Depression Prediction based on Individual's Lifestyle using Machine Learning Techniques

Minor project report submitted in partial fulfillment of the requirement for the degree of Bachelor of Technology

in

Computer Science and Engineering

By

Jasmeen Kaur (211429)
Ishita Gupta (211472)

UNDER THE SUPERVISION OF

Dr. Kushal Kanwar

Department of Computer Science & Engineering and Information Technology

Jaypee University of Information Technology, Waknaghat, 173234, Himachal Pradesh, INDIA

TABLE OF CONTENT

CERTIFICATE

I hereby certify that the work which is being presented in the project report titled “Depression Prediction based on Individual’s Lifestyle using Machine Learning Techniques” in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out during the period from January 2024 to May 2024 under the supervision of Dr. Kushal Kanwar, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

The matter presented in this project report has not been submitted for the award of any other degree of this or any other university.

Jasmeen Kaur (211429)

Ishita Gupta (211472)

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

(Dr. Kushal Kanwar)

Assistant Professor (SG)

Computer Science & Engineering and Information Technology

Jaypee University of Information Technology, Waknaghat

ACKNOWLEDGEMENT

Firstly, I express my heartiest thanks and gratefulness to almighty God for His divine blessing makes it possible to complete the project work successfully.

I am really grateful and wish my profound indebtedness to Supervisor **Dr. Kushal Kanwar, Assistant Professor (SG)**, Department of CSE Jaypee University of Information Technology, Wakhnaghat. Deep Knowledge & keen interest of my supervisor in the field of "**Machine Learning**" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stages have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Kushal Kanwar,** Department of CSE, for his kind help to finish my project.

I would also generously welcome each one of those individuals who have helped me straightforwardly or in a roundabout way in making this project a win. In this unique situation, I might want to thank the various staff individuals, both educating and non-instructing, which have developed their convenient help and facilitated my undertaking.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

Jasmeen Kaur (211429)
Ishita Gupta (211472)

ABSTRACT

In a 2021 UNICEF survey, around 14% of 15 to 25-year-olds in India reported frequently feeling depressed or disinterested. The National Mental Health Survey of India 2015-2016 revealed that nearly 15% Indian adults need active intervention for one or more mental heath issues and one in 20 Indians suffers from depression. According to the World Health Organization (WHO), in 2019, anxiety and depression were estimated among 970 million people worldwide. More over anxiety disorders are the most common mental disorder, an estimated 275 million people suffered from anxiety disorders in 2016. It is an alarming situation as mental health conditions start by age 14 and in most cases, they go undetected and untreated. Suicide has become the third leading cause of death in 15–19-year-olds. It is found that major reason for such sufferings is poor lifestyle and it is true that a good lifestyle has a positive effect on mental heath and helps boost overall mood.

So, we thought to create a website where the user can go and check their mental heath status. It detects early symptoms of depression which impacts the overall wellness of the user. The web application consists of a comprehensive lifestyle-based questionnaire that covers various aspects of mental well-being. Questions we have provided are clear, sensitive to some, and non-stigmatizing. After taking the test, if a person is defected with symptoms of depression, then they must seek professional guidance and help.

We have used Python, HTML, CSS, JavaScript, Flask, and various ML Libraries (Scikit-learn, NumPy etc.)

Chapter 01: INTRODUCTION

1.1 Introduction

The biggest problem affecting people's emotions, cognition, and social interactions in this generation is most likely mental illness. It has an impact on feelings, thoughts, and behavior. We need evaluation tools that employ statistical techniques and algorithms for precise clinical diagnosis in order to address this. Our website seeks to assist users in determining if they are suffering from a mental disorder or not. After receiving comments from users on depression, tiredness, sleep issues, suicidal thoughts, etc., it determines the type of mental illness and suggests if the user should get professional assistance.

1.2 Objective

Our objective is to create a user-friendly web application that effectively predicts a person's risk of depression using machine learning, allowing for prompt support and intervention. By putting an emphasis on simplicity and clarity in interface design, our project aims to guarantee accessibility and usability for a wide range of user demographics.

1.3 Motivation

The motivation behind the project is that there is a prevailing stigma present around the topic of mental wellbeing today. There is reluctance in people to get diagnosed proffesionally. Furthermore, people frequently hesitate to seek therapy from medical professionals or mental health specialists after receiving a diagnosis.

It would be highly effective if people could obtain information directly from their screens about whether they are experiencing a mental health issue. They can quickly find out if their symptoms are indicative of depression or not. This incentive seeks to dispel stigmas by facilitating quick assessments and on-the-go analyses of mental health issues.

1.4 Language Used

- Language Used: The machine learning model is developed using Python language.
- Frontend: JavaScript is used to create the front-end of the website, allowing dynamic content and interactive user interfaces.
- Machine Learning Libraries: The machine learning model is trained using Scikit-learn for effective modelling and data analysis tools. Pandas used for preprocessing, data analysis, and manipulation as it offers robust functions and data structures for handling structured data.
- Deployment: Flask is used to launch the web application-based machine learning model. Flask is a Python web framework that is adaptable and lightweight, ideal for creating web applications and APIs.

1.5 Technical Requirements (Hardware)

Completely software-based application, hence not applicable in our project.

1.6 Deliverables/Outcomes

- We aim to create a user-friendly, fully functional web application that allows users to enter pertinent data and get predictions on whether or not they have depression.
- Next, based on input data, we built a Machine Learning model utilizing Random Forest algorithm. We trained the model and integrated it into the web application to accurately predict the risk of depression.
- User Interface Design: An intuitive and user-friendly interface that makes the online application easy to use and accessible to a wide range of user demographics.
- Deployment: The web application was successfully deployed using the Flask framework, enabling users to view it online from a variety of devices.

Chapter 02: Feasibility Study, Requirements Analysis and Design

2.1 Feasibility Study

2.1.1 Problem Definition

The prevalence of mental health issues among young people in India, as reported by recent surveys, is a serious public health concern. A significant percentage of adults need treatment for mental health issues, while 14% of those aged 15 to 25 have been reported claiming consistent feeling of lack of interest ultimately decreasing their work efficiency even at younger ages.

Moreover, it becomes more important to address these disorders as they often go unnoticed and untreated. Adding on to unhealthy habits of our generation have worsened these mental health issues, highlighting the importance of conveniently accessible early detection techniques. By offering a web application that assesses mental health status using an extensive lifestyle-based questionnaire, this initiative seeks to close this gap by giving users early warning signs of potential mental health problems due to poor lifestyle habits.

2.1.2 Problem Analysis

The study reveals a critical need for tools to aid in the early detection of mental health problems. According to recent data, there is an elevated number of anxiety and depression, especially among young people. These medical conditions get worse by lifestyle choices including eating poorly, sleeping insufficiently and neglecting exercise. Due to taboo or accessibility issues, current mental health evaluation procedures often come up short of serving individuals who require them. The goal of the suggested web application is to lessen these difficulties by providing a user-friendly, non-stigmatizing platform that evaluates several lifestyle aspects that affect mental health. Accuracy and relevance are guaranteed by the data-driven method, which offers customized feedback depending on user input but we recommend taking guidance of certified doctor if user is detected with depression of any percentage.

