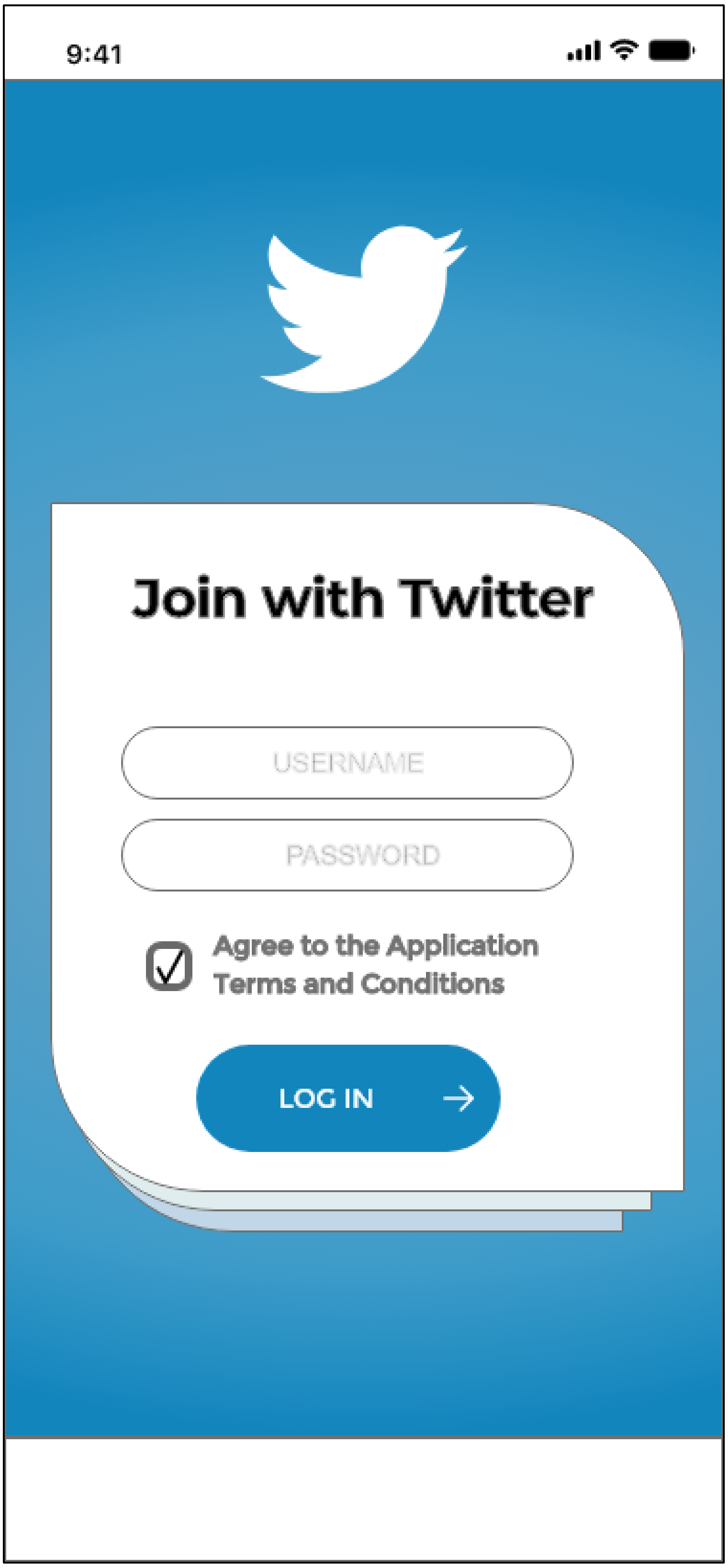
https://thecleverprogrammer.com/2021/07/07/classification-report-in-machine-learning/. [Accessed: 08-Oct-2021].

