ThoughtTherapy- A Machine Learning Guided Website for Mental Health

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Abstract—In recent times, a significant number of people have been overlooking the importance of mental health. The state of our psychological well-being deeply impacts multiple factors of our lives, including our thoughts, feelings, and actions, which consequently shape our relationships, professional performance, and capacity to handle difficulties. The objective of this initiative is to create a webapplication to offer a safe, secure, and cost-effective platform designed to aid individuals in addressing and controlling their mental health concerns, including conditions like depression, stress, and anxiety. While numerous applications focus on cognitive health, these web tools are often not cost-efficient for many people who are in need of treatment. Moreover, traditional therapies are time-consuming, expensive,have limited accessibility, and the associated stigma can discourage individuals from seeking help or discussing their struggles openly. The primary goal of our digital service is to provide personalized activities based on the user's unique mental health score obtained from the DASS-42 (Depression Anxiety Stress Scale- 42) questionnaire. As a result, users can easily assess their emotional health on a secure platform,and the machine learning models integrated into the application are utilized to predict the severity levels of users using the dataset and provide corresponding activities to help themovercome their emotional health issues. Additionally, user data is securely stored in the MySQL database.

Keywords—Depression, Anxiety, Stress, DASS-42, ReactJS, CSS, MySQL, Machine Learning, SVM (Support Vector Machine), Decision Tree, Random Forest, Flask.

I. INTRODUCTION

In today's world, depression, anxiety, and stress are widespread health concerns globally, affecting individuals regardless of their employment or age. Many professionals handle multiple responsibilities simultaneously, leading to exhaustion and stress in their daily lives. Similarly, young people and individuals from all walks of life encounter various environmental, medical, social, and psychological factors contributing to these feelings. The younger generation often faces unique challenges such as academic pressure, relationship issues, and parental expectations, which can exacerbate their mental health struggles. Many find it difficult to cope with these pressures and may neglect self-care practices. In severe cases, they may experience profound sadness, loss of interest in activities, and increased negative thoughts, which can lead to feelings of isolation. Cognitive health holds paramount importance for individuals, as imbalances in mental well-being can have profound effects on physical health. These effects include increased blood pressure, heart disease, and weakened immune function, rendering individuals more susceptible to infections and illnesses. Heightened stress and anxiety levels are associated with gastrointestinal problems and asthma. Furthermore, they disrupt sleep patterns, leading to insomnia or excessive sleeping. Emotionally, distress can manifest as difficulty concentrating, making decisions, memory issues, and potentially triggering eating disorders. To mitigate these adverse effects, engaging in relaxation exercises is crucial. While online therapy and counseling sessions are available, they are often costly. Therefore, our platform offers an accessible solution for individuals who cannot afford expensive sessions, allowing them to assess their mental health and monitor it from the comfort of their homes. Innovations in technology have revolutionized mental health care, enhancing access to resources, personalizing treatment, and delivering therapy. Mobile applications and wearable devices assist in managing stress and tracking physiological indicators, while virtual reality and AI-powered chatbots provide immersive therapy experiences and immediate support. These advancements offer potential for improving mental health care worldwide, making it more accessible, cost-effective, and impactful.ThoughtTherapy aims to address the rising demand for accessible and affordable mental health services among people. It recognizes the profound impact of conditions like depression, anxiety, and stress on individuals' lives and productivity. However, stigma often prevents them from seeking help, and traditional therapy can be expensive and inaccessible. Thus, ThoughtTherapy leverages technology to provide readily available, cost-effective, and confidential mental health services. Using machine learning algorithms, the platform provides tailored suggestions and evidence-supported activities to assist individuals in addressing their mental health concerns and enhancing their overall wellness. The project combines efficiency with versatility, offering a multifaceted solution to cognitive health challenges. Through personalized activities and recommendations tailored to individual needs, it efficiently addresses issues of distress. Its versatility lies in its adaptability to diverse user profiles and situations, catering to the unique requirements of each individual. By leveraging machine learning algorithms and intuitive interfaces, the project ensures accessibility and ease of use for users from various backgrounds. The DASS42, or Depression, Anxiety, and Stress Scale 42-item version, is a well-known self-assessment tool designed to assess the severity of depression, anxiety, and stress symptoms experienced by an individual in the past week. This questionnaire consists of 42 items divided into three sections: Depression, Anxiety, and Stress, each comprising 14 items targeting various aspects of these mental health conditions. Widely used in research and clinical settings, the DASS42 assists in evaluating and monitoring mental health symptoms.