According to research paper “Detection of child depression using machine learning methods” published in December 2021, Random Forest algorithm outperformed all other algorithms with accuracy of 83%. Though this research chose too many attributes, so choosing the relevant one becomes difficult.

According to research paper “Predicting Mental Health Illness using Machine Learning Algorithms” publishes in January 2022, upon using logistic regression, KNN classifier and decision tree classifier, the accuracy of all the classifiers were found above 79% and below 83%. It had an issues of sampling biases as data had been taken randomly from social media.

According to research paper “Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms” published under ICCIDS in 2019, it predicted best accuracy by Random Forest Classifier of 83% among five algorithms namely Decision Tree, Random Forest Tree, Naïve Bayes, Support Vector Machine, and K-Nearest Neighbour. But it still had a limitation as attributes were so specific that to even answer them, we need a pre medical diagnosis in some cases which everyone might not have done resulting in biased data.

According to research paper “Machine Learning Model to predict mental health crisis from Electronic health records” published on 16 May 2022, upon analysing Decision Tree, Probabilistic, Extreme Gradient Boost, Deep Learning-Based classifiers, Extreme Gradient Boost outperformed most of the other methods. Its limitation was that it only considered medical history and neglected the other factors including individual’s lifestyle and socio-economic factors affecting personality of a person.

According to research paper “Prediction of Mental Heath problems Using Annual Student health Survey: machine Learning Approach” published in May 2023, Light GBM model was adopted as both analysis and conditions achieved adequate performance. Other models used were Logistic regression, random forest and XGBoost. It also had a limitation as data was collected only from one university therefore, it was inappropriate method to generalize the same model for other universities, moreover the research on university students were done during COVID-19 pandemic time which could have variably affected the results.

2.1.3 Solution

We have created a user-friendly online application as part of a complete solution to address depression prediction. Our platform is user-friendly and can be accessed from anywhere simply with internet connection and it is built using Python for Machine Learning Algorithms, Flask for deployment, HTML, CSS, JavaScript for website designing, and multiple machine learning frameworks.

Our machine learning algorithms can generate accurate predictions of depression risk by allowing users to enter data specifically answering our questionnaire. We have used decision tree and random forest in our model to accurately predict the severity of depression user is facing. We do recommend assisting professional help in case a user is diagnosed with depression instead of relying on online solutions. This website can be considered as an initial step to identify the problems of users but not an ultimate solution to treat the disease.

Our comprehensive questionnaire includes various aspects needed to predict depression in an individual. Our questions mainly focuses on the physical and mental state of a person stating questions on lacking interest in doing things, felling down and hopelessness, either having trouble in sleeping or end up sleeping too much, consistent feeling of tiredness, analyzing appetite of a person if person is having poor appetite or he/she is eating too much these days, feeling a burden on oneself or feeling like a failure or having feeling that he/she have let everyone down, feeling difficult to concentrate on anything he/she tries to do and getting distracted by everything and nothing, or even moving from one place to another or even a friendly conversion with family, co-workers, knows feels like a chore, having no energy or interest left for being social, and sometimes even feel like dying would end up these burdens I have created on me everyone else around me. After assessing the above questions and implicitly applying Random Forest Algorithm our website successfully classifies the person into 5 categories: Not Depressed, Mildly Depressed, Moderately Depressed, Severely Depressed, and Critically Depressed.

2.2 Requirements

Requirements are the basic constrains that are required to develop a system. Requirements are collected while designing the system.

2.2.1 Functional Requirements

- **User-Friendly Interface**: The program should have an easy-to-use interface that is available on any internet-connected device.
- **Data Input**: A thorough questionnaire aimed at precisely determining the likelihood of depression should allow users to provide pertinent data.
- **Algorithms for Machine Learning**: Utilizing user-provided data, the platform should apply decision tree and random forest algorithms to produce accurate predictions of depression severity.
- **Recommendation for Professional Help**: If the program results in a positive diagnosis of depression, it should advise obtaining professional help instead of depending just on internet resources.
- **Scalability**: The program must be scalable in order to handle an increase in the number of users and the volume of data it processes without sacrificing its functionality.
- **Libraries Used** : We have used Sk-learn, Pandas, NumPy, Matplotlib and Seaborn and Flask to create this project.

2.2.2 Non-Functional Requirements

- **Security:** To safeguard users' sensitive information, the platform should guarantee data privacy and security while abiding by industry norms.
- **Reliability:** The program should minimize mistakes or inconsistencies in the findings by making predictions that are precise and consistent.
- **Performance:** Even at times of high demand, the platform should respond quickly and have little latency.
- **Accessibility:** In order to guarantee inclusivity, the website must adhere to accessibility guidelines and be usable by people with impairments.
- **Maintainability:** To make maintenance and future improvements easier, the codebase ought to be well-organized and documented.
- **Compatibility:** To guarantee a smooth user experience across several platforms, the application should work with a range of web browsers and devices.