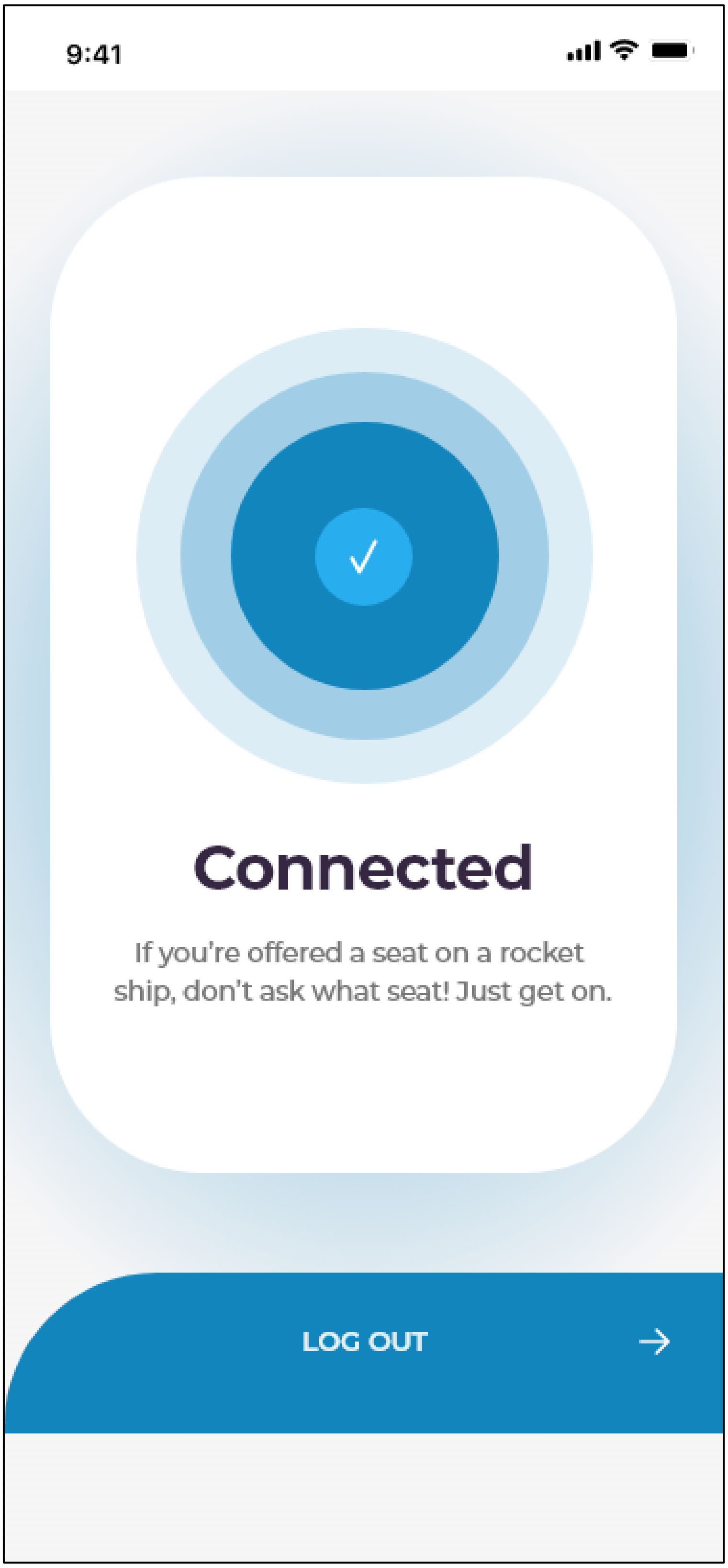
[40] D. Steen, “Understanding the ROC Curve and AUC,” *Towards Data Science*, 13-Sep-2020. [Online]. Available: https://towardsdatascience.com/understanding-the-roc-curve-and-auc-dd4f9a192ecb. [Accessed: 08-Oct-2021].

