IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

INTERVENTION RECOMMENDATION WEB APPLICATION BASED ON USER INTERESTS FOR MENTAL WELL-BEING

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Abstract: The sensitive topic of 'mental health' is increasingly gaining more recognition and respect among people of all age groups. Starting from children to senior citizens, everyone needs aid that will help them keep their mental state healthy. The seemingly fast-paced world and rising competition have contributed to disturbing one's mental condition to an extent. The Coronavirus pandemic has accelerated the decline in the mental health of the majority of people. In such a condition, it becomes both - necessary and beneficial - to use the power of technology in helping people maintain a positive state of mind. With the vast range of advantages that machine learning offers, it becomes easy and effective to cater to individuals as per their choices and preferences. Machine learning is used widely in the healthcare sector because of the benefits it provides by equipping the ability to train models to perform specific tasks based on the information supplied. Similarly, machine learning can be used to help people improve their mental state by learning their favorite activities to engage in to feel better and generate recommendations for activities accordingly. In such a way, it can help uplift a person's mood by giving him a range of options for tasks to perform based on his liking. In an attempt to help people of all age groups improve their mental health, an application was developed which takes into consideration the user's likings and current mental state and recommends intervening activities to participate in.

Index Terms **- mood, mental health, social media, Gmail, chrome extension, deep learning, LSTM, recommendation, hobby, intervention, activity.**

I. INTRODUCTION

The World Health Organization (WHO) announced in September 2021 [1] that depression affects around 280 million people worldwide. Aside from depression, there are numerous other mental disorders that affect people's daily lives. Since 2012, the percentage of youth depression has risen from 5.9 to 8.2 percent [2]. Depression symptoms can have an impact on academic performance as well as personal relationships.

Mental illness affects people of all ages, but teenagers are the most vulnerable demographic. Mental illness affects or will impact 1 in 5 teenagers at any given point in their teenage life [3]. The majority of youngsters are uncomfortable sharing or expressing their emotions in front of their family members. People who work or own businesses frequently face enormous stress, which, if not managed effectively, can lead to major emotional problems. Senior persons frequently suffer feelings of loneliness, anger, aggravation, emptiness, and other negative emotions that, if unaddressed, can contribute to mental illness.

Even if people know that they are hurting emotionally, not everyone is financially secure to seek professional medical care. People frequently neglect mental health issues in favour of their physical ailments. As a result of the aforementioned concerns, there is a need for a solution that is free and at the public's fingertips.

With the help of machine learning, we can devise an application that recommends activities to the users that will elevate their mental state. These activities will be suggested by keeping the user's interest in mind so that the user can benefit the most from the recommendation. This recommendation by the application will act as an intervention to alert the user of a fall in their mental health condition. By engaging in such activities, the user can start feeling better and his mood can be uplifted before it gets out of hand. This application is an extension of the application which detects the mood of the user by monitoring his social media engagement. If the user exhibits symptoms of declining mental health for more than 7-12 days, these intervention activities will be recommended before the user falls into the endless spiral of mental illnesses.

This article is organized as follows: Section 2 describes the literature review that was conducted to research the existing products and tactics on the market. Section 3 discusses the suggested system design. Section 4 describes the resulting application's tech stack, dataset, and implementation, as well as how the program works in its totality. Section 5 contains the results of the application's development. Section 6 concludes the paper and contains the future scope of application and acknowledgment, and the last section lists the references.

II. LITERATURE SURVEY

The following data proposed by WHO [1], around 75% of people belonging to low-and middle-income countries do not obtain therapy due to a lack of finances, lack of qualified specialists, and associated stigma. In the US, a vast majority of children in need of mental health care don't receive enough support. The main drawback of traditional intervention delivery techniques is their inability to scale to the number of needy people [4]. With the aim of overcoming this barrier, research was conducted to discuss new models of delivering interventions [4]. The authors give more emphasis on methods including social media, mobile apps, and social networks because these channels are not only most used by children and adolescents but also convey the ability to scale to a larger user base. The research [4] also states the possibility of the use of social media for obtaining assessments and delivering interventions. It was found that this method is less expensive [4] [5] and is a more convenient way for helping children and adolescents who do not have the privilege to receive professional treatment. Mental health has moved towards secondary prevention [5]. It is found that integrated multi-disciplinary services are needed to increase the range of interventions [5].