2.3 E-R Diagram / Data-Flow Diagram (DFD)

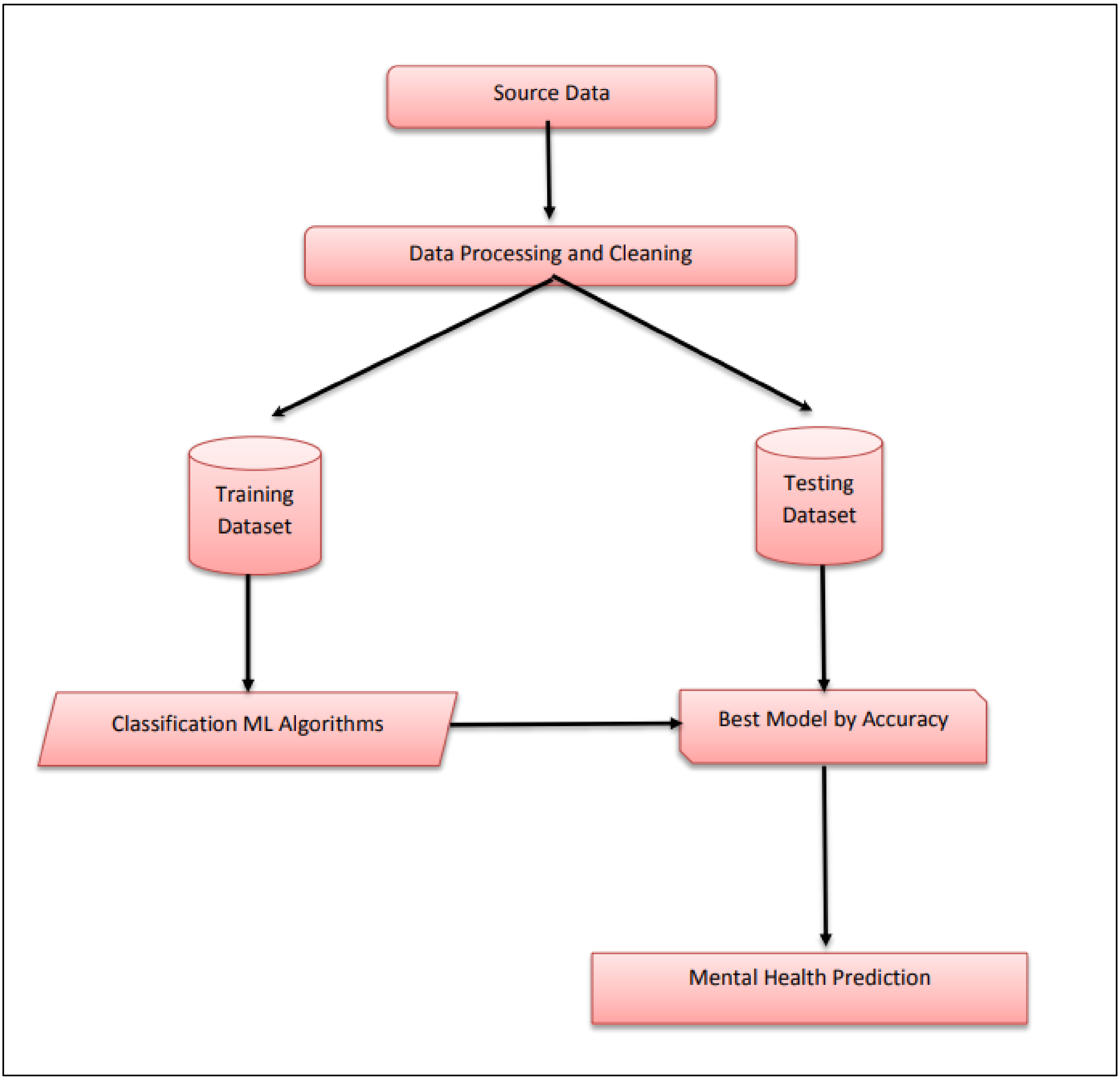

Figure 1: The Work Flow Diagram of the web application.

Chapter 03: IMPLEMENTATION

3.1 Date Set Used in the Minor Project

Table 1: Snapshot of the various attributes present in the dataset in the form of CSV file.

user_id	age	gender	hopeless	sleep	tiredness	appetite	burden / failure	concentration	social	happiness.score
1	20	female	0	12	1	0	0	1	NA	3
2	23	female	1	9	0	1	1	0	1	1
3	40	male	1	9	1	0	0	1	0	2
4	35	female	0	12	0	0	1	1	NA	1
5	22	female	1	3	1	1	0	0	1	0
6	47	male	1	6	1	0	0	NA	0	3
7	45	male	0	15	0	1	1	0	1	1
8	47	male	1	9	0	0	0	1	0	2
9	52	female	0	7	0	0	1	1	NA	1
10	22	male	1	3	1	1	0	0	1	0

3.2 Date Set Features

3.2.1 Types of Data Set

The dataset that is offered includes a wide range of features that are necessary for mental health study. This dataset is structured categorical in nature and includes both categorical and numerical attributes. Every row corresponds to a unique person, and the columns show different psychological markers like depressive symptoms, irregular sleep cycles, changes in appetite, and emotional strain. Interestingly, certain attributes include missing values that are shown with 'NA,' indicating that the dataset is complex in real life. By using this structured information, machine learning algorithms may be trained to identify trends, categorize people according to their mental health status, and even forecast future results. This can lead to the development of preventive interventions and individualized support plans.

3.2.2 Number of Attributes, fields, description of the data set

With 10 categories and 16151 rows, the dataset used for this study offers insightful information about mental health and wellbeing. Every row denotes a distinct participant, and the features encompass diverse elements pertaining to their mental well-being and personal characteristics.

In mental health research, age, a numerical characteristic, is essential for identifying patterns in the prevalence of depression in various age groups. Another important factor that affects mental health outcomes is gender; women frequently report higher rates of depression. Examining possible variations in depression incidence and symptoms between genders is made possible by the analysis of gender data.

Scores from the Patient Health Questionnaire-9 (PHQ-9), a measure of depression severity, are included in the dataset. The hopelessness, sleep quality, changes in appetite, feelings of failure or burden, focus, social functioning, and general happiness are all measured by these scores. They shed light on a number of crucial areas that are necessary to comprehend depression, including emotional states, sleep patterns, cognitive function, social interactions, and subjective well-being.

Depression frequently manifests as symptoms like disturbed sleep, changes in appetite, trouble concentrating, and social disengagement. By examining these scores, it is possible to determine who is at risk for depression and how likely it is that they would exhibit depressed symptoms. Happiness ratings may be correlated with depressed symptoms and a lower quality of life, even if they are not direct markers of depression.

1) user_id(numeric): A numeric value that denotes each user's serial number. For monitoring and reference needs, every user is given a distinct identification.

2) age(numeric): The participant's age, expressed in numbers. The numerical age of every person in the dataset is represented by this feature.

3) gender (Category): The participant's gender. With the use of this feature, people can be categorized as either "male," "female," or "other" according to their gender.

4) hopeless (Numeric): the tenth day's Patient Health Questionnaire-9 (PHQ-9) score. More severe symptoms are indicated by higher scores on the PHQ-9, a standardized questionnaire designed to measure the severity of depressive symptoms.

5) sleep (Numeric): eleventh-day PHQ-9 (Patient Health Questionnaire-9) score. In addition to evaluating depression, this score evaluates the participant's sleep habits

6) appetite (Numeric): Patient Health Questionnaire-9 (PHQ-9) score for the twelfth day. This score measures changes in appetite as a symptom of depression.

7) burden / failure (Numeric): Patient Health Questionnaire-9 (PHQ-9) score for the thirteenth day. This score evaluates feelings of burden or failure experienced by the participant.

8) concentration (Numeric): Patient Health Questionnaire-9 (PHQ-9) score for the fourteenth day. This score assesses the participant's ability to concentrate, which can be affected by depression.

9) social (Numeric): Patient Health Questionnaire-9 (PHQ-9) score for the sixteenth day. This score measures social functioning and interactions as part of the depression assessment.

10) happiness.score (Numeric): Happiness score of the participant. This attribute represents a numerical score indicating the participant's overall level of happiness or subjective well-being.

3.3 Design of Problem Statement

We have designed a questionnaire for users, they have the answer each question according to their state of mind how they are feeling. These extensive questions analyses the persons state of mind, physical, social and mental well being if he is able to concentrate on his work, able to socialize with people, having sound sleep, good appetite, is he exercising regularly or not. These questions basically judges the lifestyle of a person and uses random forest to predict the outcomes classifies into 5 categories describing severity of depression in the user.

