BEHAVIOR ANALYSIS FOR DEPRESSION DETECTION.

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DECLARATION

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ABSTRACT

Depression is a chronic mental condition that requires immediate medical and psychiatric consideration. Although depression is not curable, it can be remit with effective treatments. Detecting the early risk of depression is very important to help the affected individual to get medical treatment. Currently, the mental health industry has no reliable diagnostic laboratory tests for depression, and clinicians are much more likely to assess mental health using the series of standard questions to detect and treat depression. Technological involvement could be more advance in diagnosing depression.

Currently, the mobile applications associated with depression are using standard questionnaires to assess the depression level. In Sri Lanka, people may obscure the state of their minds due to social stigma and fear. However, a self-awareness mobile application that can evaluate own mental health and identify early depression risk can be more valuable to remit the danger.

This study aimed to develop a mobile application to analyze the unexpected behavior changes that might have a high chance of having depression. The depression risk is assessed by analyzing facial cues, content from the social network, mobile utilization, and biometrics. Natural Language Processing (NLP) and machine learning algorithms are employed to train classifiers. In addition, the proposed system is implemented using the flutter.

Keywords: Depression risk, Heart Rate Analysis, Phone usage, Natural Learning Processing, Neural Network

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1. INTRODUCTION

1.1. Background & Literature Survey

1.1.1. Background

Mental health is the foundation for individual well-being and community productivity. Mental health preserves human emotional, psychological, and social well-being aspects in a satisfactory state. Moreover, mental health affects positivity, how individuals feel about other people, and even sentimental exchange. A healthy mind is an essential factor to empower the growth of the community for the next generation. However, the psychological well-being of an individual can be affected by various reasons and consequences. According to the World Health Organization (WHO), depression is one of the primary causes of disability [1] that can direct to suicide at its most critical level [2]. The suicide rate among untreated depressive disorder individuals is nearly 20% [3].

Depression has become the second leading cause of deaths age between 15 – 19 worldwide [4]. The reports of the WHO claim that more than 264 million people of all ages suffer from depression. The disorder is most common among the 18 – 29 age group by 21.0% [5]. The major challenge with the risen number of depressed people is a lack of resources and support services. In low and middle-income countries, limited or underdeveloped treatment and support services accommodate for psychological health. As stated in [4], limited access to treatment in these countries increases the number of individuals suffering from mental health. Moreover, underdeveloped countries fronted 77% of global suicide in 2019 [6].

Mental health is becoming an ongoing epidemic in the Sri Lankan community as a result of a lack of professional support and community stigma surrounding mental health. As a result, depressed people are hesitant to seek treatment from mental health specialists. However, it is vital to keep track of those who are depressed to give better treatment. We anticipate developing a mobile application to identify early depression risk using non-verbal bio-markers. The proposed mobile application focused on identifying depression risk using facial cues, content from the social network, mobile utilization, and biometrics.

1.1.2. Literature survey

In the past few decades, studies have been carried out to identify depression in various aspects. Several deep learning models based on facial emotions [7], spatial-temporal facial traits [8], face landmarks [9], and head pose [10], [11] have been proposed for depression analysis. Similarly, information from social networks has been taken into account in several studies [12-16]. The majority of the research explored English-based linguistics [13], while few studies evaluated Bangla [14], Chinese [12], Thai [15], and Arabic [16]. Furthermore, experiments have been undertaken to identify depression in those who use mobile devices [17-19], as well as to assess the relationship between social media, internet use, and depression in younger generations [20], [21]. Researchers have focused on applying machine-learning algorithms to screen for depression using wearable devices [22 - 24] and identify physical and biometric changes associated with depression [25], [26].

J. F. Cohn et al. investigated facial and vocal behavior relation in diagnosing depression by employing the person-specific Active Appearance Model (AAMs), Manual Facial Action Coding System (FACS), and vocal prosody to detect depression [33]. S. P. Namboodiri and Venkataraman proposed a system to detect depression among college students, which considered frontal face images of happy, contempt, and disgusted faces in the video frame to analyze depression [34]. The link between depression and upper body movement has been studied in a few studies. S. Alghowinem et al. considered temporal aspects of the eye gaze and head position of the participants by using video-recorded clinical interviews (Australian, US, German) from three different datasets (BlackDog, AVEC, Pittsburgh) [11]. Moreover, the statical analysis on the head pose and movement patterns showed a significant difference between healthy and depressed individuals [35]. J. Joshi et al. explored the upper body movements and intra-facial movements using Space-Time Interest Points (STIP) feature, while head movement analysis was assessed by selecting rigid facial fiducial points [36].

De Choudhury M et al. proposed an SVM classifier using behavioral cues (linguistic styles, depressive language, ego network) to estimate the depression risk with an accuracy of approximately 70% [37]. 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) acquired from Twitter history activities [38]. The study extended the De Choudhury M et al. prediction framework to Japanese-speaking Twitter users [37]. Delahunty et al. developed a machine learning classifier to identify the depression level of the user by considering the chatbot conversation [39]. C. S. A. Raza et al. used three different techniques (Naive Bayes Classifier technique, NLP techniques, Deep Learning technique) to analyze the depression risk by considering positive and negative tweets [40]. Md. Rafiqul Islam et al. focused on evaluating depression using Facebook user activities. In comparison to other machine learning techniques, the decision tree algorithm was found to have the highest accuracy in emotional processes and language style (KNN, SVM, Ensemble). The use of Facebook comments was used to predict depression among Facebook users [41]. Schwartz et al. studied a shortlist of words, topics, phrases to analyze depression. Further, the study focused on seasonal fluctuations of depression [42].

Sleep is one of the most common physiological alterations in a depressed patient. According to Maurice M Ohayon's study Epidemiology of Insomnia, around 80% of those who have recently experienced a major depressive episode also have sleep problems [25]. Aside from sleep patterns, another physical characteristic that we can detect in depressed patients is heart rate. As a result, a study conducted by Danni Kuang et al. at the South China University of Technology in Guangzhou found that depressed patients have lower HRV than healthy people. As a result, Bayesian Networks can be utilized to identify depressed patients from healthy people using HRV [26]. Based on data from the wearable gadget, researchers at Keio University's Faculty of Science and Technology in Kanagawa, Japan, built a machine-learning algorithm to screen for depression and measure severity [22]. Furthermore, Dartmouth College in the United States conducted a study on tracking depression using an app and wearable data, collecting heart rate via warble and other factors like sleep information and movement using the app The Student Life [24]. A study from the Media Lab at

MIT in Cambridge, MA, used data from E4 wearable wristbands and sensors in an Android phone to predict the Hamilton Depression Rating Scale (HDRS) [43].

According to studies, excessive phone usage among students and depression are linked together [17-19]. Deakin University's School of Health and Social Development reviewed the relationship between the amount of time spent on the Internet for leisure and depressive symptoms among Australian adolescents. They discovered that depressive symptoms were more common among higher Internet users (3 or more hours per day only among females) with comparing to adolescents who only use the Internet for two hours or less [20]. Addiction to social media may be a symptom of a depressive condition. According to Amit Chowdhry's research, people who use social media very frequently have 2.7 times the risk of depression as people who use it less frequently. And people who spend the most total time on social media throughout the day have 1.7 times the risk of depression as people who spend less time [21]. The study [44] track depression using Touchscreen typing pattern analysis data from the TypeOfMood app to acquire data. A study from Dartmouth College in the United States analyzed whether there is a link between depressive disorder and obtained data through an app and wearables. They used excessive phone usage from the Student Life app as a factor to track depressive disorder using a mobile phone and wearable [24].

1.2. Research Gap

As the Literature survey (section 1.1.2.) we can identify in the are of emotion-based early depression risk analysis non of the studies have conducted Probability of early depression features based on facial expression and Probability of early depression features based on head movement analysis. We have identified the area of content-based early depression risk analysis Probability of early depression features based on social media content and Probability of early depression features based on Chatbot conversation have not been considered in any of the studies that have been reviewed. The biometric data analysis of early depression risk analysis any of review research has not considered early depression risk analysis, Non – invasive methods as alternatively obtain data from users. Lastly, when we consider phone usage-based analysis no of the researchers have conducted early depression risk analysis based on phone usage data. Following is the summary of the research gap according to research papers.

- Consider early depression risk analysis based on both emotions and head pose.
- Consider early depression risk analysis based on both AI bot chat conversation and social media content.
- Consider early depression risk analysis based on both Biometric data collected both invasively and non-invasively.
- Consider early depression risk analysis based on phone usage patterns.

The proposed system " Mind Guardian" mobile application consists of all factors of emotion, content, biometric, and phone usage analysis on early depression risk.

The mobile application gaps have been studied according to each area of emotional analysis, social media content analysis, biometric data analysis, and phone usage data analysis. Each is application gap can be shown as following,

Table 1. 1: Comparison of Current Mobile Application Gaps

		Mind Doc	**Imood Journal**	**Sanvello**	**UP!**	**Proposed System**
Emotion and head pose based	Identify Emotion	✓	✓	✓	✓	✓
	Identify Head Pose angles	✗	✗	✗	✗	✓
	Analyze depression risk	✗	✗	✗	✗	✓

	based on emotion, facial expressions, and head pose angles					
		Happify	**Wysa**	**Woebot**	**Youper**	
Content-Based analysis	AI chatbot	✓	✓	✓	✓	✓
	Depression risk analysis based on social media content	✗	✗	✗	✗	✓
	Sinhala content-based depression risk analysis	✗	✗	✗	✗	✓
	Analyze positive thoughts.	✗	✗	✗	✗	✓
		Sleepio	**StressScan**	**Welltory**	**Moodpath**	
Biometric-based analysis	Invasive method to collect Factor's data	✗	✗	✗	✗	✓
	Non- invasive method to collect Factor's data	✗	✗	✗	✗	✓
	Depression analysis based on Biomatrix data (HRV, Sleep pattern)	✗	✗	✗	✗	✓

		PROSIT	App Usage	TypeOf Mood app		
Phone usage-based analysis	Depression analysis based on Phone usage data	✓	✗	✓		✓
	Monitor phone usage characteristics related to depression	✗	✗	✗	✗	✓
Extensive summary about all 4 areas		✗	✗	✗	✗	✓

As above Table (1.2) indicates the proposed "mind guardian" application covers a wide area of Emotion, content, biometric, and phone usage analysis on early depression risk analysis altogether.

2. RESEARCH PROBLEM

Mental health disorders like major depressive disorder or anxiety disorder have been increasing rapidly among the younger generation due to various reasons. As a result of this, suicide rates have been rising among young people [45]. Even though mental illness causes life damages, people are not confident enough to believe that they are suffering from depression or anxiety due to social stigma. Also, the most critical part is not receiving medications for these mental problems by consulting a psychiatrist or psychologist. However, we should identify the risk of having a depressive disorder in the early stages before starting medications. It is not an easy task to understand depression levels by ourselves rather than a professional psychiatrist. With the issue of identifying the early-stage disorder, the majority of the people do not have an idea that they are suffering from depression or not.