II. RELATED WORK

Numerous methodologies have been put forth and documented in various journals to tackle the issue. Each paper examined in this section takes a distinct approach to addressing the problem. The subsequent section offers a summary of the techniques employed:

[1] The study introduces a music recommendation service utilizing the DASS-21 questionnaire to identify and assess symptoms of anxiety, depression, and stress. Through fuzzy clustering for user data, individuals were categorized into groups based on their psychological states. The dataset, drawn from the Open – Source Psychometrics Project, encompassed approximately 39,000 respondents. Results showed average scores of 23.6 for depression, 17.4 for anxiety, and 23.3 for stress. Recommendations were tailored to user's psychological states, with different music selections for varying severity levels. The service aims to provide personalized music recommendations aligned with user's psychological profiles.

[2] Depression and anxiety are serious issues that can have severe consequences, including suicide. Stress is common, but when not managed properly, it can escalate. This project aims to develop a mobile app using the DASS-21 questionnaire to help students monitor their mental health. The app consists of 21 questions assessing symptoms of depression and anxiety over the past week. Students can track their mental wellness and seek help if their scores indicate high severity of depression, anxiety, or stress.

[3] Recent academic studies have increasingly focused on mental health, particularly stress, anxiety, and depression. One study by Srinath explores machine learning algorithms like Support Vector Machine and Logistic Regression to predict severity levels of these conditions using the DASS42 questionnaire. Logistic Regression showed higher accuracy compared to SVM, but the study didn't delve into deep learning models. Another study by Priya, predicts stress, anxiety, and depression using the DASS21 questionnaire, with the Random Forest classifier proving most accurate despite a small dataset, suggesting potential advancements in mental health prediction beyond traditional algorithms.

[4] "The development and assessment of MoodHacker" is a research paper outlining the creation and testing of a smartphone app designed to manage depression. Authored by individuals from the Center for Behavioral Intervention Technologies at Northwestern University, the paper provides a detailed overview of MoodHacker's development, including its theoretical basis, functionalities, and user interface. Additionally, it presents findings from a randomized controlled trial assessing the app's effectiveness. The study concludes that MoodHacker successfully alleviated depression symptoms and enhanced mood. This article offers insightful information about the creation and assessment of mobile apps for managing mental health, which may help with the planning and assessment of apps that are comparable to ThoughtTherapy.

[5]Indonesian students jointly adopted remote learning, also referred to as "bold learning," during the Covid-19 pandemic. This strategy, however, proved unproductive and resulted in difficulties in the classroom, particularly with assignments. As a result of internal circumstances and academic expectations, students experienced psychological problems such as stress, anxiety, and depression that negatively impacted their mental health. Significant psychological issues were found among respondents over 60 and in the 19 to 24 age group in a study conducted by the Association of Indonesian Mental Medicine Specialists (PDSKJI) during the epidemic. In response, the author suggests developing a system to evaluate students for stress, anxiety, and depression and to recommend treatments based on test results. The system applies the Naïve Bayes approach on the DASS-42 scale and achieves an 86.44% dataset accuracy, effectively meeting its goal.

[6] This study focuses on depression among university undergraduates in Bangladesh. It utilizes survey data with input from psychologists, counsellors, and professors to predict depression using three algorithms. The goal is to identify depression early and intervene promptly to prevent adverse outcomes such as suicide.

III. METHODOLOGY

In our model, we focused on providing personalized activities to users to address their cognitive health issues using the DASS-42 scores dataset as our primary source. Initially, we collected the dataset from an online source containing scores for each question provided by different users. Our web application is built using ReactJS, a popular JavaScript library with various components and features to offer a user-friendly interface. ThoughtTherapy aims to provide information on people's mental health, assisting them in overcoming challenges by employing the DASS-42 questionnaire. Additionally, it predicts severity levels using machine learning models. The user interface showcases the questionnaire and presents assessment results visually. The web tool includes a dashboard for tracking progress, assessing results, and managing activities. Moreover, user authentication and privacy measures are implemented to safeguard sensitive data. The client side application is built using Node.js in a JavaScript runtime environment, allowing developers to create server-side applications using JavaScript. The frontend, database, and backend communication are developed using the Flask framework. It is perfect for creating web applications and APIs since it is lightweight and has an intuitive architecture. Flask is frequently utilized for smaller projects, prototyping, or applications with specific needs where a fully functional web framework might not be required.