3.4 Algorithm / Pseudo code of the Project Problem

- **Main() Function:**

  Import necessary libraries

  dataset = Read CSV ("depressionDataset.csv")

  dataset = Preprocess(dataset)

  X, y = Split Features and Target (dataset)

  X_train, X_test, y_train, y_test = TrainTestSplit(X, y)

  model = Train Random Forest Classifier (X_train, y_train)

  accuracy = Evaluate Model(model, X_test, y_test)

  print("The accuracy of the trained model is:", accuracy)

  Make Predictions(model)

  Save Model(model)

- **Read CSV(filename) function**: to read csv file from data frame

  Return DataFrame read from CSV file

- **Preprocess(dataset) function**: pre-process the dataset and remove unnecessary columns from it

  dataset = RemoveUnnecessaryColumns(dataset)

  dataset = DropRowsWithMissingValues(dataset)

  dataset = ReplaceMissingValues(dataset)

  return pre-processed dataset

- **RemoveUnnecessaryColumns(dataset) function**: to remove unnecessary columns from dataset

  return dataset with unnecessary columns removed

- **DropRowsWithMissingValues(dataset) function:** to remove rows with missing values

- **ReplaceMissingValues(dataset):** here we are replacing missing values with mode

- **SplitFeaturesAndTarget(dataset)**: for splitting our dataset into features and target values and return X and y.

- **TrainTestSplit(X, y) function**: dividing the dataset into training and testing set in 70 and 30 percent respectively and return the following : X_train, X_test, y_train, y_test

- **TrainRandomForestClassifier(X_train, y_train) function**: train our random Forest Classifier model with 100 decision trees using training and return the final trained model.

- **EvaluateModel(model, X_test, y_test):** return the accuracy to check trained model.

- **MakePredictions(model) function**:
  print("Predictions for new instances:")
  print("Prediction 1")
  print("Prediction 2")

- **SaveModel(model):** save model to file

- **Call main( ):** We have utilized Random Forest method to calculate the presence of depression in an individual. Random forest is being used in the project because it has lower error rates compared with other methods. The accuracy of 89.44% is obtained after the classification

2.5 Flow graph of the Minor Project Problem

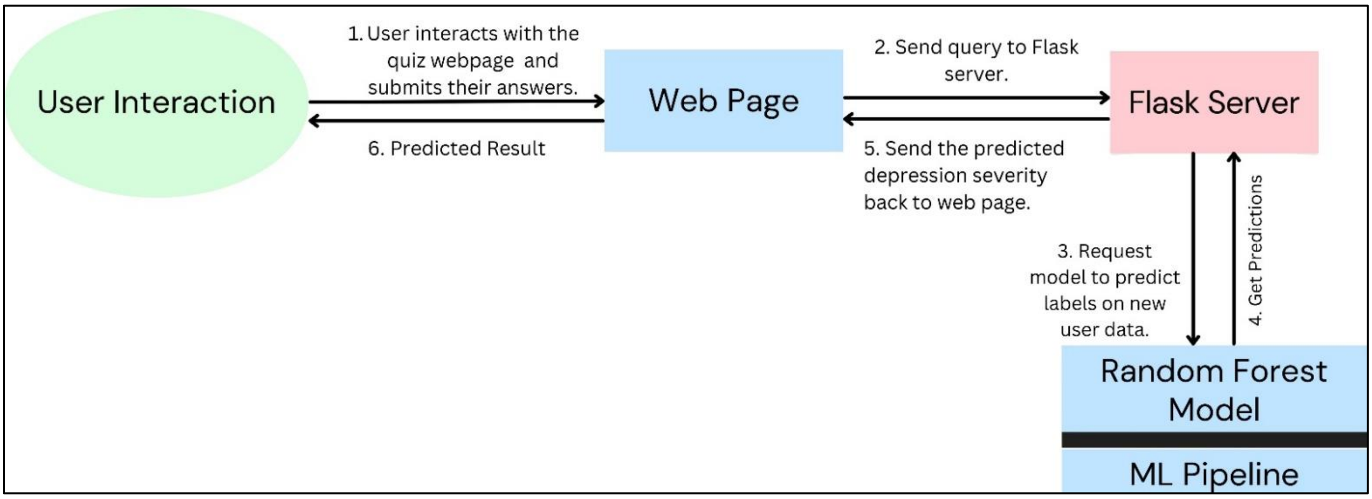

Figure 2: Flow Graph of the prediction model.

Input: input_data which is the form data containing user responses.

Output: predicted_severity that represent the severity level of depression present in the user.

Flowchart Description:

1. First, the user interacts with a web page containing a depression assessment form. And answers questions from physical health to the user's mental health.
2. Next, the user submits the form and sends the data to the Flask server.
3. Then we do data processing where the Flask server receives a POST request with the form data. And extracts from form data (answers to questions). The data is then organized into the appropriate DataFrame for the model.
4. Further prediction of the model is done when the DataFrame data is sent to a pre-trained machine learning model. The model predicts the severity of depression based on users' responses.
5. Finally, we assign a predicted label (severity of depression) based on the output of the model. The site maps the predicted identifier to a human-readable difficulty level.
6. The Flask server sends the predicted depression severity back to the web page.
7. Refresh the web page with the original input data and the predicted result.
8. The Flask server stays active and listens for new requests.

3.6 Screenshots of the various stages of the Project

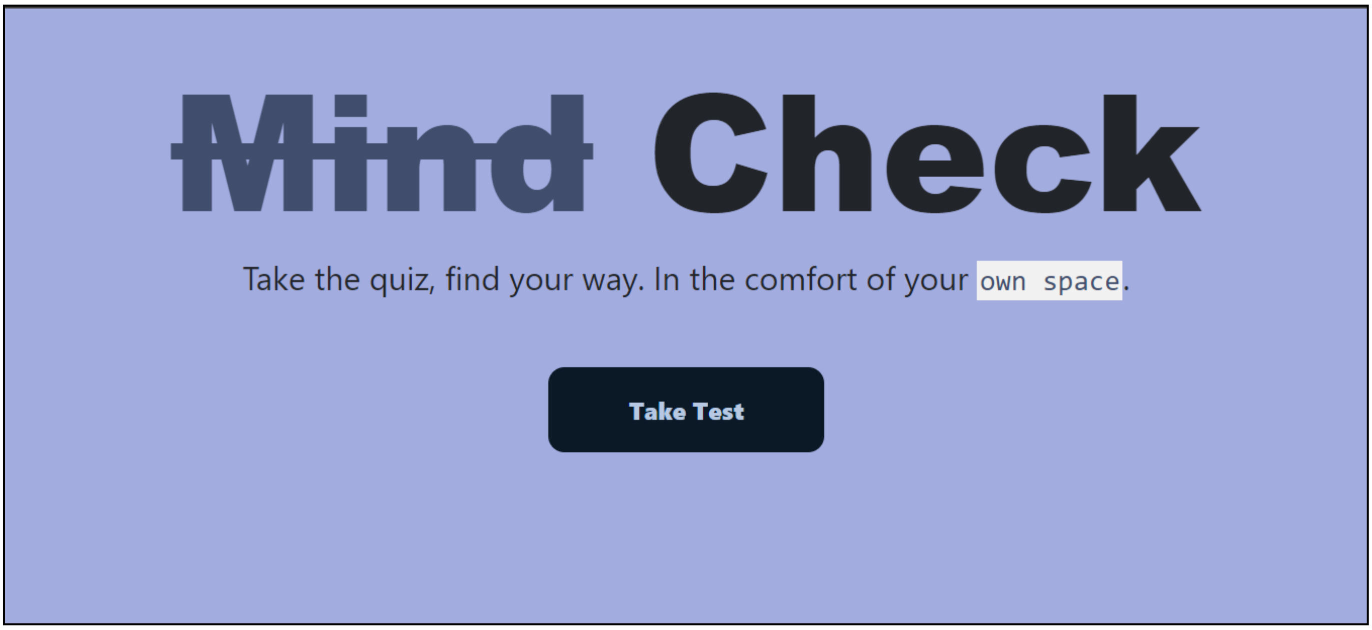

Figure 3: "Mind Check" Welcome Screen - Your Personal Mental Health Assessment Tool.