The standard methods used to identify depressed individuals are the use of questionnaires or advanced medical testing systems for severe patients. These tests are available for people who think they have depression, and they may have identified their symptoms at the high-risk level. When we consider these problems, we should have an easily accessible application with suitable parameters to identify the people who are at risk of suffering from depression in the early stages. However, most of the currently available mental health-related mobile applications developed to track the status of depression by using questions to understand the mental stage and suggest solutions for mood changes, sleep disorders, and mind relaxation methods for patients [46]. To the best of our knowledge, an automated analysis of depressive disorder using unexpected behavior changes that might have a chance of having depression risk is not yet studied in Sri Lanka.

3. RESEARCH OBJECTIVES

3.1.1. Main Objective

The study focused to develop a mobile application that may be utilized as non - verbal biomarkers for automatic depression risk analysis.

3.1.2. Specific Objectives

The main objective of the project has been divided into four different areas according to the depression risk analysis usage. The Subarea can be described as follows,

1) Identifying the early depressive behavior risk based on Emotion-based behavior.
2) Social media content analysis for the early risk identification of depressive disorder.
3) Acquire invasive and non-invasive data analysis for early depression risk analysis identification.
4) Individual phone usage data analysis for early depression risk analysis identification.

4. METHODOLOGY

4.1. Introduction

In this section, the “Mind Guardian” mobile application system process with a system diagram, the “Mind Guardian” mobile application designing, application development tools, and technologies and, commercialization aspects will be discussed.

There are two primary phases to evolution. The Model Implementation for early depression risk analysis and predictions. The Mobile app development with model integration user data obtains method development, mobile function development, and User Interface implementation.

The Model implementation phase consists of 6 different model implementation procedures which are,

1. Early depression risk analysis on Facial and emotional features (EDRAE).
2. Early depression risk analysis on Head posture and Emotional features (EDRAH).
3. Early depression risk analysis on social network content. (EDRASN).
4. Early depression risk analysis on Mobile Phone Usage. (EDRAP).
5. Early depression risk analysis on Heart Rate (EDRAHR).
6. Early depression risk analysis on sleep pattern (EDRASP)

Each model implementation process consists of Data collection, feature extraction and pre-processing, model implementation and API implementation, deployment. The procedure has in detail explained in section (5.1).

The Mobile development phase consists of Mobile Application development with user data obtaining method implementation, model API Integration, DB connectivity, Front end development. The procedure has in detail explained in section (5.2).

4.2. System Flow

The study designed a mobile application to identify early depression risk using non-verbal bio-markers. The proposed mobile application focused on identifying depression risk using facial cues, content from the social network, mobile utilization, and biometrics.

As indicated in Figure 4. 1, the end-user should be able to provide images and videos by accessing the camera or browsing the files in mobile storage. Similarly, public tweets and chat dialogues should be extracted by accessing the Twitter platform or the Chat history. Note that the mobile implemented a chatbot to express personal thoughts. MI band 5 can be used to access biometric data invasively, and accelerometer and phone flasher to access biometric data non-invasively. However, both invasive and non-invasive procedures have been enhanced for the user's convenience. Biometric data can be accessed using either an invasive or non-invasive method. Further, the phone usage data is accessed with the consent form end-user.

The accessed features will be input to the classifiers to analyze and obtain the probability of depressive risk based on bio-markers. The depression risk and extracted features will be stored in the database. Further, An extensive summary will appear on the home screen of the mobile application.

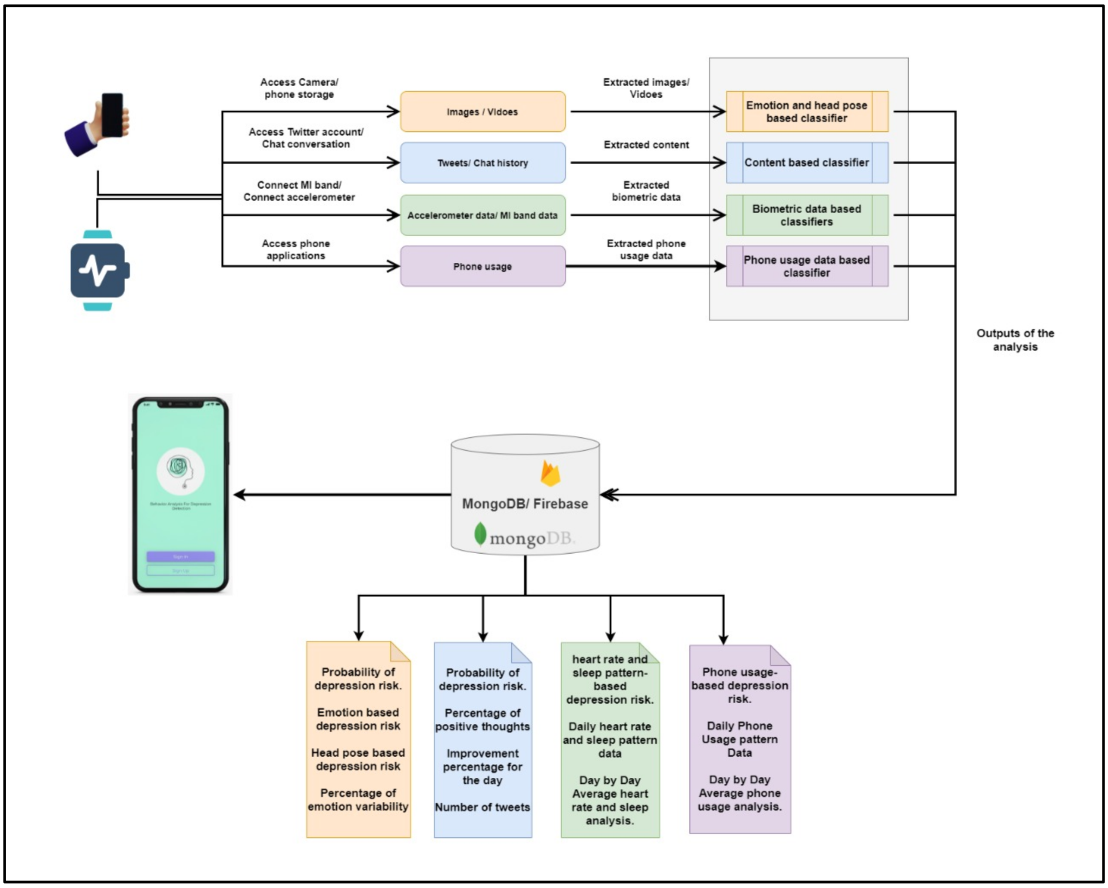

Figure 4. 1: System Flow Diagram.

4.3. Application Designing.

Information Gathering

The first step for mobile application development was to gather information regarding current mobile applications in the mental health analysis area and study them as well as identify the downsides of the current applications. Therefore, the information gathering has been conducted with 4 different areas of mobile applications which are,

1. Emotion and head pose analysis applications for depression risk analysis.
2. Social media content analysis applications for depression risk analysis.
3. Biometric data analysis applications for depression risk analysis.
4. Phone utilization data analysis applications for depression risk analysis.

The Mobile application comparison and analysis have explained in section (1.2).

The ethical and health processes that must be followed in the production of the "Mind Guardian" mobile application have been compiled with the help of an experienced clinical psychologist.

Application Design Thinking

Designing the "Mind Guardian" mobile application required extra attention because the app's target users are likely to be stressed or depressed. As a result, the design process was carried out in accordance with the requirements and an understanding of the target study group's mentality.

Following aspects have been taken to account at the design thinking stage:

- Features of a simple application include: The application's navigation and functionality have been designed so that the user does not become confused or anxious or stressed while conversing with the "Mind Guardian" application.

- Simple and uncomplicated User interface (UI) design: The "Mind Guardian" application's UI colors, elements, and font sizes have all been designed to make users feel at ease. The UI design features muted colors and basic text forms.

- Mental health summary display in a simple format: The mental health summary has been designed in such a way that the user does not become more sad or worried; as a result, straightforward language has been avoided, and the majority of the information has been presented in the form of diagrams or elements.

“Mind Guardian” Mobile Application flow

The mobile application flow can be explained and display as follows, Figure (4.2) indicates the Mobile application flow.

1) If the user has not yet registered with the system, the first step is for the user to log in and provide basic information such as "Name," "Email," "Birthday," "Gender," and so on.
2) After Register to the Application user must log in to the system using “user name ” and “password” provided by the register.
3) After that, the mobile app takes the user to the user agreements and privacy policy screen. This entails obtaining approval to access user facts for the purposes of depression risk analysis, as well as offering assurances that the user details and accessed information would be protected.
4) Then the user leads to the Home screen which is consists of display the user's mental health score and activity summary according to personal thoughts, socially shared thoughts, level of feelings, level of phone usage, and heart rate, sleep data.
5) From the home screen, using the bottom navigation users can get in detailed summary in Emotional analysis, personal thoughts and shared thoughts analysis, phone usage analysis, and biometric data analysis.

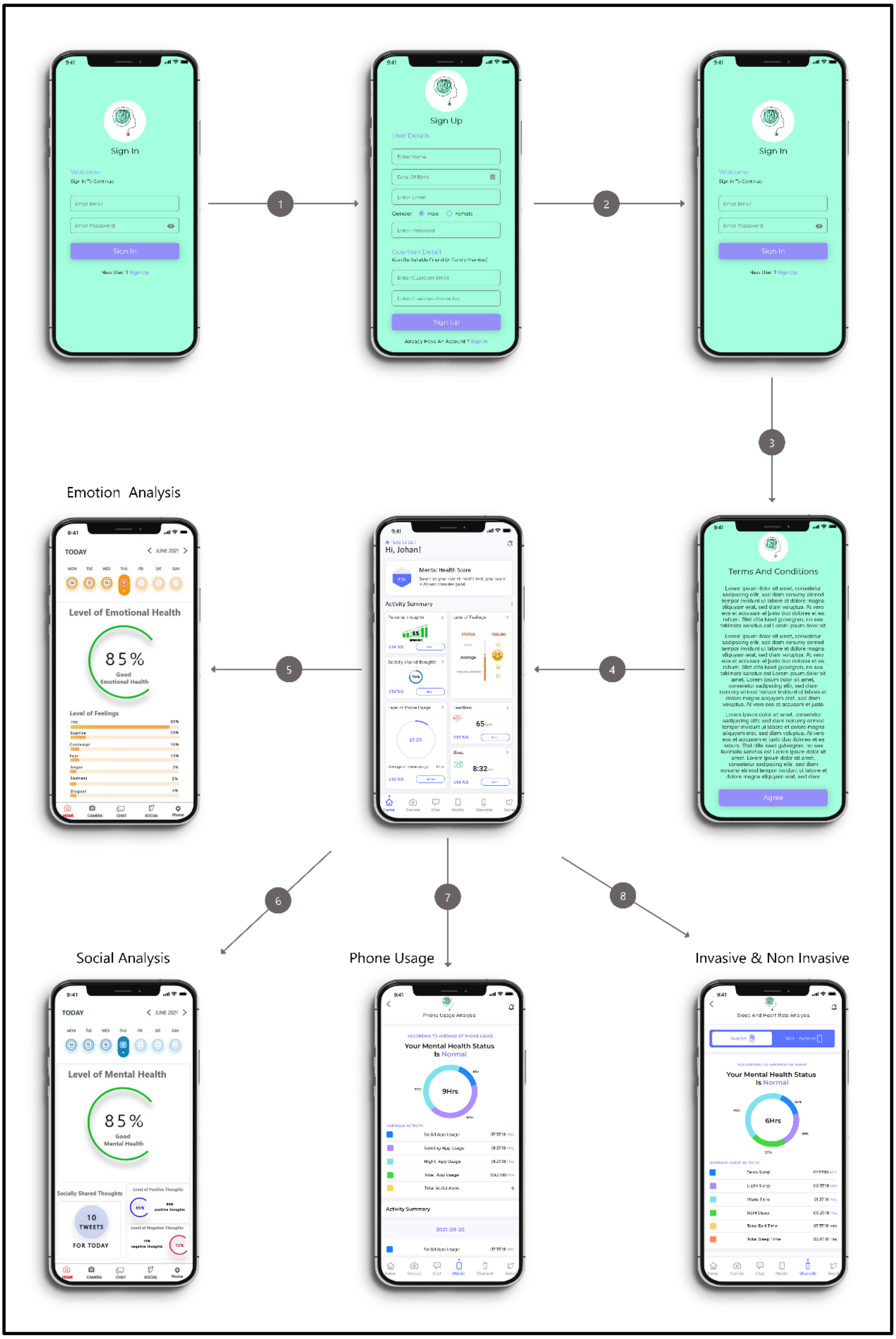

Figure 4. 2: Mobile Application Flow

4.4. Tools and Technologies

The Tools and technologies used for the "Mind guardian" application process can be divided into two parts which are Tools and Technologies used for analysis model implementation and Mobile application implementation.