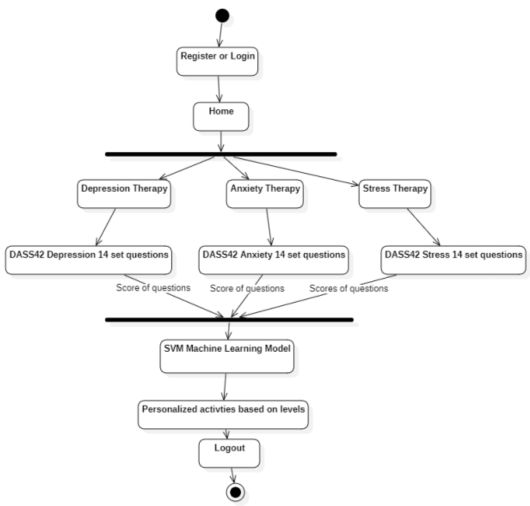

Fig.1. Activity Diagram of proposed model

A. DATASET

We have collected the DASS-42 scores dataset for our problem statement. It contains the score values for each question, totaling 42: 14 for depression, 14 for anxiety, and 14 for stress questions. This data is collected from different people, such as students, working professionals, etc. The entire dataset contains 39,775 rows and 42 columns. The dataset is used to identify an individual's severity of emotional health.

	Q1A	Q2A	Q3A	Q4A	Q5A	Q6A	Q7A	Q8A	Q9A	Q10A	...	Q33A	Q34A	Q35A	Q36A	Q37A	Q38A	Q39A	Q40A	Q41A
0	4	4	2	4	4	4	4	4	2	1	...	2	3	4	4	1	2	4	3	4
1	4	1	2	3	4	4	3	4	3	2	...	3	2	2	3	4	2	2	1	2
2	3	1	4	1	4	3	1	3	2	4	...	1	4	3	4	4	4	2	2	1
3	2	3	2	1	3	3	4	2	3	3	...	2	4	1	1	2	1	3	4	4
4	2	2	3	4	4	2	4	4	4	3	...	4	4	3	4	3	3	3	4	4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
39770	2	1	3	2	3	2	1	3	1	4	...	2	4	1	2	4	4	2	3	1
39771	3	4	3	4	3	4	4	4	3	4	...	3	4	3	3	3	4	3	3	3
39772	2	1	2	1	1	1	1	1	2	1	...	2	1	1	1	1	1	2	1	1
39773	3	1	2	2	3	3	3	4	3	1	...	4	2	3	2	1	2	3	2	4
39774	2	1	2	1	4	2	1	1	1	1	...	2	3	2	2	2	4	3	3	1

39775 rows × 42 columns

Fig.2. DASS-42 scores Dataset

B. IMPLEMENTATION

i. FRONTEND DEVELOPMENT:

In frontend web development, ReactJS is responsible for constructing user interfaces, offering features such as a component-based architecture and declarative syntax. Initially, we are required to install Node.js for package management and running JavaScript code outside the browser because ReactJs relies on Node.js. After installing Node.js, we can create a React app by using "npx create-react-app". The React DOM (Document Object Model), a package within the React library, handles rendering React components into the browser's DOM. This facilitates maintaining a virtual representation of the DOM, serving as a replica of the actual DOM. When a React component is rendered, it generates a virtual representation of the component's UI structure in the virtual DOM. Updating involves changing the component's state; it first updates in the virtual DOM before syncing with the actual DOM. React selectively updates only the changed parts of the DOM, rather than re-rendering the entire UI. The react-router DOM enables client-side routing, facilitating navigation between different components within a React application without requiring full page reloads. For the styling framework, we have used CSS (Cascading Style Sheets), which offers a wide variety of styling options for web pages. Bootstrap icons are also utilized in the web application to create a user-friendly interface. In our application, we have created pages like signup, login, home, dashboard, and therapy page, where therapy pages contain the depression, stress, and anxiety therapy, each containing 14 questions. When the user completes the whole assessment on 14 questions, the submit button will be enabled for assessing the result, and the dashboard contains a side menu that shows what therapy the user has taken and it also displays the personalized tasks for the user.