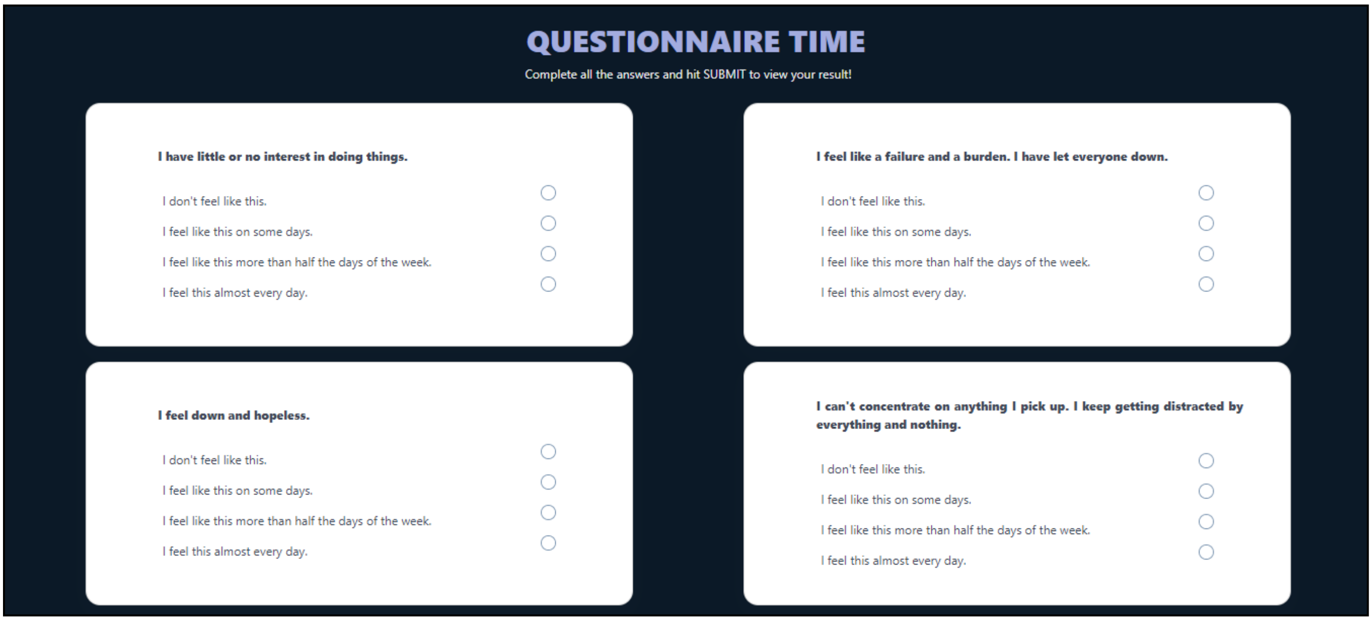

Figure 4: Questionnaire Screen to attempt the quiz.

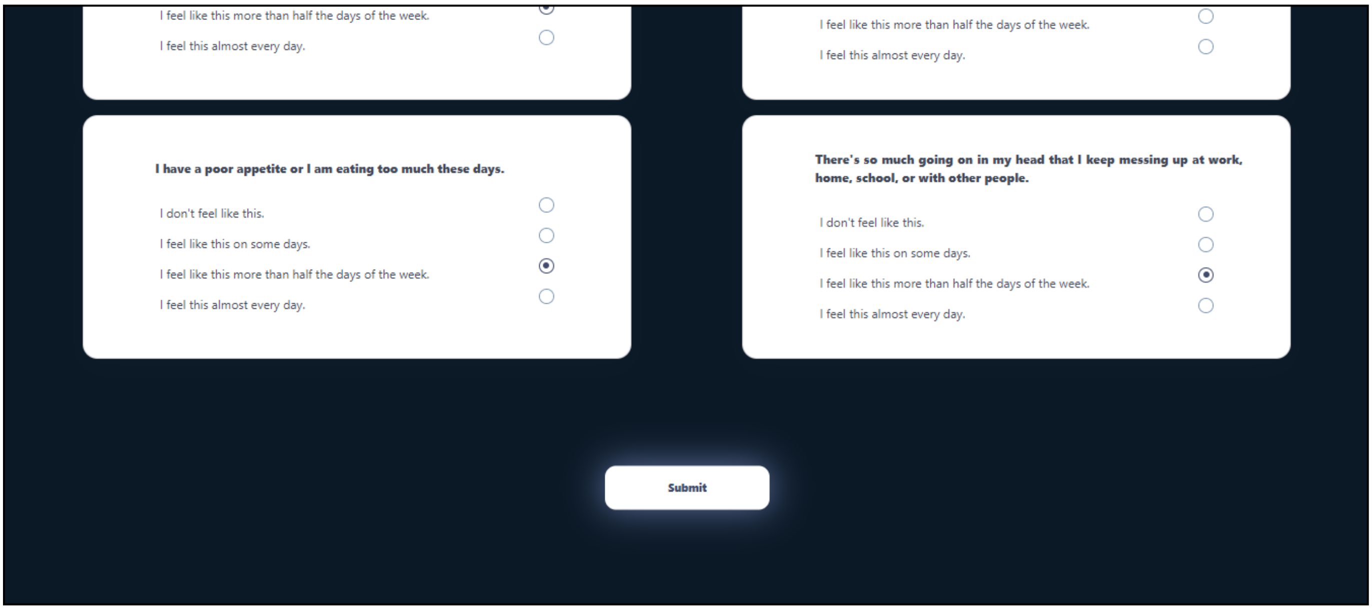

Figure 5: User submits their answers on the webpage.