One such channel to deliver interventions to the masses is with the use of technology, but the use of technology in this context has very little research done on it. Artificial Intelligence and Machine Learning techniques are currently being explored in the healthcare sector and the recommender technology for overall healthcare is still in its infancy [6]. Healthcare recommendation systems have a significant opportunity in helping the health sector [7]. Machine learning techniques are popularly used in implementing recommender systems in all sectors. One of the problems that a Machine Learning system encounters in making a recommender system is the cold start problem. Research done on the current healthcare recommender systems [6] identifies the need for developing newer patterns for the cold start problem. A survey [8] conducted on personality-aware recommender systems has found that personality-aware recommender systems outperform traditional recommender systems and also help with the cold start problem. But a huge issue that arises is the responsibility of safeguarding users' sensitive data and maintaining high accuracy in personality detection.

A comparative study [9] was done on 5 Machine Learning algorithms on a movie dataset, it was concluded that the Naive Bayes algorithm is the best fit for implementing a recommendation system. Another comparative study [10] found that using only Content-based filtering and Collaborative filtering have their own disadvantages and that combining these filtering techniques with different approaches yields better results. Another popularly used technique is Cosine similarity for determining the similarity between two given texts. A set of authors [11] implemented both TF-IDF and Cosine similarity techniques for building a recommender system for a digital library system that searches for the most relevant research paper as per the user's need. Feedback is an important aspect when the recommendation is driven by the user's preference. One such research [12] for Friendship Recommendation System makes use of feedback from the user to improve the implemented recommendation system and make it work as per the user's preference. Another research [13] proposes an Activity Recommendation System that gives personalization to the user by taking into consideration the user's preferred activities and recommending the most similar activities. If the user's preference or interest is taken into consideration along with the weightage given to it, better prediction can be achieved as compared to only using the filtering techniques [14]. The system proposed in research [14] finds the user's interest in each group of an item and makes a prediction based on the weightage given to previous ratings given by the user. Although Machine Learning and recommender systems may prove to be immensely helpful in the mental health sector, there are some ethical concerns that need to be taken into account. The first ethical challenge viewed by the authors in recent research [15] is that the recommendation system may have poor clarity regarding the sensitive and personal information of a user. Authors of the research [15] suggest that instead of making a sensitive recommendation that the system lacks confidence in or cannot explain that recommendation properly, the system should make a safer or less risky suggestion or hold the suggestion from the user. The second ethical challenge faced is the compromise of a user's privacy and suggestion quality [15] and one must stay transparent regarding the privacy statements made and the inaccuracies of the system. The third one is regarding the app usage history data [15] and the user must have control over the storage of personal information. Considering these points is important while building a recommender system for understanding the user's mental state and making recommendations on it.

Recommendation systems in mental Health provide users with the opportunities to curate and personalize self-guided content and it has the potential to supplement one's mental health therapy in a flexible way [16]. The research was conducted to increase engagement in the self-guided mental health content and it was found that user responses in the form of dialogue were helpful in creating better recommendations in a dynamic fashion [16]. The research studies an application named Ginger and it is an on-demand mental health platform with self-guided mental health content. A review [17] was conducted on the user-centered design approach used in various different intervention delivery platforms. This study [17] consists of 23 different studies focusing on higher education students as the target audience and interventions targeting various areas of mental health such as anxiety, depression, overall well-being, etc. This study [17] highlights that the current research in online interventions for mental health lack personalization for the users and maintenance of user privacy. Another platform for mental health named Project Synergy [18] is built to assist in the assessment, feedback, management and monitoring of people with mental disorders. The platform [18] supports users by suggesting suitable care options. It specifically seeks to use technologies that can deliver interventions early during the course. It was found that the usability score of the platform [18] was 68.2 and falls into the "high marginal acceptable range". Another such platform named Mental App [19] is built with the aim to help university students receive proper help for their mental health. The research [19] studied the changes in the student's mental health before and after usage of the smartphone application. A significant difference was observed after frequent usage of the application and it was concluded that such an application can prove to be effective in the short term [19].