Model Implementation.

Table 4. 1: Model Implementation Tools and Technology.

Tools and Technologies.	**Usage**
Anaconda 3	Anaconda environment has been used to perform the Model.
Jupyter Notebook	EDRAP, EDRAHR, and EDRASP models have been implemented on JN IDE.
Scikit-Learn	Scikit-Learn Libraries have been used for the model implementation process.
OpenCV	OpenCV library has been used for real-time computer vision process in the EDRAE and EDRAH models.
TensorFlow	TensorFlow open – source library has been used on EDRAE and EDRAH model training process.
Keras	EDRAE and EDRAH model development stage Keras open–source library has been used.
PyTorch	PyTorch machine learning library has been used on model training of EDRASN model.
Postman	Postman has used on the stage model API testing.

Mobile Implementation.

Table 4. 2: Mobile Application Implementation Tools and Technology.

Tools and Technologies.	**Usage**
Android Studio	The IDE for mobile application development.
Visual Code	Visual code IDE ave used in the Mobile application implementation phase.
Flutter and Dart	The mobile application language.
Firebase Real-Time	The database that has connected with the Mobile application.
MongoDB	No-SQL database program used to store data.

4.5. Commercialization of the Product

Individuals must be monitored for two weeks to come up with a decision about their depression level and provide effective therapy. However, people facing social stigma to receiving medication for mental disorders.

They suggest “Mind Guardian ” mobile application can monitor individuals' mental levels according to emotions, linguistic, biometric, and phone utilization.

The benefits of the product can be list down as below,

- In-depth analysis of emotion, linguistic, biometric, phone utilization of the individuals.
- Automated two-week individual monitoring without user’s self-reported details.
- A daily overview of individual emotion, linguistic, biometric, and phone utilization.
- Users can receive a sense of their mental health without fear of social repercussions.
- clinical phycologists can begin medication as soon as the two-week monitoring period is completed.
- Easy use of the application.

5. IMPLEMENTATION AND TESTING.

5.1. Analysis Models Implementation

This section explains the processes utilized to implement the model for predicting early detection of the risk of depression in individuals. This method includes data labeling, preprocessing, feature extraction, and depression risk assessment.

5.1.1. Data collection

For the visual cues-based depression risk study, the required data were obtained from mental health-specific YouTube channels. For videos of Psychiatric Interviews with Depressed People, three YouTube channels in the mental health arena were recommended. The YouTube channel "Make the Connection" was chosen to gather a nondepressed dataset, which comprised videos of TrueDepression Recovery Stories of US Army Officers. There were 18 videos in total that were used to build depressed and non-depressed datasets. All of the videos are longer than 1 minute, with the longest-lasting almost 38 minutes. A professional psychologist approved the movies and divided them into depressive and non-depressive categories. 1322 frames from depressed people and 1747 frames from non-depressed people were chosen and examined in this study. Figure (5.1) shows the Depressed and non-depressed data collection.

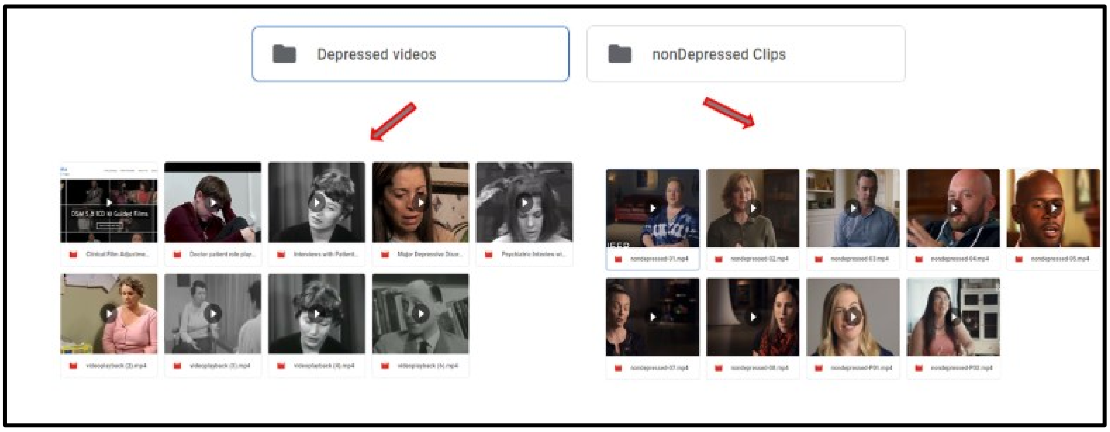

Figure 5. 1: Depressed and non-depressed Individual Data collection

Furthermore, from Kazakhstan research [27], we gathered the necessary data for the content-based depression risk analysis. It gathered Depressive Posts from VKontakte's social network's public accounts in Commonwealth of Independent States countries. The dataset consists of 32 018 depressive posts and 32 021 non-depressive posts classified by psychologists, as detailed in [27]. We also gathered a discussion content dataset from the DAIC-WOZ database. The database contains recordings of interviews done by Ellie, an animated virtual interviewer operated by a human interviewer in a separate room [28]. The database contains 189 sessions of recorded interviews with lengths ranging from 7 to 33 minutes. The transcript of the interview is included in each session. Figure (5.2) indicates the chatbot conversation dataset.

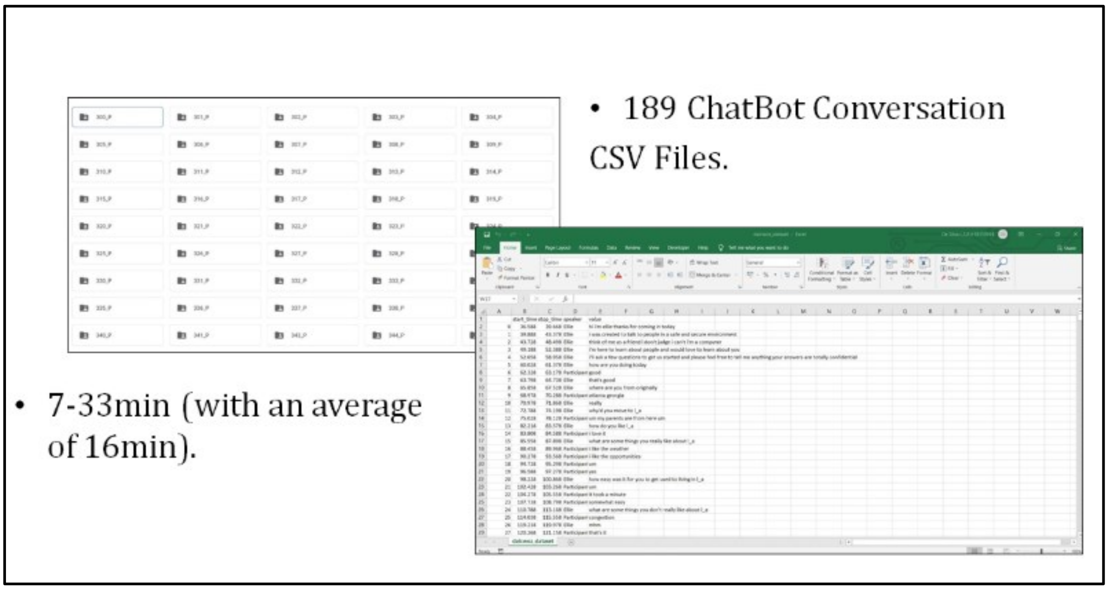

Figure 5. 2: Chatbot Conversation Data

The heart rate data came from a study called Health assessment of French university students and risk factors for mental health issues [29]. We collected data from 483 depressed people. Researchers from Stockholm University, the University of Sao Paulo, and the University of Surrey gathered data on sleep patterns [30]. Because the dataset contains both data on light exposure and data on sleep patterns, we must use an appropriate machine learning approach to choose solely sleep parameters. In section II-B, the technique is explained. With the outcomes. We gathered sleep data from 71 depressed people.

Data for the Early Depression Risk Analysis on Phone Usage (EDRAP) was obtained using a questionnaire that combined phone usage patterns and PHQ-9 questions[31] and was based on psychological norms. We were able to collect data from 350 people between the ages of 16 and 30. PHQ-9 scores and Proposed Treatment Actions were utilized to label the data. Following data labeling, we discovered that 100/350 indicates a risk of early depression. All of the following procedures were carried out under the supervision of a qualified Clinical Psychologist. The CSV file containing the collected data is shown in Figure (5.3).

A1 Age

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Age	Gender	No Of Soci	Social Mec	Freaquenc	Gaming Ap	Night Time	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Score	Depression	
2	23	1	3	1.3	1	1.3	0.3	1	1	1	1	1	1	1	1	1	9	0	
3	22	0	5	3.3	3	0	2	3	0	1	1	3	0	1	3	3	15	2	
4	24	0	1	10	5	0	0	0	0	0	1	0	0	0	0	0	1	0	
5	23	1	4	7.3	1	3.3	4	1	2	2	2	3	1	3	2	2	18	2	
6	16	1	5	9.3	5	0	2	1	0	3	1	0	0	0	0	0	5	0	
7	23	1	5	3.3	5	0	0.3	0	0	0	0	0	0	0	0	0	0	0	
8	23	1	4	3.3	4	1.3	0.3	1	1	1	1	1	1	1	1	1	9	0	
9	21	1	3	3.3	5	1.3	0	1	0	3	1	2	0	0	0	0	7	0	
10	23	1	2	1.3	5	0	0.3	2	1	1	2	1	1	1	1	1	11	1	
11	23	0	3	3.3	5	0	2	0	3	1	1	1	0	0	0	0	6	0	
12	24	1	3	5.3	1	3.3	1	1	1	1	1	1	1	1	1	1	9	0	
13	22	1	5	7.3	4	0	3	1	3	3	2	0	3	2	2	1	17	2	
14	19	1	5	10	4	0	3	1	1	1	0	1	0	1	0	0	5	0	
15	25	1	4	3.3	1	1.3	0.3	1	1	1	1	1	1	1	1	1	9	0	
16	23	1	3	5.3	1	3.3	1	1	0	2	1	1	1	1	1	1	9	0	
17	22	1	5	3.3	1	0	0	1	1	2	2	1	2	1	2	1	13	1	
18	23	1	5	5.3	4	0	4	1	1	0	0	0	0	0	0	0	2	0	
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21	23	1	5	3.3	1	1.3	3	0	2	3	1	2	1	1	1	3	14	0	
22	24	1	3	3.3	0	0	1	1	1	0	1	0	0	1	0	0	4	0	
23	23	1	5	3.3	5	1.3	3	1	0	0	2	1	0	0	0	0	4	0	
24	22	1	4	3.3	4	1.3	2	1	1	2	1	1	1	1	1	0	9	0	
25	26	0	2	1.3	0	0	1	1	2	0	3	0	0	0	0	0	6	0	
26	22	0	3	3.3	1	0	1	1	1	1	1	1	1	1	0	1	8	0	
27	22	0	4	3.3	1	1.3	0.3	1	1	3	1	0	0	1	0	0	7	0	

PhoneUsage_Preprocess_withScore

Figure 5. 3: Phone Usage Data collection.