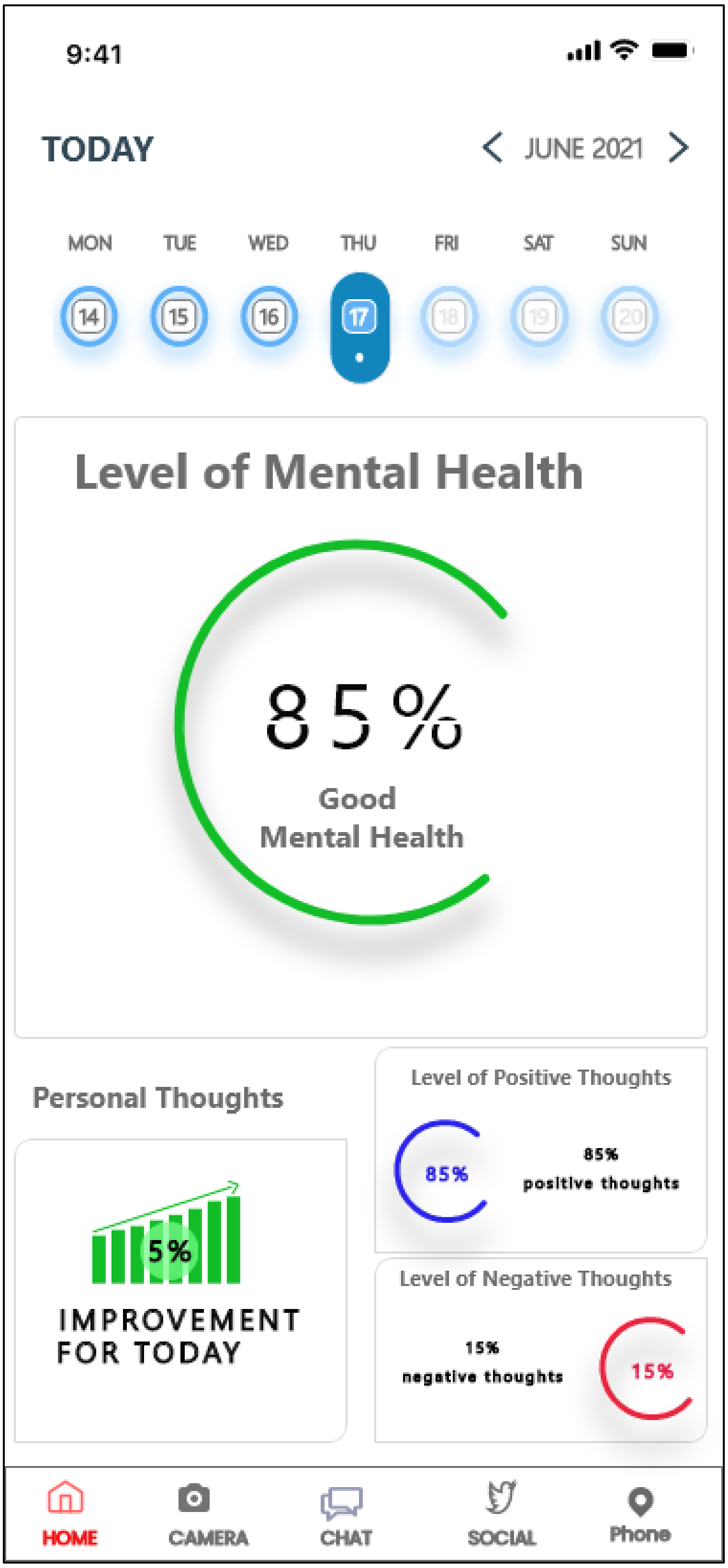
[41] K. Markham, “Simple guide to confusion matrix terminology,” *Dataschool.io*, 26-Mar-2014. [Online]. Available: https://www.dataschool.io/simple-guide-to-confusion-matrix-terminology/. [Accessed: 08-Oct-2021].