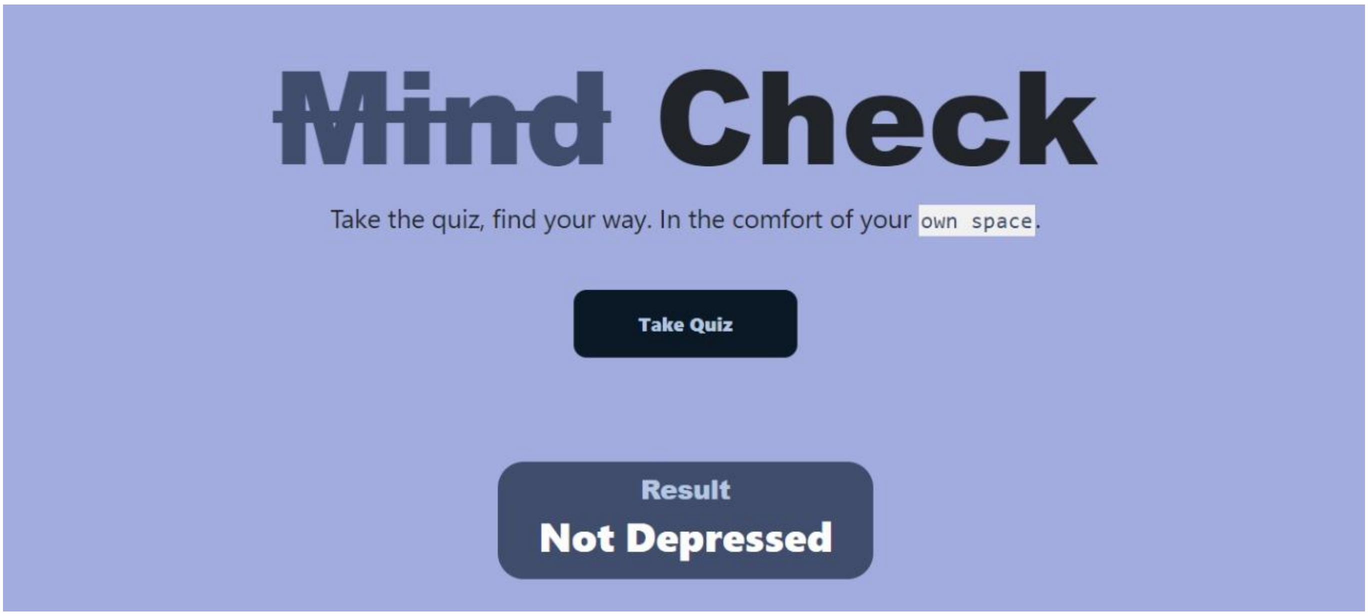

Figure 6: Predicted Output (Case 1: Not Depressed)

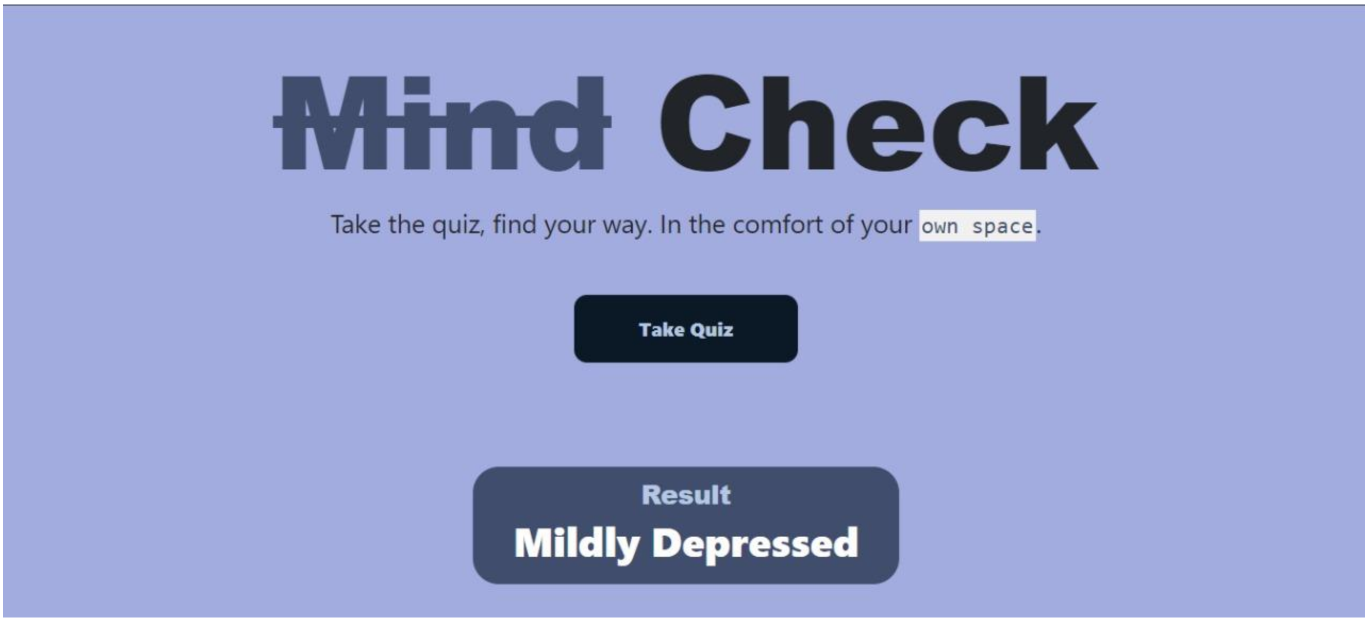

Figure 7: Predicted Output (Case 2: Mildly Depressed)

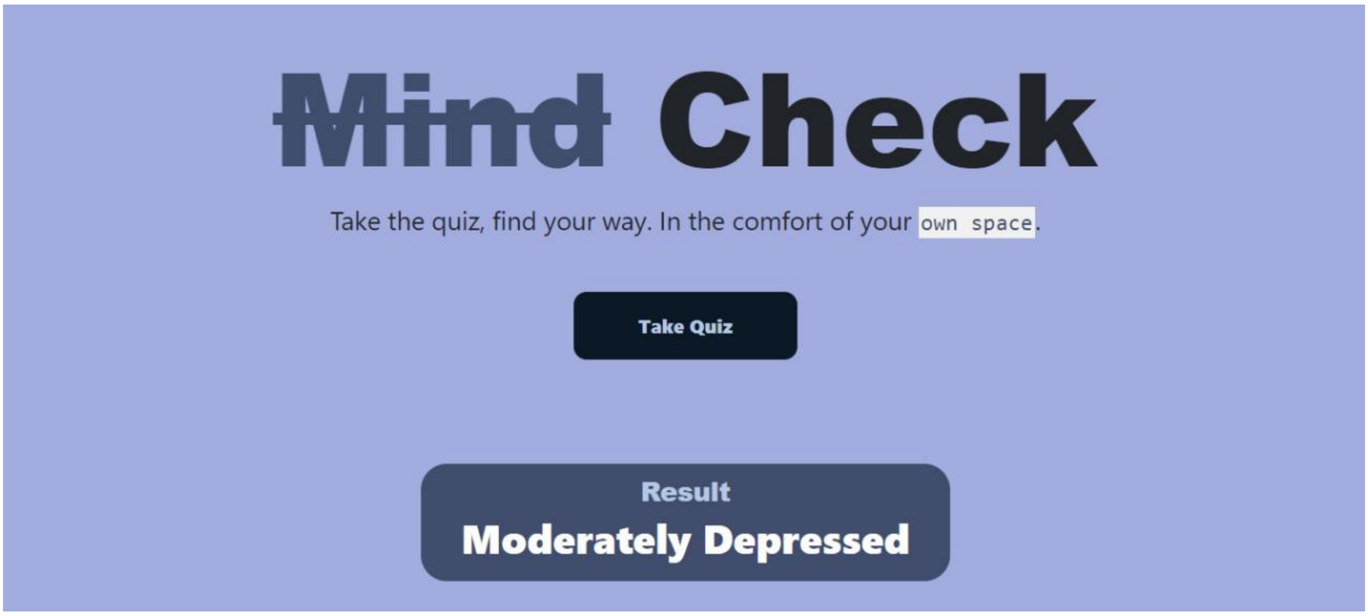

Figure 8 : Predicted Output (Case 3: Moderately Depressed)