5.1.2. Feature Extraction & Preprocessing

To extract facial features and emotions, a model for the emotion-based depression risk analysis classifier was required. To obtain facial features and emotions, we used the Affectiva JavaScript API. Affectiva is a pioneer in the field of emotion recognition [32]. The pre-defined model RealHePoNet was utilized for Head Pose Estimation to represent the head pose-based depression analysis. It calculates angles both vertically and horizontally. The accuracy of the RealHePoNet model is the best [47]. Similarly, the Russian dataset has to be converted to English and Sinhala as the first stage in modeling both English and Sinhala content-based classifiers. We used a preexisting model, MarianMT Transformers, for Russian to English and Google Translator for Russian to Sinhala. Prior to feature extraction and model training, all of the selected datasets were preprocessed. We've completed the necessary preprocessing processes at this point. Add relevant headings, delete rows with missing values, encode, label data, and categorize data. Furthermore, the pre-trained Glove word vector was used for word embedding in English prior to the Early Depression, Risk Analysis on Social Network (EDRASN) model training [48]. The Sinhalese Vector Model was also utilized to embed words in Sinhala [49]. The following diagrams show various examples of feature extraction and preprocessing.

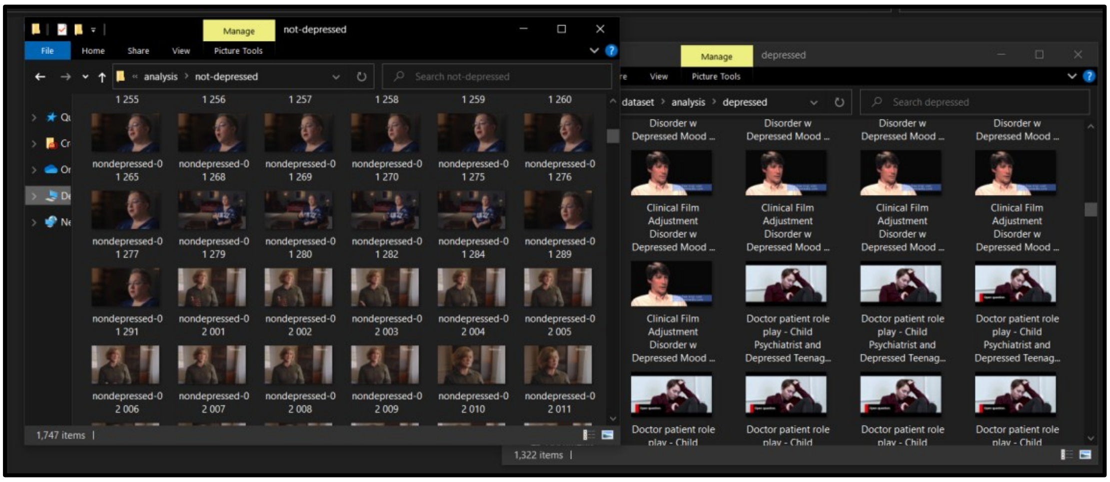


Figure 5. 4: Emotion-based Feature Extraction

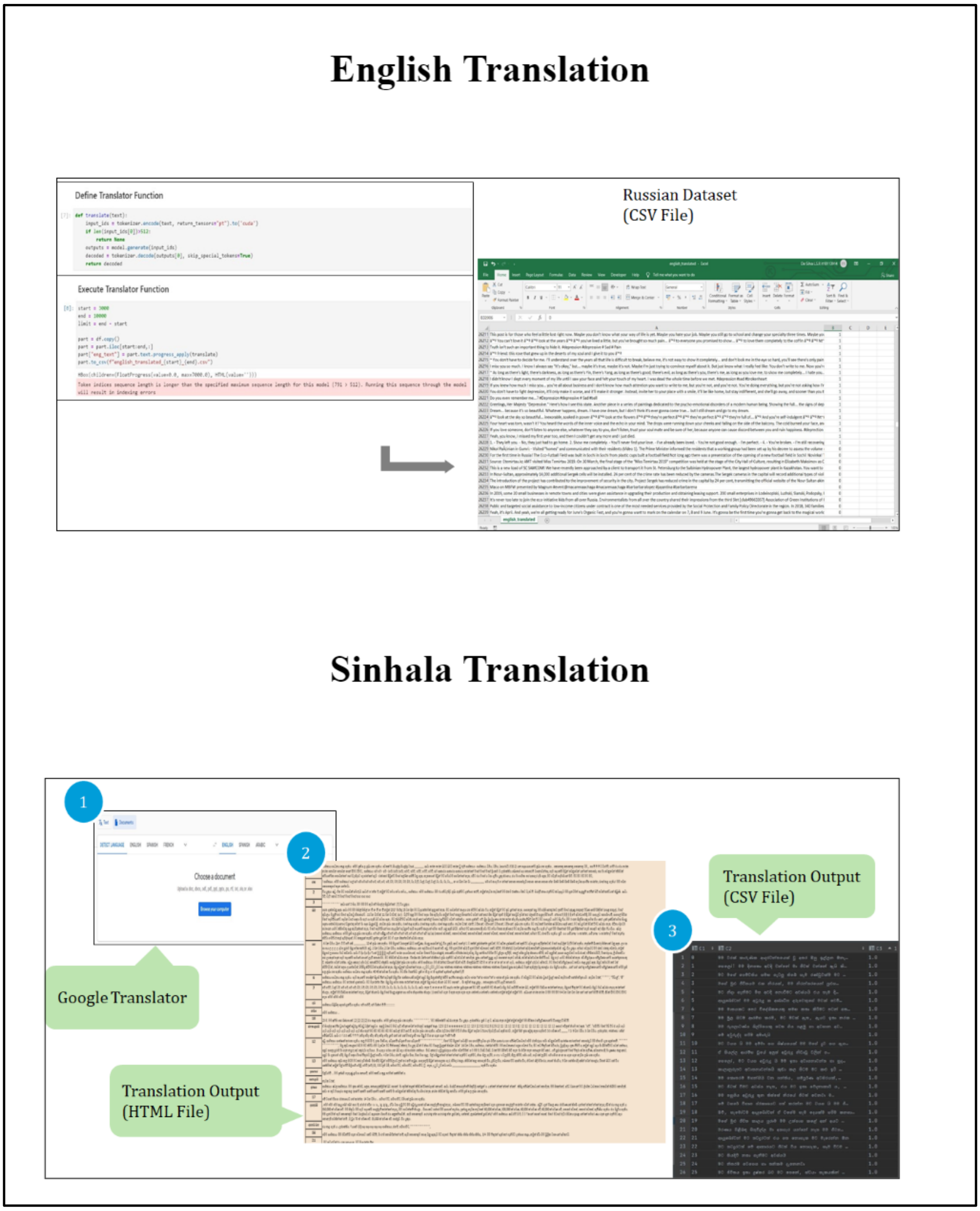


Figure 5. 5: Content-based English and Sinhala Translation.

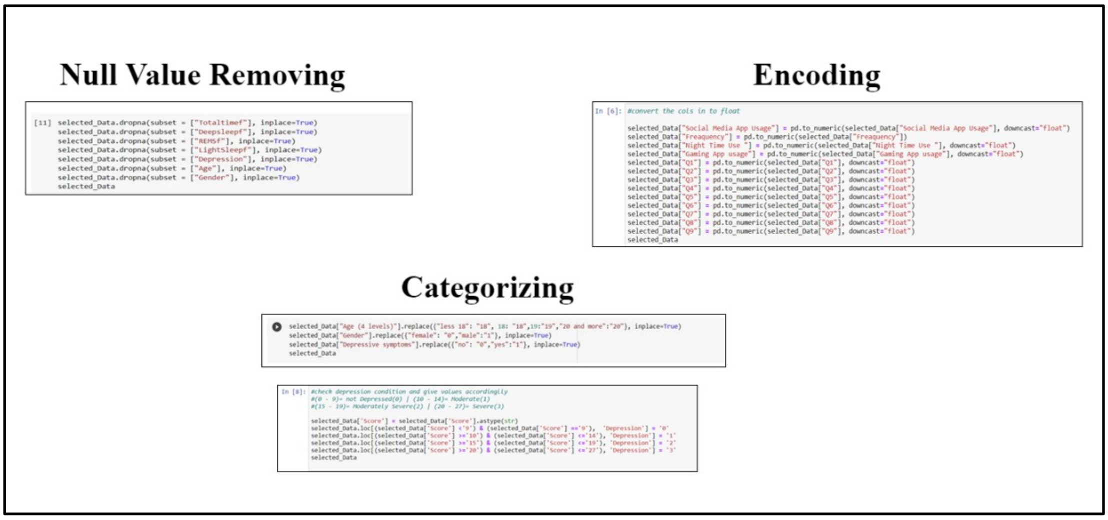


Figure 5. 6: Data Pre-processing.

5.1.3. Model Implementation

We employed a sequential model with numerous deep layers in the Early Depression Risk Analysis on Emotion (EDRAE) model. Because we had 33 embedded features, the first dense layer has a 33-neuron input dimension. The dense layer output was initially 100 neurons in size. Three fully connected dense layers and the output layer followed the input layer. The Early Depression Risk Analysis on Head Pose (EDRAH) model, which was constructed as a sequential model, has four dense layers. The input dimension of the first dense layer was 11 neurons, and the output dimension was 100 neurons. The layer was followed by two thick layers that were totally coupled and the output layer. Furthermore, after each Dense Layer, LeakyReLU activation was used. The probability distribution over the defined classes was computed using sigmoid as the activation function in the final dense layer. Adam Optimizer was used to create the models. It's worth noting that the model's input is a video.

For both English and Sinhala-based depression risk assessments, the EDRASN model employed the pre-trained model fastText. fastText is a text classification and word embedding library [50]. It can achieve excellent accuracy while using the fewest resources possible.