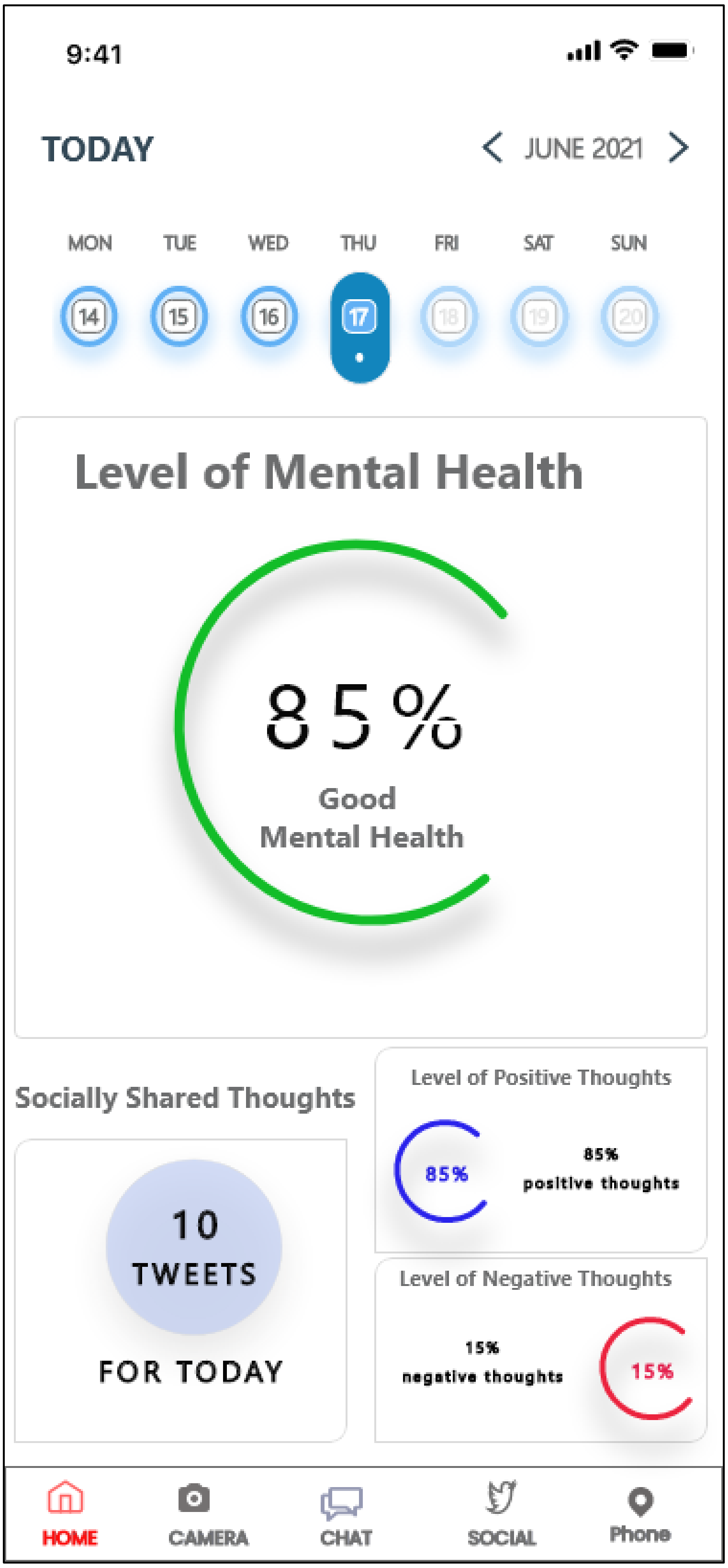
Appendix A: UI Wireframes




9:41
Join with Twitter
USERNAME
PASSWORD
Agree to the Application
Terms and Conditions
LOG IN


9:41
Connected
If you're offered a seat on a rocket ship, don't ask what seat! Just get on.
LOG OUT


9:41
TODAY
JUNE 2021
MON
TUE
WED
THU
FRI
SAT
SUN
14
15
16
17
18
19
20
Level of Mental Health
85%
Good
Mental Health
Personal Thoughts
5%
IMPROVEMENT
FOR TODAY
Level of Positive Thoughts
85%
85%
positive thoughts
Level of Negative Thoughts
15%
negative thoughts
15%
HOME
CAMERA
CHAT
SOCIAL
Phone


9:41
TODAY
JUNE 2021
MON
TUE
WED
THU
FRI
SAT
SUN
14
15
16
17
18
19
20
Level of Mental Health
85%
Good
Mental Health
Socially Shared Thoughts
10
TWEETS
FOR TODAY
Level of Positive Thoughts
85%
85%
positive thoughts
Level of Negative Thoughts
15%
negative thoughts
15%
HOME
CAMERA
CHAT
SOCIAL
Phone

Appendix B: Test cases

English content-based classifier – high risk

```
I found that with depression, one of the most important things you could realize is that you're not alone.
        score: 0.77
        High Risk of Depression
```

English content-based classifier – low risk

```
I'm gonna sell the kits all the questions to the bass!.
        score: 0.06
        Low Risk of depression
```

Sinhala content-based classifier – high risk

```
මොනා බයිලා කිව්වත් සමහර අයට අලුත් අය ලැබුණ ගමන් පරණ අයිව ලොකු කරදරයක් වෙනවා. අත්දැකීමෙන් දන්නවා.
        score: 0.52
        High Risk of Depression
```

Sinhala content-based classifier – low risk

```
--------------------
මහ මුහුදට පැණි දැම්මට මුහුදෙ ලුණු රස වෙනස් වෙන්නෙ නෑ වගේ සමහරු වෙනුවෙන් අපි මොන තරම් කැප කිරීම් කළත් එයාලට ඒක වටින්නෙ නෑ
        score: 0.32
        Less Risk of depression
--------------------
```