ii. DATABASE DEVELOPMENT:

To store user data, we utilized MySQL, an open-source relational database management system that helps to store and retrieve data securely. It offers features such as transactions, indexing, and querying. MySQL can be connected to Flask by using the URL of the database. The database port number helps Flask to know where the database is located. The React frontend interacts with the backend Flask using HTTP requests, and these requests are sent to endpoints in the backend. Creating, querying, and updating data in the database is achieved using "from flask_sqlalchemy import SQLAlchemy." When updating the table, handling errors and providing error messages to users is an essential part. In our project, we created different tables for handling data such as: user (UserID, Username, email, DOB, Age,), active_user (UserID), severity_levels(user_id,depression_level,anxiety_level,stress_level), depression_tasks (task1, task2...), stress_tasks (task1, task2...), anxiety_tasks (task1, task2...). The active user data can only be seen by the web developer who handles the database.

iii. MACHINE LEARNING MODELS:

Creating a new model:
We have created a model for predicting the level of severity of depression, stress, and anxiety based on the data provided by the user in the application. The severity levels - normal, mild, moderate, severe, and extremely severe - are predicted by using SVM (Support Vector Machine), decision trees, and random forest models. In our application, we created three different machine learning models for each separate therapy (i.e., depression, stress, and anxiety models) to assess the state of cognitive health. Based on the performance evaluation of the model we choose the best fit model from chosen three algorithms.
Data preprocessing:

During the data preprocessing stage, several key steps are undertaken. Firstly, relevant columns are extracted from the dataset based on a defined pattern “Q<number>A”, resulting in the creation of a new Data Frame called “extracted_data”. Subsequently, the presence of missing values is checked within this extracted_data to ensure data integrity. Following this, a function is implemented to regularize the data by subtracting 1 from all responses, thus transforming the scale from 1-4 to 0-3. The regularized data is then used to create separate datasets for depression, stress, and anxiety by filtering out specific columns identified by predefined keys and the predefined key are: {'Depression': [3, 5, 10, 13, 16, 17, 21, 24, 26, 31, 34, 37, 38, 42], 'Anxiety': [2, 4, 7, 9, 15, 19, 20, 23, 25, 28, 30, 36, 40, 41], 'Stress': [1, 6, 8, 11, 12, 14, 18, 22, 27, 29, 32, 33, 35, 39]}. Labels are assigned to the datasets based on the total count of symptoms using a defined function, resulting in the creation of a new column labeled 'Label'. Finally, the frequency distribution of labels within the generated datasets are visualized through a bar chart, allowing for a comprehensive understanding of the distribution of severity levels among the dataset.

Generating Training and testing data:

The process of generating training and testing data involves several crucial steps. Initially, the dataset is divides into two parts: the features (“emotional_issue_X”) and the corresponding labels (“emotional_issue_labels”).except for the 'Label' column, while the labels specifically indicate the severity levels of mental health issues. Subsequently, the labels are transformed into numerical values using the `LabelEncoder()` function to facilitate model training. Furthermore, the datasets are split into training and testing sets using the `train_test_split()` function, with 70% of the data allocated for training (`X_Train` and `Y_Train`) and the remaining 30% for testing (`X_Test` and `Y_Test`). This ensures that the model is trained on a substantial portion of the data while reserving a separate set for evaluation. Lastly, the distribution of labels within both the training and testing datasets is analyzed to ensure a balanced representation of each severity level, offering valuable insights into the dataset's composition and suitability for training machine learning models. This comprehensive approach ensures the reliability and effectiveness of the subsequent machine learning algorithms employed to predict mental health severity levels.