To ensure compatibility with the Glove word embedding vectors, the hyperparameters were fine-tuned. The three layers of the EDRASN model are the embedding layer, linear layer, and average pooling 2D layer. The word embedding for each word is calculated by the embedding layer, and the average for all embeddings is computed by the liner layer. The linear layer's output is fed into a 2D average pooling layer for classification. To compute the probability distribution over the classes, the model used sigmoid as the activation function. The sigmoid activation function was chosen because the analysis involves a binary classification problem. Adam Optimizer was used to create the models. It's worth noting that the model's input is text.

Early Depression Risk Analysis on Heart Rate (EDRAHR) and Early Depression Risk Analysis on Sleep Patterns are two types of biometric data analysis. Both studies used three supervised learning classification algorithms (EDRASP). This is how EDRAHR models are explained. First, we found the optimum feasible K value for the model train, which is 5, using the KNN technique. The best K model was used to train. For EDRAHR, the Support Vector Machine (SVM) algorithm uses kernel poly of degree 1. With the "GaussianNB" classifier, the Naive-Bayes algorithm was utilized. The EDRASP also includes KNN, Naive-Bayes, and SVM models. We discovered the best K for the KNN model and used it to train the model, which is k = 5. The poly kernel was used to train the SVM model, which has a degree of one. A "GaussianNB" classifier was used to train the Naive-Bayes algorithm on the same dataset. The heart rate and sleep patterns are the inputs to the above models.

To determine an accurate model, the EDRAP uses four supervised learning classification methods. For the KNN model, we first determined the best k, which is 14, and then used KNeighborsClassifier to train the model to k = 14. For the same dataset, an SVM model train with kernel poly for degree 2 was performed. A "GaussianNB" classifier was used to train the Naive-Bayes algorithm. Finally, we used RandomForestClassifier to train a random forest model with 20 estimators and a random state of 0. Note that the above models' inputs are phone usage parameters.

5.1.4. API Implementation and Deployment.

Implemented EDRAE, EDRAH, EDRASN, EDRASP, and EDRAP models need to be integrated into the “Mind Guardian” mobile application for user early depression analysis and predictions. Therefore each model has been serialized and implemented as an API. The APIs have been Implemented in “Spyder”, “Jupyter notebook” and “pycharm”, The APIs deployed in Heroku and google cloud to access them from the mobile application. The IDEs and servers were selected based on how each analytical model works.

5.2. Mobile Implementation

The proposed system mobile application plays an important role which obtains data from the user for early depression risk analysis and provides an analysis summary to the user. Therefore the mobile application development is the main development phase. The mobile implementation phase includes. User data obtained methods implementation, Model API integration, Database integration, and front–end development.

Data Obtained from user Method Implementation.

For data collection for Emotion, Social Network, Biometric, and Phone Usage Analysis, there are seven main implementation approaches. The implementations can be explained as follows,

Emotion-based analysis of user data obtained from the phone camera, which includes photographs and videos of the user. As a result, utilizing the flutter package "image picker" to retrieve images and video from the camera is required. The user's mobile phone gallery is saved with the accessed photographs and videos.

The user's Twitter account and chatbot dialogues provided the data for social network content analysis. The Twitter content has been accessible through the mobile application's integration with a developer account. "WebView" was used to link the app to the Twitter platform during the procedure. The chatbot was implemented into the mobile app to collect user thoughts for the analysis.

The user's biometric data, such as sleep pattern and heart rate, were collected using both invasive and non-invasive approaches. Integrating the MI band 5 with the mobile application was used to process the invasive procedure. the flutter "fit kit" package to incorporate the MI band 5 into a mobile application to collect data invasively. Sleep and heart rate data were collected non-invasively utilizing mobile phone sensors such as an accelerometer, phone camera, and flasher. Using the "rawsensor" package and the "Camara" dependency, the sensors have integrated the mobile application.

The Phone usage data which are mobile app details of the user have been acquired by accessing the user's phone with the mobile application. To access the phone using the flutter "App_usage" package has integrated to the mobile application. Figure (5.7) indicates the packages and dependencies integration to the application.

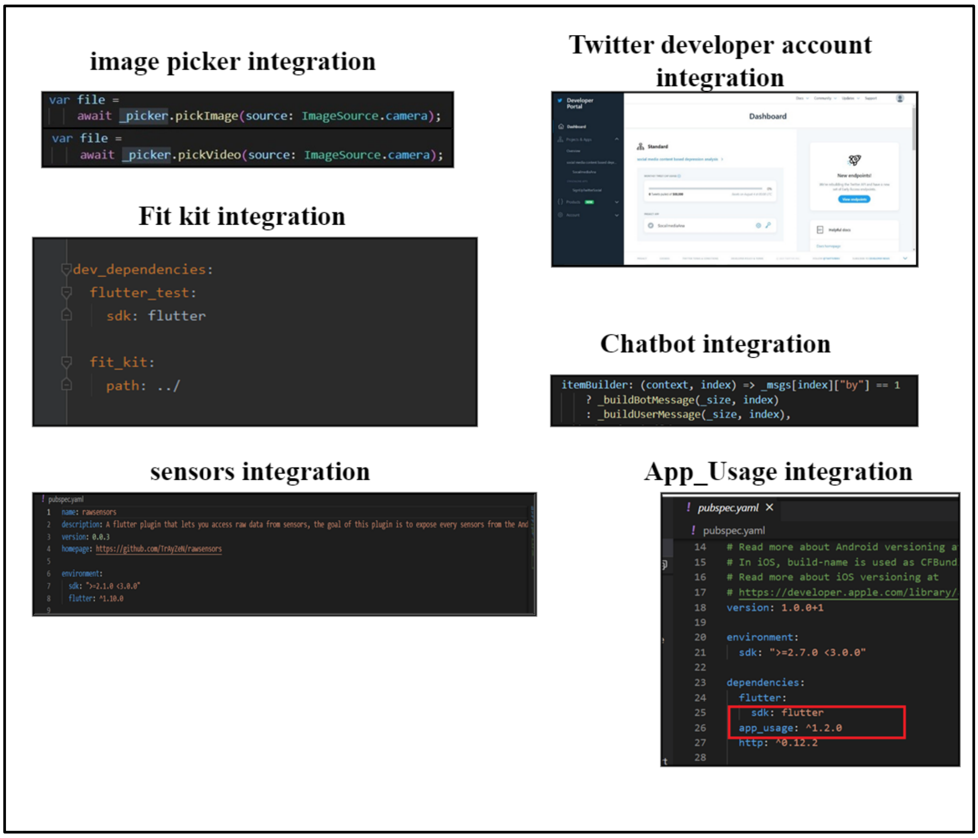


Figure 5. 7: Packages and Dependencies Integration

Model Integration to the Application.

The EDRAE, EDRAH, EDRASN, EDRAP, EDRAHR, and EDRASP models have been integrated into the mobile application for the analysis process. The models have been integrated using the APIs that have been explained in section (5.1.4).

Database Integration.

After obtaining the data from the user in each method data has been stored in the database for access for the analysis process. Firebase and MongoDB have been used as databases in the system.

As the last step, the calculated and summarized pieces of information will be displayed to the user according to each analysis Emotion, social network, biometrics, and phone usage. How the data is retrieved to the user is shown in Figure (5.8).

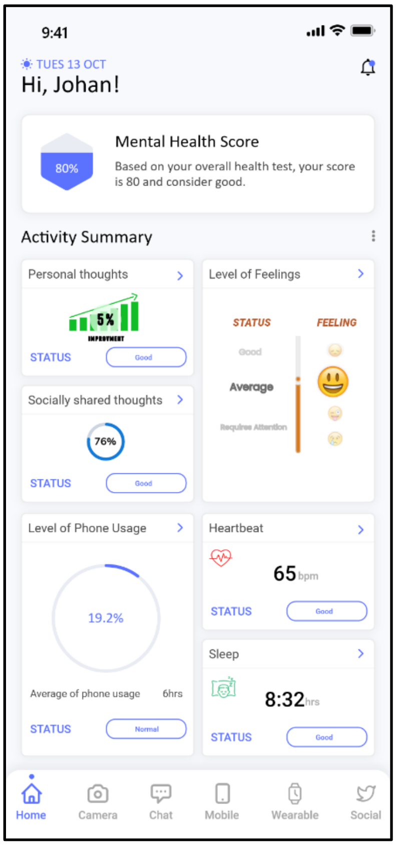


Figure 5. 8: Mobile Application summary view.

5.3. Testing

The analysis models EDRAE , EDRAH , EDRASN – English, EDRASN – Sinhala, EDRASP, EDRHR, and EDRAP have been tested on test data. The test data have chosen to test the High risk of depression (HRD) and Low Risk Of Depression performance of the models.

Table 5. 1: Model Testing

Test case	Scenario	Test data	Expected value	Actual value	Satus
T001	Validate depressive risk of a depressed individual using the EDRAE classifier.		HRD	0.75 (HRD)	pass
T002	Validate depressive risk of a non-depressed individual using the EDRAE classifier.		LRD	0.09 (LRD)	pass
T003	Verify whether the EDRASN – English Model can identify a person with HRD.	I found that with depression, one of the most important things you could realize is that you're not alone.	HRD	0.77 (HRD)	pass
T004	Verify whether the EDRASN – English Model can identify a person with an LRD.	I'm gonna sell the kits all the questions to the bass!	LRD	0.06 (LRD)	pass
T005	Verify whether the EDRASN – Sinhala Model can identify a person with an HRD.	මොන බයිලා කිවුවත් සමහර අයට අලුත් අය ලැබුණ ගමන් පරණ අපිව ලොකු කරදරයක් වෙනවා.	HRD	0.52 (HRD)	pass

		අත්දැකීමෙන් දන්නවා.			
T006	Verify whether the EDRASN – Sinhala Model can identify a person with an LRD.	මහ මුහුදට පැණි දැම්මට මුහුදෙ ලුණු රස වෙනස් වෙන්නෙ නෑ වගේ සමහරු වෙනුවෙන් අපි මොන තරම් කැප කිරීම් කළත් එයාලට ඒක වටින්නෙ නෑ.	LRD	0.32 (LRD)	pass
T007	Verify whether the EDRASP model Naïve Bayes identifies a person with HRD.	Gender: Male Age: 25 Total Sleep: 8.0 Deep Sleep: 42 REM Sleep: 159 Light Sleep: 242	HRD	1 (HRD)	pass
T008	Verify whether the EDRASP model Naïve Bayes identifies a person with LRD.	Gender: Male Age: 25 Total Sleep: 6.5 Deep Sleep: 78 REM Sleep: 90 Light Sleep: 201	LRD	0 (LRD)	pass
T009	Verify whether the EDRAHR KNN model identifies a person with HRD.	Gender: Female Age: 18 Heart rate: 60	HRD	1 (HRD)	pass
T010	Verify whether the EDRAHR KNN model identifies a person with LRD.	Gender: Female Age: 19 Heart rate: 80	LRD	0 (LRD)	pass
T011	Verify whether the EDRAP KNN model identifies a person with HRD.	No Social Media Apps: 9 Social Media App usage:6 Gaming App Usage: 7 Night Usage: 12	HRD	1(HRD)	pass
T012	Verify whether the EDRAP KNN model identifies a person with LRD.	No Social Media Apps: 5 Social Media App usage:4 Gaming App Usage: 3 Night Usage: 3	LRD	0 (LRD)	pass

6. RESULTS & DISCUSSION

The results and performance of each model in predicting early detection of depression risk in individuals are detailed in the next section.