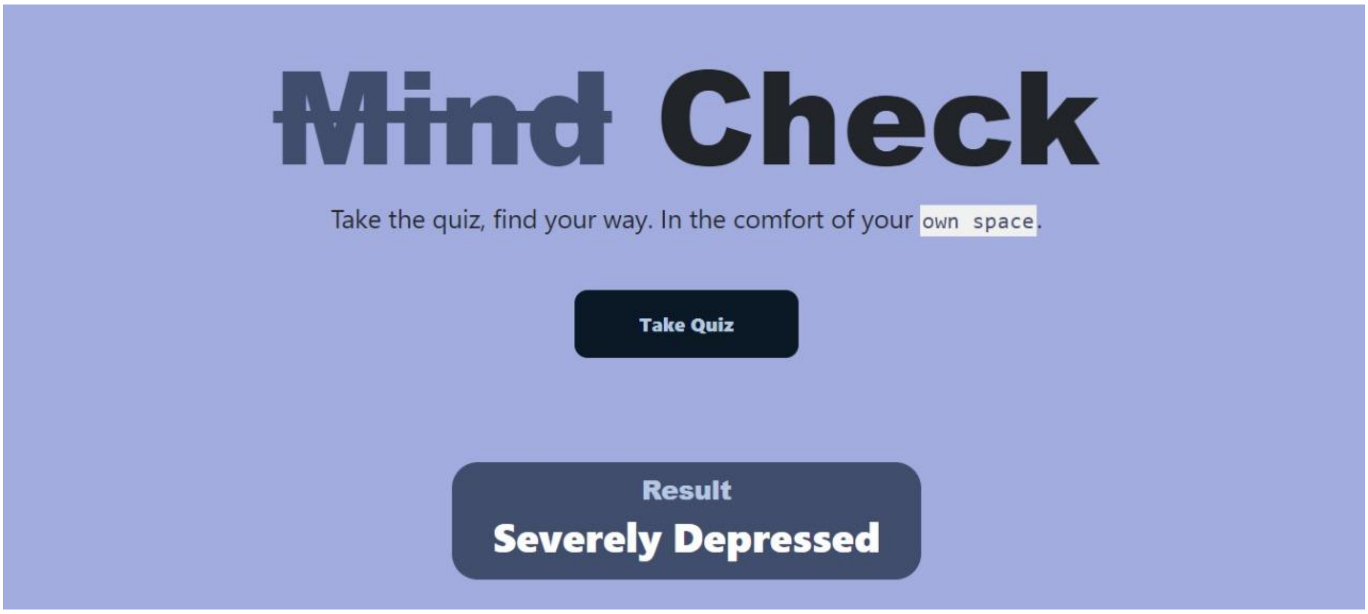

Figure 9 Predicted Output (Case 4: Severely Depressed)

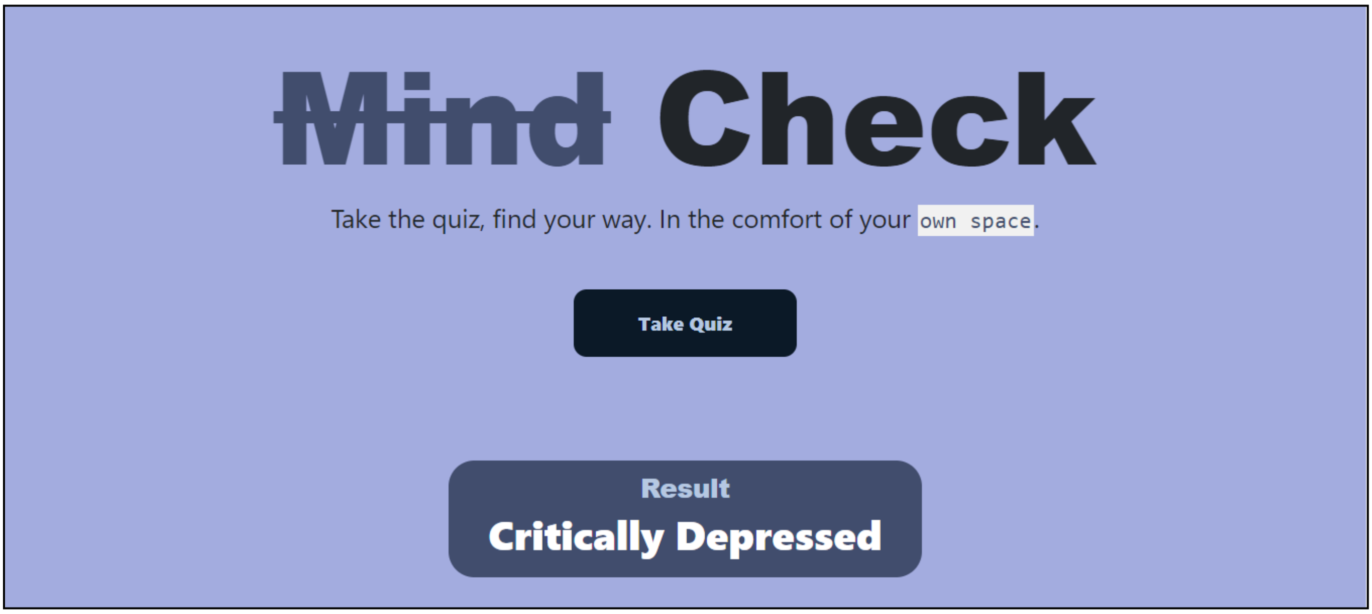

Figure 10: Predicted Output (Case 5: Critically Depressed)

<u>Chapter 04</u>: <u>RESULTS</u>

4.1 Discussion on the Results Achieved

The user is categorized as either Not Depressed, Mildly Depressed, Moderately Depressed, Severely Depressed, or Critically Depressed based on the expected outputs. The program evaluates input data to ascertain the degree of depression, and these forecasts are predicated on answers to ten questions. Using past data as training, this system finds trends and connections between input features and depression severity.

The model learns to link input properties with particular depression levels using labeled training data. The model was assessed and improved using metrics such as accuracy, which guaranteed the model's dependability. User responses are organized into a DataFrame that may be used as model input when they are gathered through an online form.