Model Training and testing:

In the model training phase, we trained the models by using decision tree, SVM, and random forest on the X_Train and Y_Train data and the predictions are made on the testing data X_Test. A classification report is generated to provide a detailed breakdown of the model's precision, recall, and F1-score for each severity level. Finally, evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's overall performance in predicting severity levels. This process is similar to 3 datasets (depression, stress, and anxiety). Consequently, based on the testing information and performance evaluation, we saved the SVM model as our preferred machine learning model. Subsequently, we tested it with the random data individually for each of the three models, yielding precise results.

Algorithm	Depression dataset	Anxiety dataset	Stress dataset
Decision Tree	Accuracy: 83 Precision: 78 Recall: 79 F1-score: 78	Accuracy: 77 Precision: 69 Recall: 69 F1-score: 69	Accuracy: 78 Precision: 76 Recall: 76 F1-score: 76
SVM	Accuracy: 99 Precision: 99 Recall: 99 F1-score: 99	Accuracy: 99 Precision: 99 Recall: 98 F1-score: 98	Accuracy: 99 Precision: 99 Recall: 99 F1-score: 99
Random Forest	Accuracy: 93 Precision: 91 Recall: 90 F1-score: 90	Accuracy: 88 Precision: 83 Recall: 80 F1-score: 81	Accuracy:91 Precision: 91 Recall: 90 F1-score: 90

Table 1: Performance Evaluation

C. INTEGRATION AND DEPLOYMENT:

Flask, a backend server framework, offers Flask-RESTful for creating APIs that facilitate communication between frontend and backend systems. In our application, this framework assists in linking the frontend and database alongside ML models. Flask-RESTful streamlines API development by providing tools for common tasks like serialization, authentication, and URL routing. APIs are defined as Python classes inheriting from the `Resource` class, with methods such as `get`, `post`, `put`, and `delete` handling different HTTP request types. These classes are then mapped to URLs using Flask's routing mechanism, simplifying the management of API endpoints. Data exchanged between frontend and backend is typically in JSON format due to its lightweight nature and ease of parsing in JavaScript. On the frontend, Axios is commonly utilized to make HTTP requests to the backend API. Upon receiving user-provided data, the entire database updates, and the ML model prediction result is transmitted to the frontend, where the UI adjusts accordingly.

The frontend project consists of several React components that handle different aspects of our application, including user authentication, user signup, login, the homepage, the dashboard, the main page for selecting therapy programs, and task content for each therapy program. Each component manages its state using hooks like useState and useEffect, and they communicate with backend server via asynchronous fetch requests or Axios for handling HTTP requests. For example, the Signup component manages user registration by sending user data to the backend API endpoint '/signup', while the Login component handles user authentication by sending credentials to the '/login' endpoint. The Dashboard component fetches user details from the '/dashboard' endpoint and renders a sidebar and task content based on the user's therapy levels. The MainPage component displays different therapy programs and links to corresponding pages. The Header and Sidebar components provide navigation functionalities.

IV. RESULT ANALYSIS

This part presents a through examination of results obtained from the implementation of our system:

Web Design while compared to traditional approaches, the frontend's development took 30% less time while using Visual Studio in conjunction with React.

When we open ThoughtTherapy application, we can view signup and login buttons on the header. If a person is new to the application, he/she should go through the signup and if a person is an old user, then we can just login into the site.