Visual Cues based Depression Risk Analysis

We were able to obtain 70% to 75 % test accuracy for mood and head posture analysis despite training the machine learning algorithms, random forest, and SVM on highly correlated parameters. As a result, for our baseline model, we used machine learning techniques and used a deep learning method, as discussed in Section (2.3.1). With an AUC of 81.54, the sequential model for EDRAE achieved 81% test accuracy. Using the sequential approach, EDRAH achieved 77% test accuracy and a 76.79 AUC score. The proposed deep learning architectures beat the usual machine learning algorithm, according to the analysis. Note that the dataset split for all the models was the ratio of 50 training, 20 validation, and 30 test sets. Figure (6.1) and (6.1) illustrate the ROC curve of the EDRAE model and Confusion Matrix of the EDRAH model, respectively.

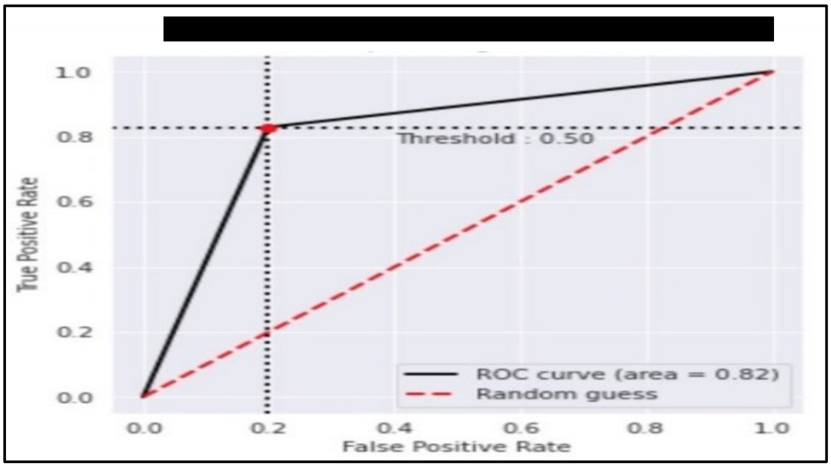
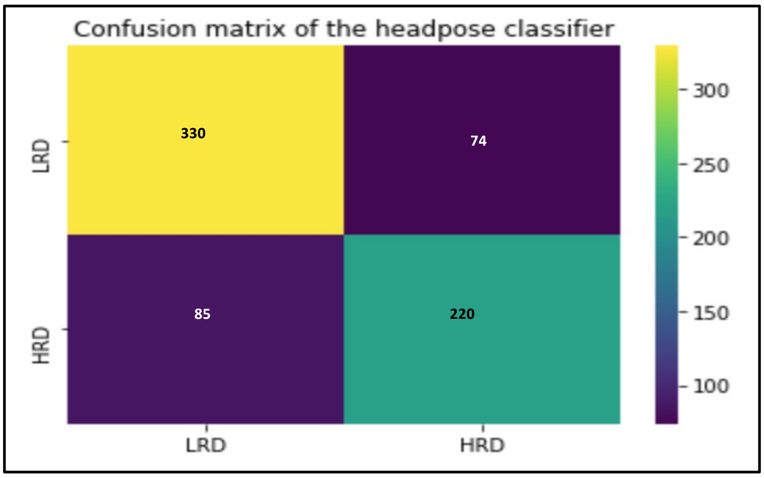


Figure 6. 1: ROC curve of the EDRAE



LRD – Low Risk on Depression

HRD – High Risk on Depression

Figure 6. 2: Confusion Matrix of the EDRAH

Linguistic-based Depression Risk Analysis.

For text classification in English and Sinhala, the typical machine learning technique SVM may obtain 80% to 85% test accuracy. As a result, for our baseline model, we used machine learning techniques and used a deep learning method, as discussed in Section (2.3.1). The EDRASN fastText model achieved 95% accuracy for Sinhala content and 96% accuracy for English content. The proposed deep learning architectures beat the usual machine learning algorithm, according to the analysis. Note that the dataset split for all the models was the ratio of 60 training, 20 validations, and 20 test sets. Figure (6.3) and Figure (6.4) indicate the ROC curve of the EDRASN model for Sinhala and English content, respectively.

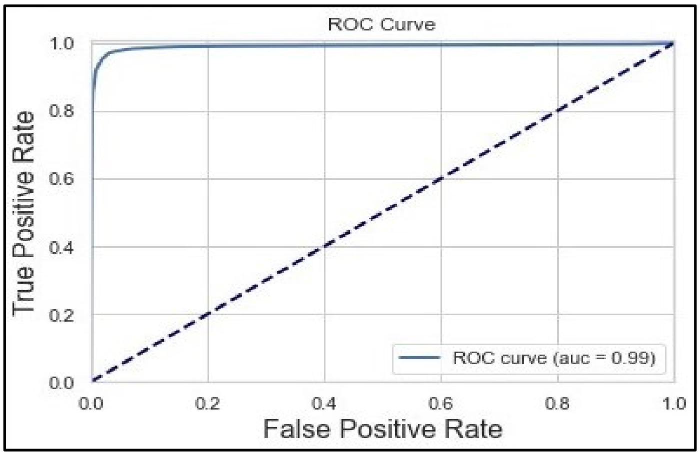


Figure 6. 3: ROC curve of the EDRASN model Sinhala

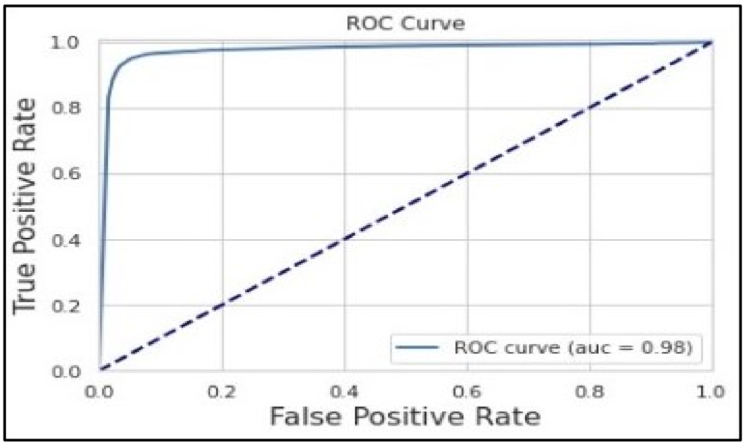


Figure 6. 4: ROC curve of the EDRASN model Sinhala

Biometrics based Depression Risk Analysis

The EDRAHR was conducted with two algorithms as mentioned in Section II-C. The KNN algorithm trainset achieved 89% of maximum accuracy, while minimum k was marked as k = 5 with a misclassification rate of 10%. For the test, the data model obtains AUC of 84% sensitivity of 5%, and Specificity of 94%. Meanwhile, The Support Vector Machine (SVM) algorithm attains 86% of accuracy with kernel poly at degree = 1. The Naive Bayes algorithm yielded an AUC of 86 percent, a sensitivity of 50 percent, and a specificity of 93%, as well as a test accuracy of 86%.

The KNN for the EDRASP AUC is 95%, the model's sensitivity is marked as 60% and Specificity is 99%. KNN obtained 95% of accuracy for the test dataset while train dataset accuracy was marked as 96% at k = 5 with a misclassification rate of 3.7%. when we look at the SVM for the same sleep pattern dataset, the model achieved 95% of test accuracy with a 5% of misclassification rate, AUC of 85% as well as the model sensitivity and Specificity is 65% and 100%. the Naive Bayes algorithm achieved 92% test accuracy, with an 80% sensitivity and 96% specificity. Note that the dataset split for all the models was the ratio of 80 training and 20 test sets. The following Figure (6.5) and Figure (6.6) exhibit the confusion matrix of EDRAHR and the ROC curve of the Naive Bayes algorithm.

```
[[638  38]
 [ 80   4]]

              precision    recall  f1-score   support

           0       0.89      0.94      0.92       676
           1       0.10      0.05      0.06        84

    accuracy                           0.84       760
   macro avg       0.49      0.50      0.49       760
weighted avg       0.80      0.84      0.82       760
```

Figure 6. 5: Confusion matrix of EDRAHR

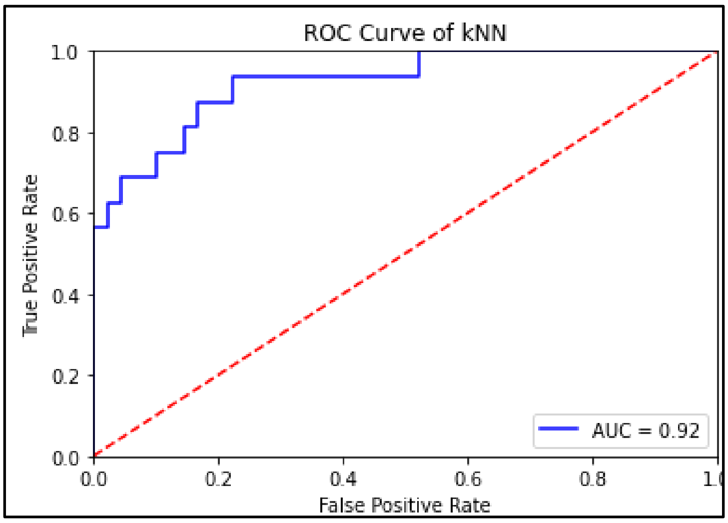


Figure 6. 6: ROC Curve of the Naive Bayes Algorithm

KNN algorithm achieved 81% of test accuracy while the train set maximum accuracy is marked as 82% at k = 14. Model's AUC is 81% sensitivity is 31% and Specificity is 87%, as well as the model, showed a 17% of misclassification rate. The random forest model has obtained 62% overall accuracy meanwhile sensitivity and Specificity are marked as 37% and 73% with a misclassification rate of 38%. We have observed even the SVM obtained 72% test accuracy, 63% of AUC, and 27% of misclassification rate but the model has failed to achieve a good sensitivity rate. The Naive-Bayes algorithm, on the other hand, achieved 76% AUC, 65% sensitivity, and 88% specificity. Note that the dataset split for all the models was the ratio of 80 training and 20 test sets. The following Figure (6.7) indicates the ROC curve of the KNN algorithm.

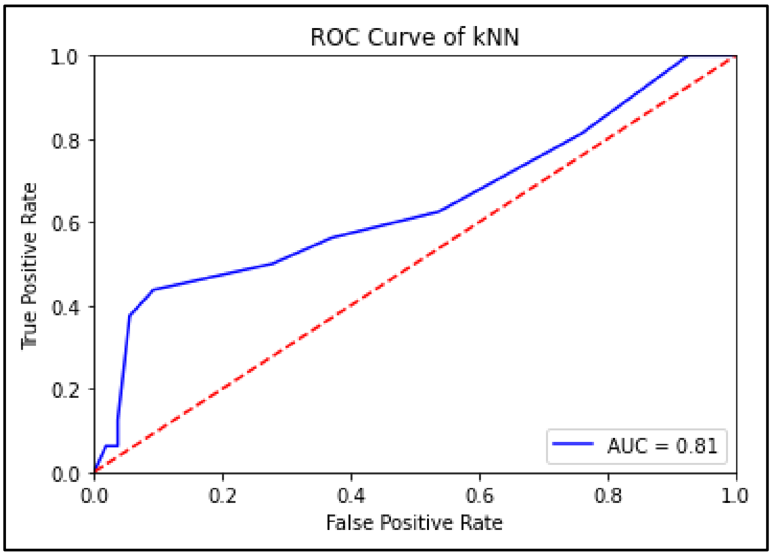


Figure 6. 7: ROC Curve of the KNN

Table (6.1) and Table (6.2) indicate the performance comparison of all the Models and Algorithms.