Using past data as training, this algorithm finds trends and connections between input features and depression severity. The model learns to associate input features with particular depression levels using labeled training data. The model was assessed and improved using metrics such as accuracy, which guaranteed the model's dependability. User responses are organized into a DataFrame that can be used as model input when they are gathered through an online form. After analyzing the incoming data, the model generates a numerical prediction that is mapped to a descriptive category (such as "Mildly Depressed"). At last, the user receives an evaluation of their mental health along with the prediction displayed on the webpage. Based on user inputs, this workflow guarantees accurate predictions and provides insightful information that can be put to use.

4.2 Application of the Minor Project

There are several uses for this project in the treatment and wellbeing of mental health. First off, for those looking for a convenient and unobtrusive way to evaluate their mental health, it can be a priceless screening tool. With its ability to classify individuals into "Not Depressed" and "Critically Depressed," among other levels of depression severity, the system provides users with instantaneous emotional well-being information. Because of its accessibility, more people might be inspired to get the professional assistance or support they need, which could result in earlier interventions and better outcomes for mental health.
Secondly, mental health practitioners might enhance their diagnostic procedures by utilizing the model's prediction powers. Through the examination of user answers to a series of basic questions, the computer

finds trends and connections that point to different levels of sadness. This helps physicians make better-informed choices about interventions and treatment strategies. Furthermore, the model's success and dependability in clinical contexts are guaranteed by its reliance on labeled training data and ongoing assessment, which eventually improves the standard of treatment given to patients.

Moreover, the incorporation of this prediction model into an online platform facilitates scalability and broad accessibility to instruments for mental health assessment. The system can handle a high number of users at once since user responses are gathered via an online form and fed into the model. Its deployment across a range of groups is made easier by its scalability, including underprivileged communities and isolated areas with little access to mental health treatments. Overall, the research will benefit public health campaigns that support general well-being and early depression intervention in addition to individual mental health **examinations**.

4.3 Limitation of the Minor Project

- **Data Interpretation:** The application depends on subjective user-provided data. Users may misunderstand questions or give false information, which would reduce the accuracy of the forecast.

- **Complexity of Depression**: A series of pre-formulated questions may not adequately represent the intricacies and diversity of this disorder. The app might overlook subtleties in certain circumstances and oversimplify the diagnosis procedure.

- **Absence of Human Judgment**: The app is unable to provide a comprehensive picture of a user's mental health or take into account environmental circumstances, in contrast to licensed mental health experts. It is devoid of human understanding and sensitivity.

- **Privacy and Security**: To safeguard user privacy when handling sensitive mental health data, strict security measures must be implemented. Any violation could have detrimental effects on morality and the law.

- **Lack of Immediate Support**: Although the app has the ability to detect possible depression, it does not provide interventions or instant support. People who have been classified as severely or critically depressed require prompt access to expert assistance, which the app is unable to offer.

- **Overreliance:** If users rely too much on the app for self-diagnosis, they may put off getting help from a professional. This can be especially dangerous if the app makes inaccurate predictions.

- **Cultural Sensitivity:** The signs and symptoms of depression might vary depending on the culture. Users from different backgrounds may receive erroneous assessments from the app since it fails to take these variables into account. Update and Maintenance: To include new research findings and increase accuracy, the model requires regular updates and maintenance. If this isn't done, the app may become less functional and outdated.

4.4 Future Work

- Examine the users' responses to the questionnaire, as well as their physical attributes and facial expressions. This aids in identifying indicators of poor energy and other bodily depressive symptoms.

- To more accurately capture the various facets of depression, include more pertinent questions and update them frequently.

- Provide tools to assist users in managing their mental health and to provide additional information for evaluation, such as diary trackers, yoga, and physical activity.

- Create a chatbot to communicate with users, provide assistance, and point them in the direction of useful resources.

- Based on users' reactions and tracked data, provide customized recommendations for coping mechanisms, lifestyle modifications, and therapy.

- Permit users to log in and monitor their progress on a frequent basis, offering comments and modifying suggestions as necessary.

- Permit users to log in and monitor their progress on a frequent basis, offering comments and modifying suggestions as necessary.

- Community Support: Establish a peer-supporting website where users can exchange stories and words of encouragement. Collaborate with professionals in the field of mental health to guarantee the precision and efficacy of the app. Ethics and Frequent Updates: Make sure the app satisfies ethical requirements and safeguards user privacy by keeping it updated with fresh research and user input.

REFERENCES

[1] Umme Marzia Haque 1, Enamul Kabir 1, Rasheda Khanam 2, the U.S. National Library of Medicine (NLM), 2021 Dec 16;16(12):e0261131. doi: 10.1371/journal.pone.0261131. eCollection 2021.

[2] Konda Vaishnavi, U Nikhitha Kamath, B Ashwath Rao and N V Subba Reddy, Journal of Physics: Conference Series 2161 (2022) 012021 IOP Publishing doi:10.1088/1742-6596/2161/1/012021.

[3] Anu Priyaa , Shruti Garga, Neha Prerna Tigga, Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms, under responsibility of the scientific committee of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019). 10.1016/j.procs.2020.03.442.

[4] Roger Garriga, Javier Mas, Semhar Abraha, Jon Nolan, Oliver Harrison, George Tadros & Aleksandar Matic, Garriga, R., Mas, J., Abraha, S. et al. Machine learning model to predict mental health crises from electronic health records. Nat Med 28, 1240–1248 (2022). https://doi.org/10.1038/s41591-022-01811-5.

[5] Ayako Baba.and Kyosuke Bunji, JMIR Mental Health. 2023; 10: e42420.
Published online 2023 May 10. doi: 10.2196/42420.

[6] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, ―Predicting depression via social media,‖ In Proceedings of the 7th International AAAI Conference on Weblogs and Social Media, 2013.

[7] 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, 2015.

[8] M. Trotzek, S. Koitka, and C. Friedrich, ―Word embeddings and linguistic metadata at the clef 2018 tasks for early detection of depression and anorexia,‖ Proceedings of the 9th International Conference of the CLEF Association, CLEF 2018, Avignon, France, 2018.

[9] E. A. R´ıssola, M. Aliannejadi, and F. Crestani, ―Beyond modelling: Understanding mental disorders in online social media,‖ Advances in Information Retrieval: 42nd European Conference on IR Research, ECIR 2020, Lisbon, Portugal, 2020.

[10] S. Burdisso, M. Errecalde, and M. Montes-y Go´mez, ―A text classification framework for simple and effective early depression detection over social media streams,‖ Expert Systems With Applications, Vol. 133, 2019.

[11] D. Preotiuc-Pietro, J. Eichstaedt, G. Park, M. Sap, L. Smith, V. Tobolsky, H. Schwartz, and L. Ungar, ―The role of personality, age and gender in tweeting about mental illnesses,‖ In Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology, 2015.

[12] R. Ortega-Mendoza, A. Lopez-Monroy, A. Franco-Arcega, and M. Montes-YGo´mez, ―Peimex at erisk2018: Emphasizing personal information for depression and anorexia detection,‖ Proceedings of the 9th International Conference of the CLEF Association, CLEF 2018, Avignon, France, 2018.