Appendix C: Access Twitter Posts

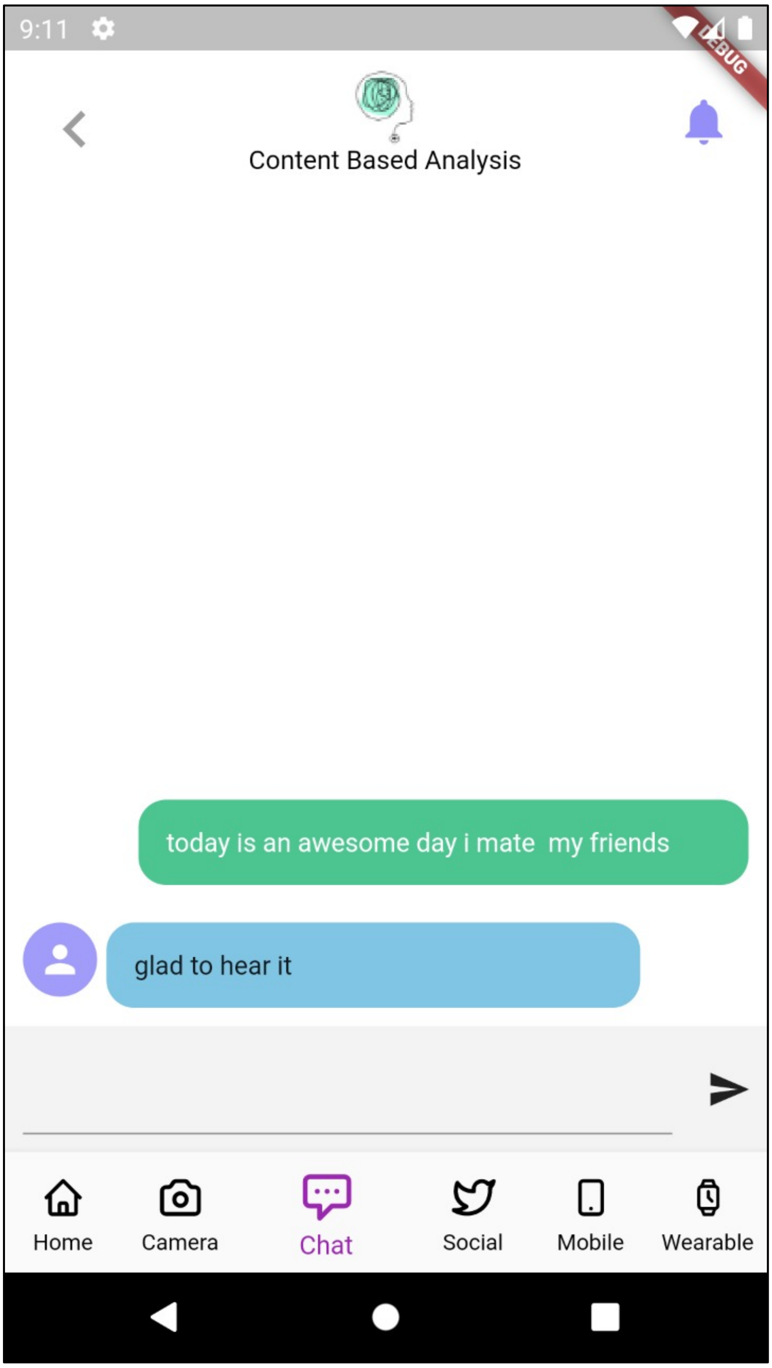
```
import 'dart:convert';
import 'package:http/http.dart' as http;
import 'package:twitter_api/twitter_api.dart';

class TwitterAPIHelper {
  final _bearerToken =
      '//key';
  final _twitterOauth = new twitterApi(
      consumerKey: '//key',
      consumerSecret: '//key',
      token: '//key',
      tokenSecret: '//key');

  getId(String userName) async {
    var result = await http.get(
        'https://api.twitter.com/2/users/by/username/' + userName,
        headers: {'Authorization': 'Bearer ' + _bearerToken});
    if (result.statusCode == 200) {
      var json = jsonDecode(result.body);
      if (json['data'] != null) {
        return json['data']['id'];
      } else
        return null;
    } else {
      return null;
    }
  }

  getPosts(String id) async {
    Future twitterRequest = _twitterOauth.getTwitterRequest(
      // Http Method
      "GET",
      // Endpoint you are trying to reach
      "statuses/user_timeline.json",
      // The options for the request
      options: {
        "user_id": id,
      },
    );
```

Appendix D: Response from ChatBot (Non-depressive Phrase)



Appendix E: Response from ChatBot (Depressive Phrase)