Table 6. 1: Accuracy Comparison of the Models

	MODEL	ALGORITHM	ACCURACY
(A)*Visual cues*	EDRAE	SVM	73%
		Random Forest	70%
		Sequential [51]	**81%**
	EDRAH	SVM	74%
		Random Forest	73%
		Sequential [51]	**77%**
(B)*Linguistic*	EDRASN – English	SVM	86%
		FastText [50]	**96%**
	EDRASN – Sinhala	SVM	83%
		FastText [50]	**95%**
(C)*Biometrics*	EDRAHR	**KNN**	**84%**
		SVM	87%
		Naive-Bayes	86%
	EDRASP	KNN	95%
		SVM	94%
		Naive-Bayes	**92%**
(D)*Mobile utilization*	EDRAP	**KNN**	**81%**
		SVM	72%
		Random Forest	62%
		Naive-Bayes	76%

Table 6. 2: Performance Comparison of the Models

	PRECISION	RECALL	F1-SCORE
EDRAE	0.82	0.81	0.81
EDRAH	0.77	0.77	0.77
EDRASN - English	0.95	0.95	0.95
EDRASN - Sinhala	1.00	1.00	1.00

EDRAHR - KNN	0.80	0.84	0.82
EDRAHR - SVM	0.76	0.87	0.82
EDRAHR - Naive-Bayes	0.43	0.50	0.46
EDRASP - KNN	0.95	0.95	0.95
EDRASP - SVM	0.96	0.96	0.96
EDRASP - Naive-Bayes	0.88	0.80	0.84
EDRAP - KNN	0.72	0.74	0.73
EDRAP - SVM	0.52	0.72	0.61
EDRAP - Random Forest	0.64	0.63	0.63
EDRAP - Naive-Bayes	0.64	0.63	0.63

6.1. Findings

The research behavioral analysis for depression detection findings can be shown as following,

The study proposed a mobile-based application to analyze unexpected behavior changes that might have a high risk of having depression. The analysis was based on social media activities, upper body movement patterns, phone usage, sleep efficiency, and heart rate variability.

The EDRAE classifier could achieve 82% accuracy, while the EDRAH classifier could obtain 77% accuracy. However, the combined classifier of EDRAE and EDRAH outperformed with 83% accuracy. Further, the study found that linguistic-based depression risk analysis performed well for Sinhala, with 95% accuracy and 96% accuracy for English. The EDRASP classifier for biometrics-based depression risk assessments could obtain 95% accuracy based on sleep patterns. The EDRAP classifier has achieved 81% accuracy for assessing the depression risk based on mobile utilization. The EDRAE classifier achieved 82% accuracy in classifying the depressive risk.

The EDRAE classifier could achieve 76% accuracy in classifying the depressive risk.

- The EDRAE classifier achieved 82% accuracy in classifying the depressive risk.
- The EDRAE classifier could achieve 76% accuracy in classifying the depressive risk.
- The combined classifier of EDRAE and EDRAH outperformed with 83% accuracy.
- The EDRASN classifier performed well for Sinhala, with 95% accuracy.
- The EDRASN classifier performed well for English, with 96% accuracy.
- The EDRASPclassifier achieved 95% accuracy in classifying the depressive risk.
- The EDREDRAPAE classifier achieved 81% accuracy in classifying the depressive risk.

6.2. Discussion

The proposed mobile application analyzes unexpected behavior changes that might have a high chance of having depression. The analysis is based on social media activities, upper body movement patterns, phone usage, sleep efficiency, and heart rate variability.

The analysis identified that facial and emotional elements can learn and recognize depression risk to determine the risk of depression. However, the combined classifier of emotions and head posture, on the other hand, outperformed the emotion-based classifier by 83% of accuracy. Moreover, the study discovered that linguistic-based depression risk analysis for Sinhala worked well, with 95% accuracy. The accuracy of the linguistic-based depression risk analysis has obtained 96% for English. The analysis based on sleep patterns has achieved 95% accuracy on the EDRASP classifier for biometrics-based depression risk analysis. The EDRAP model achieved 81% accuracy for mobile utilization-based depression risk analysis.

However, the performance of the classifiers could not validate real individuals who experience a depressive disorder. Moreover, the accuracies of classifiers would have considerably enhanced on more data points. The prevailing situation in the country has limited the collection of more data points for the study. The implementation for accessing social media posts was limited to the Twitter platform since the social media platforms (Facebook, WhatsApp, and Instagram) limit to grant access to developer accounts.

- The performance of the classifiers could not validate real individuals who experience a depressive disorder.
- The accuracies of classifiers would have considerably enhanced on more data points.
- The prevailing situation in the country has limited the collection of more data points for the study.
- The Access is limited on social media developer accounts to extend the study to other social networks.
- The data points for EDRASN analysis could only obtain in the Russian language.

6.3. Summary of Each Student's Contribution

Name	Student IT	Component	Responsibility
Oshadi Yashodhika G. B.	IT18120226	Early Depression Analysis Based on Emotion and Head pose.	Data analysis and study are of EDRAE and EDRAH. Model Implementation of EDRAE and EDRAH. Mobile Application Implementation of EDRAE and EDRAH. Mobile design of EDRAE and EDRAH.
De Silva L. S. R	IT18113914	Early Depression Analysis Based on Social media content and Chatbot	Data analysis and study are of EDRAS. Model Implementation of EDRAS. Mobile Application Implementation of EDRAS. Mobile design of EDRAS.
Chathuranga W.W.P.K	IT18119572	Invasive and non – invasive collected data analysis for Early depression Analysis.	Data analysis and study are of EDRAHR and EDRASP. Model Implementation of EDRAHR and EDRASP.

			Mobile Application Implementation of EDRAHR and EDRASP. Mobile design of EDRAHR and EDRASP.
Liyanage D.R.Y	IT18119718	Early Depression Analysis Based on Phone usage Patterns.	Data analysis and study are of EDRAP Model Implementation of EDRAP. Mobile Application Implementation of EDRAP. Mobile design of EDRAP.

7. CONCLUSION

The goal of this work is to present an automated depression risk analysis based on non-verbal biomarkers. This study evaluated facial and emotional features, head posture, linguistics, mobile usage, and biometrics to identify the depression risk. In comparison with emotion and head pose features, we have shown that facial and emotional aspects can learn and recognize depression risk. However, the combined classifier of emotions and head pose outperformed the emotion-based classifier with 83% accuracy. Further, the study found that linguistic-based depression risk analysis functioned well for Sinhala, with 95 percent accuracy. The linguistic-based depression risk analysis in English has achieved 96% accuracy. The analysis based on sleep patterns could achieve 95% accuracy on the KNN classifier for biometrics-based depression risk analysis. The KNN model achieved 81% accuracy for mobile utilization-based depression risk analysis. The study extended the analysis with the mobile application to provide a daily summary of depression risk.

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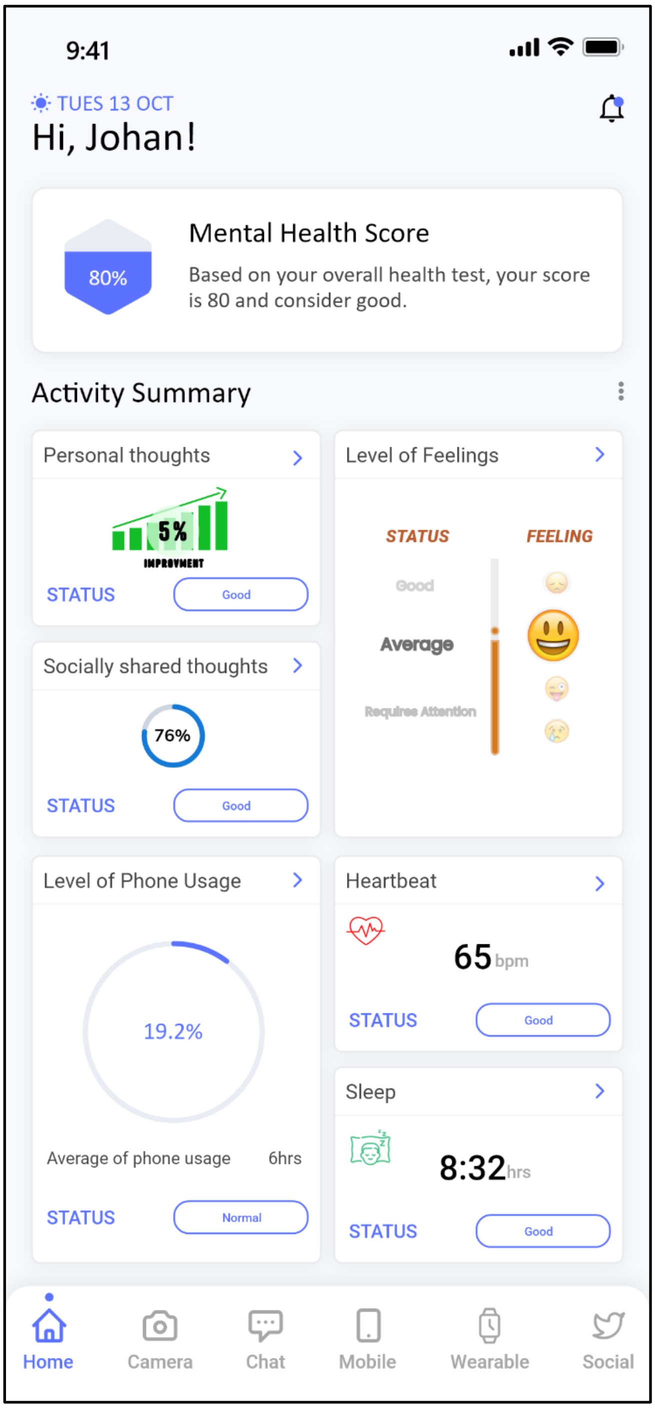
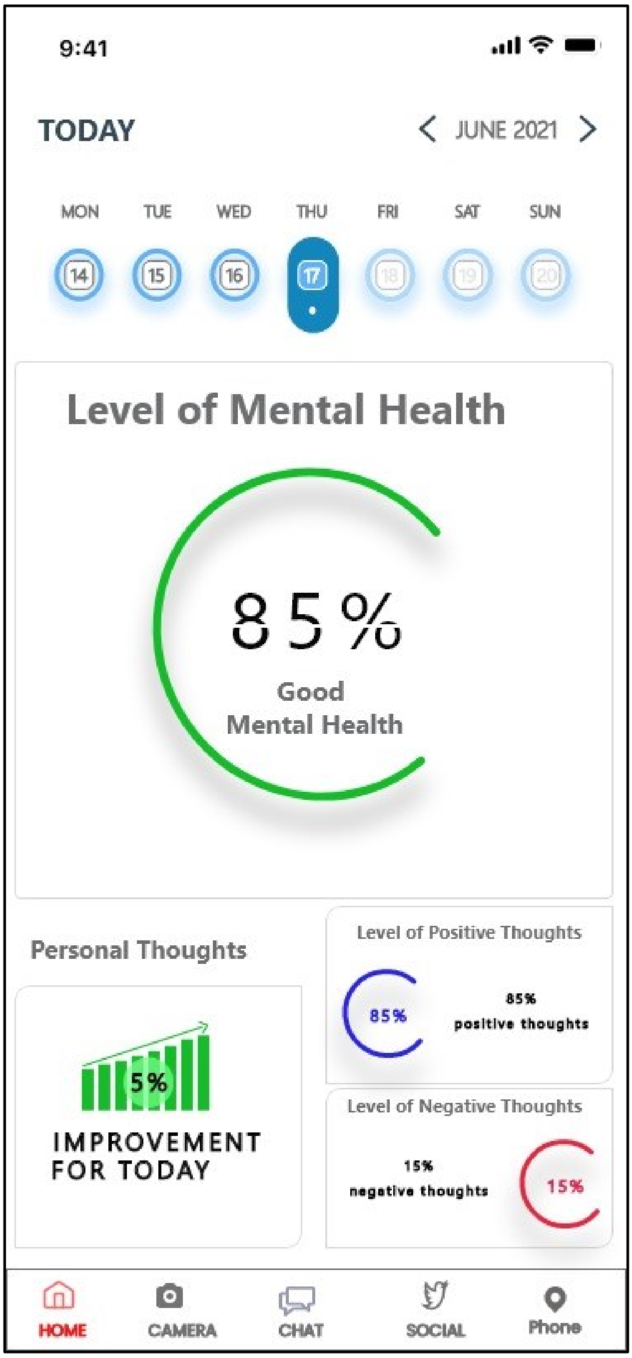
Appendix A: User Interface.