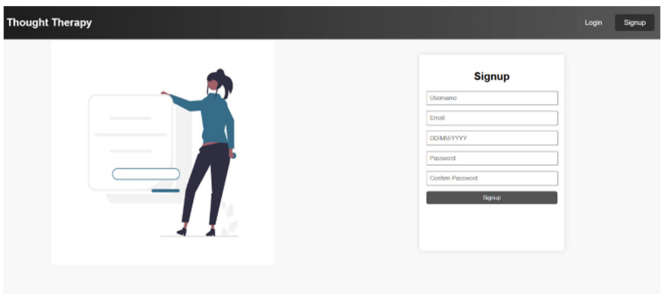

Fig.3. Signup Page

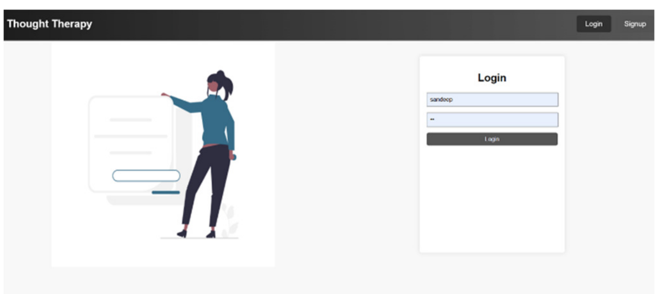

Fig.4. Login Page

After successful login, we will be directed to the Home page

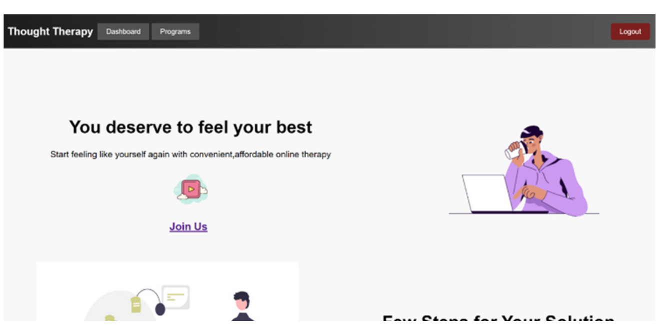

Fig.5. Home Page

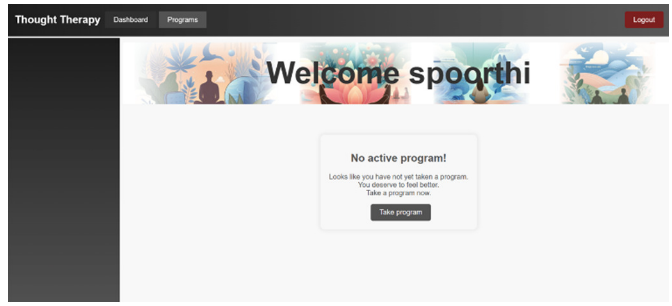

Fig.6. Dashboard of new user

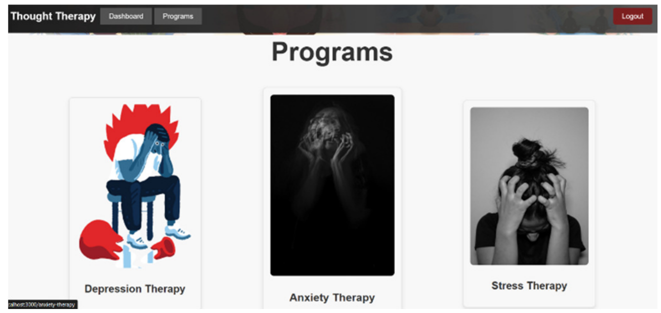

Fig.7. Therapy Page

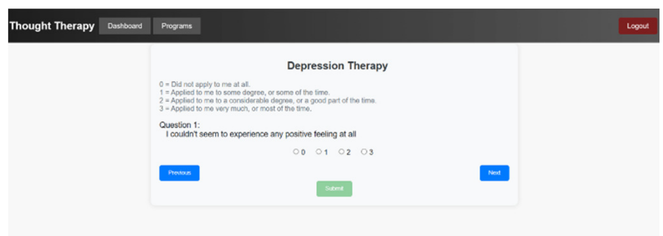

Fig.8. Questionnaire Page

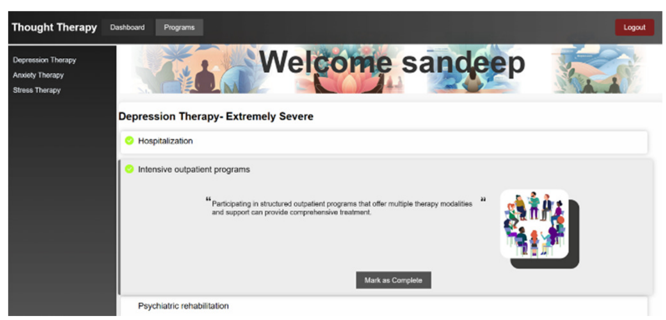

Fig.9. Dashboard of previous user

The results obtained from MySQL database:

Utilizing MySQL as the designated database, the response times for queries were notably fast. Registration operations for users typically completed in an average of 25 milliseconds, while retrieving machine learning results averaged around 60 milliseconds. These response times comfortably met the requirements for real-time applications.

user_id	username	email	dob	age	password
1001	s1	s1@gmail.com	01/01/2001	23	$2b$12$.Yz6vxl8CX8LtJRG7BuVyub/qDd/BgHBXb4kEiQsx41s2Wq3FWLjO
1002	s2	s2@gmail.com	02/02/2002	22	$2b$12$jreBiPdtZZbO/2rtVc7vIOZ2/tUBYOb2x8pIMcxbjJcRRqGx26iim
1003	sandeep	sandeepkonuri444@gmail.com	14/11/2001	22	$2b$12$yFnKU6dAudWbxjaP4a8sYuO8bAu33blG/HW6VrXCOnqfiByRH64D.
1004	Anudeep	anudeepkanaparthi@gmail.com	31/10/2002	21	$2b$12$pLJOgMVWegg/U3YGcTicQeRvshMOxZsYwd8Iv7qW5OP1WmWJQjVaK
1005	prasanna	laxmiprasanna@gmail.com	01/02/2003	21	$2b$12$Djsj4g77Iv5gH486vv4QvuWm.OZM4xZB4ZwyFH06VhA7y/BFRIl7W
1006	s3	s3@gmail.com	03/03/2003	21	$2b$12$ULqwbfiCcqaIxQxq9nll5OuuFS082Ij1Pen.pi3VH4LLVuFBm5BsC
NULL	NULL	NULL	NULL	NULL	NULL

Fig.10. User Table

user_id	depression_level	anxiety_level	stress_level
1001	Severe	Mild	Mild
1002	Mild	Mild	Mild
1003	Extremely Severe	Moderate	Mild
1004	Moderate	Severe	Severe
1006	Severe	Moderate	NULL
NULL	NULL	NULL	NULL

Fig.11. Severity Table

user_id
1007
NULL

Fig.12. Active User Table

user_id	task1	task2	task3	task4	task5	task6	task7	task8	task9	task10	task11	task12	task13	task14
1001	1	1	1	1	1	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1003	1	1	0	0	0	0	0	0	0	0	0	0	0	0
1004	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1006	1	0	0	0	0	0	0	0	0	0	0	0	0	0
NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL

Fig.13. Task Completion Table

In Task Completion table, 1 refers to task completed and 0 refers to task incomplete. This table is similar for three depression, anxiety, and stress.

The results obtained from machine learning model:
The performance of the SVM was compared to other algorithms such as Random Forest and Decision Tree. While the accuracy of the latter algorithms was comparable, the SVM distinguished itself with its interpretability and quicker prediction times with its accuracy and precision 99%.

V. CONCLUSION

ThoughtTherapy is a website developed using ReactJS, featuring a machine learning model aimed at aiding individuals in managing their mental health. Utilizing inputs from a DASS42 form, the website evaluates the user's depression, anxiety, and stress levels, offering tailored activities to enhance their mental well-being. It incorporates a Flask-RESTful API framework to connect with a MySQL database and employs CSS for frontend styling. The project stems from the pressing need to address rising mental health concerns and aims to provide an accessible platform for individuals to manage their mental well-being effectively. Beyond personal use, ThoughtTherapy serves research and educational purposes, distinguishing itself with its integration of machine learning algorithms for personalized user experiences. By leveraging Support Vector Machines for personalized activity recommendations, ThoughtTherapy pioneers a novel approach to mental health management. The SVM model undergoes rigorous steps, including data collection, preprocessing, feature selection, and training, before being deployed and seamlessly integrated into the website through Flask-RESTful API framework. Ultimately, ThoughtTherapy holds promise in revolutionizing mental health management by offering personalized solutions and fostering research and education in the field. ThoughtTherapy, the proposed website for mental wellness, presents opportunities for future enhancements. These include, real-time monitoring using wearable devices for instant interventions, and gamification elements to boost user engagement. Integration with mental health professionals allows for personalized support, while multilingual support ensures accessibility to a diverse audience. These enhancements can elevate ThoughtTherapy's effectiveness in addressing mental health challenges and fostering holistic well-being.

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