Home

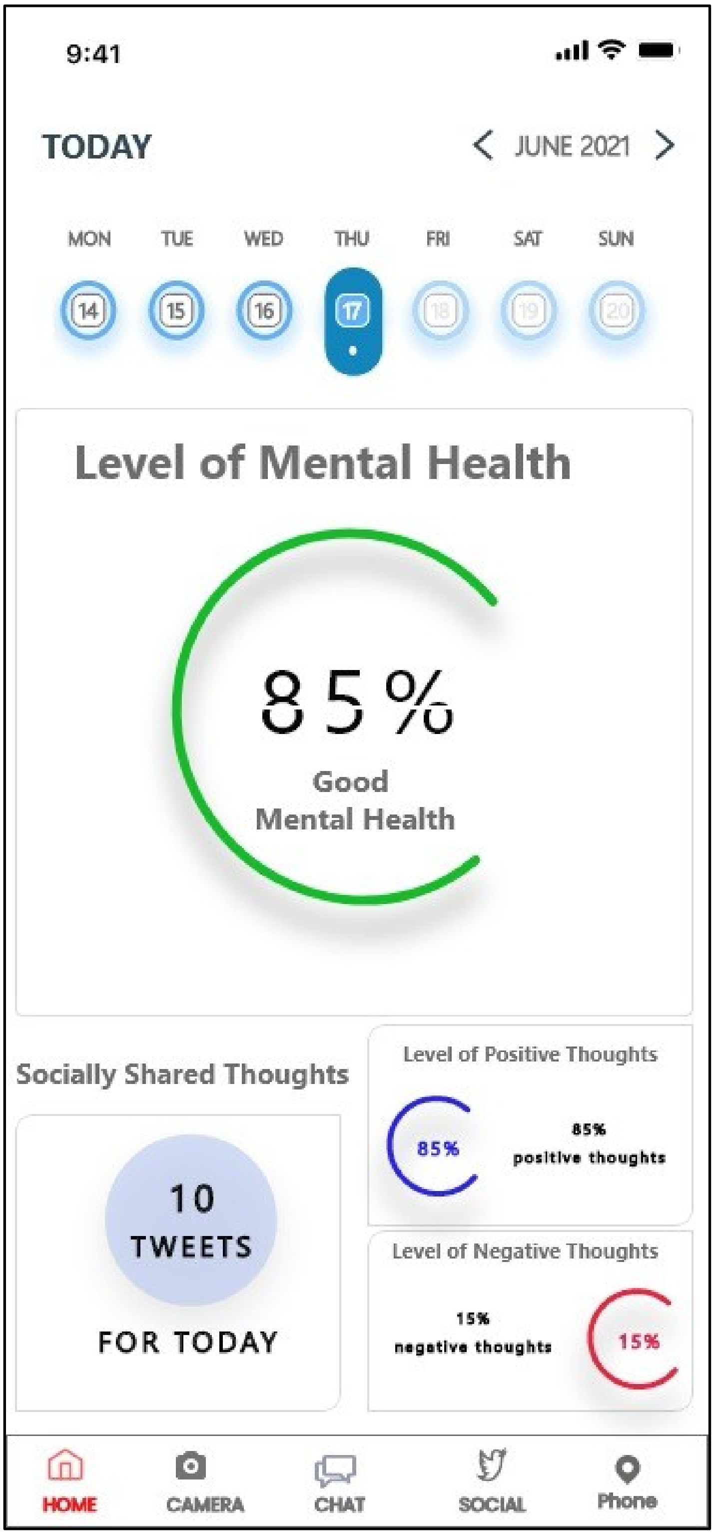


Emotion-based Summary

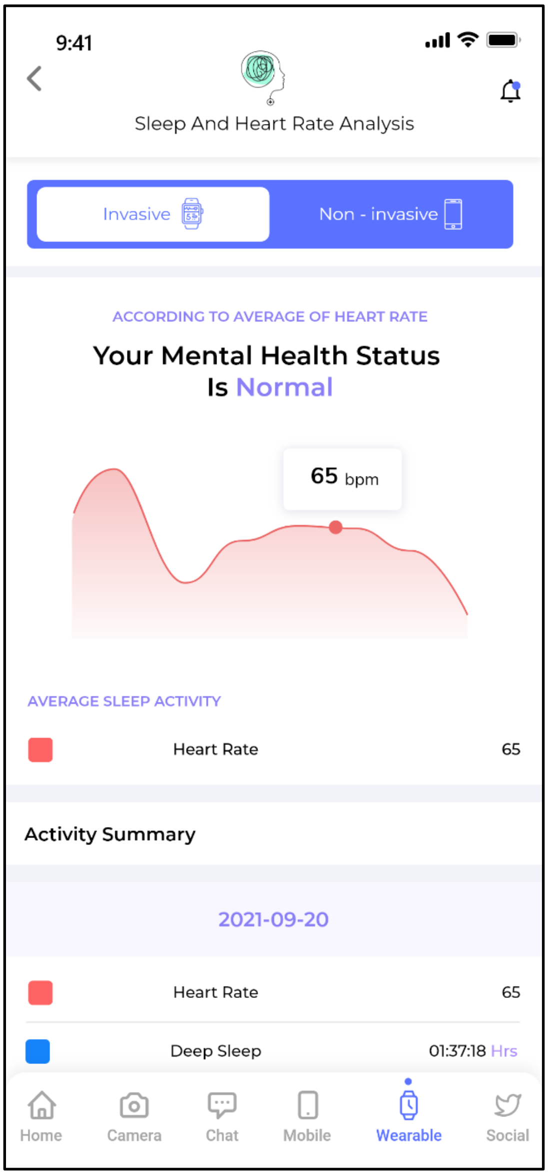
Social Network Based Summary

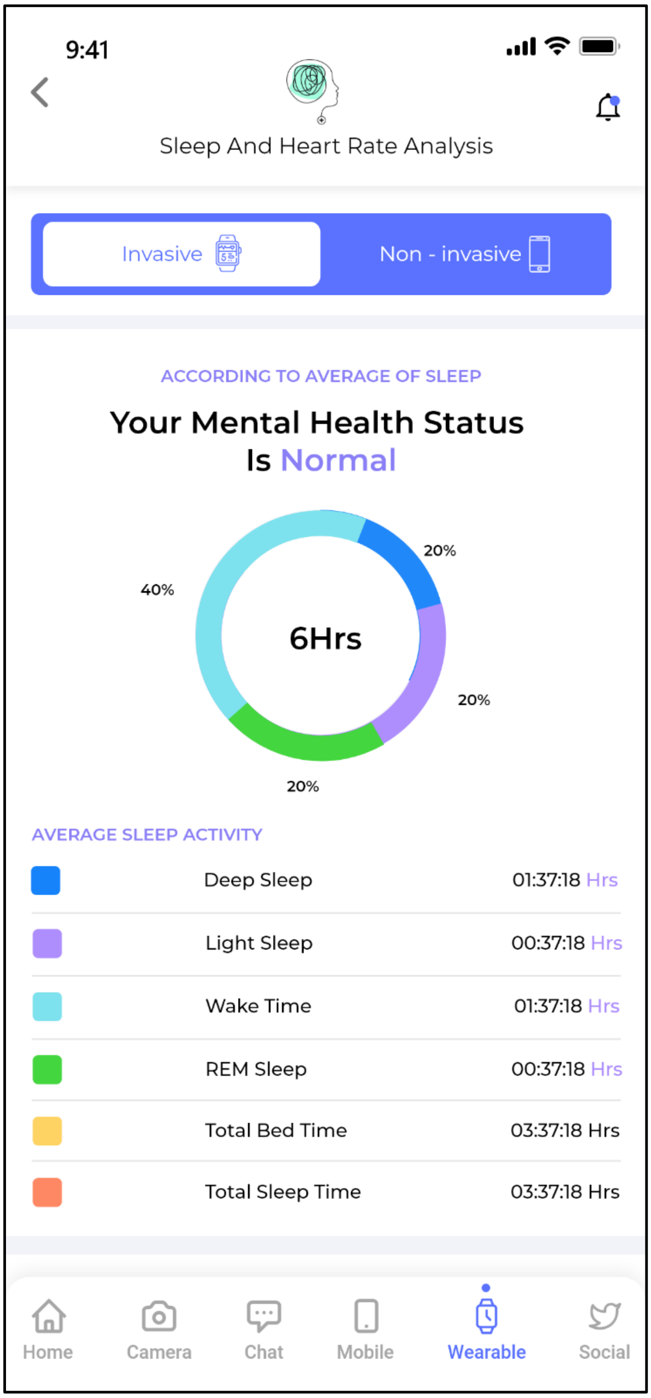


Chatbot based summary



Invasive – Non Invasive Summary




9:41
Sleep And Heart Rate Analysis
Invasive
Non - invasive
ACCORDING TO AVERAGE OF SLEEP
Your Mental Health Status
Is Normal
20%
40%
6Hrs
20%
20%
AVERAGE SLEEP ACTIVITY
Deep Sleep 01:37:18 Hrs
Light Sleep 00:37:18 Hrs
Wake Time 01:37:18 Hrs
REM Sleep 00:37:18 Hrs
Total Bed Time 03:37:18 Hrs
Total Sleep Time 03:37:18 Hrs
Home
Camera
Chat
Mobile
Wearable
Social

Phone Usage-Based Summary.