III. PROPOSED SYSTEM DESIGN

Fig. 1 Proposed System Design

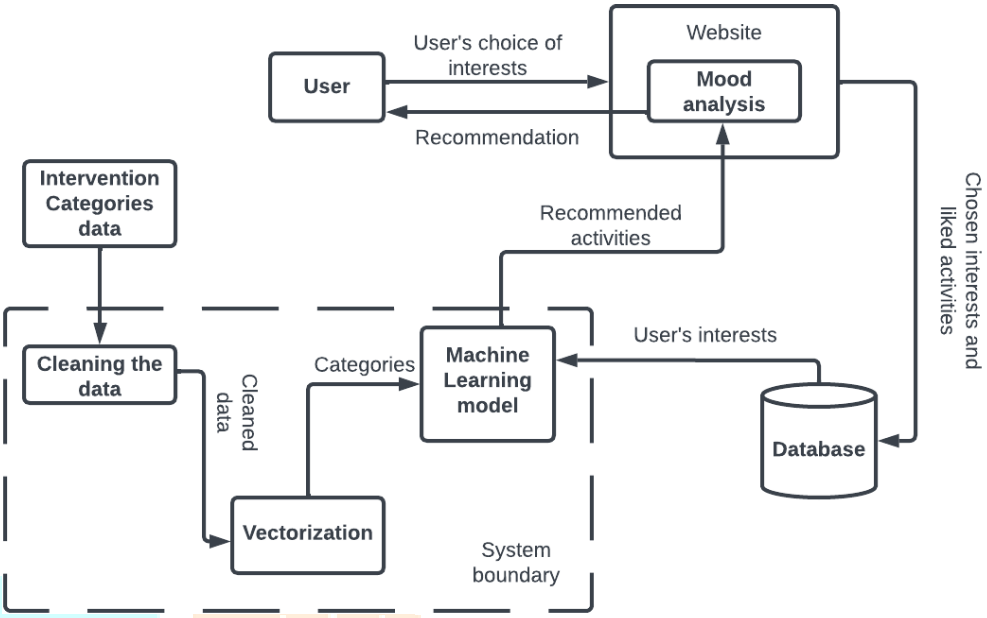


Figure 1 demonstrates how the suggested system works. The system diagram for our proposed system shown here depicts the system's input and output, flow of data, and other events occurring in various regions of the system.

III a. Activity Recommendation model

The Activity Recommendation system forms the second most important part of the system. It takes the user's interests and provides interventions as a combination of both user's liked activities as well as similar activities. This combination is based on weightages given to activities, such that the more weightage given, the more likely itis to be recommended. A list of such activities is shown to the user to select from as activities of interest.

III b. Cleaning the data and Vectorization

For the model to find similar activities to the one chosen by the user, activities are assigned one or more categories. They are as follows - Art, Sports, Music, Movies, Fitness, Games, Craft, Literature, Educational, Theatre, Adventure, Cooking, Entertainment, Travel and Collection. The categories given to a hobby are first cleaned for unwanted words, punctuation and white spaces to form vectors with categories. This helps the machine learning model to make a comparison to find the best match.

III c. Machine Learning model

The machine learning model used to find the best match is Support Vector Machine which makes use of a Sigmoid Kernel. It finds the activities with the most matching categories to add to the recommendation.

III d. Website

Users send the login/registration data to the Database via the Website for authorization. The Website for the system acts as a platform for the end user to view the profile data, user's personal interests and other recommendation related options. The data is retrieved from the Database for the corresponding user and displayed on the website for the logged in user.

IV. IMPLEMENTATION

The application's actual implementation is presented in this section. This web application is built using the Python framework Django and MySQL database. A chrome extension is also developed using JavaScript and jQuery to extract the data postedby the user. This application is a full-fledged application for mental health analysis of any user through the data collected from social media like Twitter, YouTube, and platforms like Gmail. It also allows user to report their daily activities in the form of dairy writing. It performs sentimental analysis on the data collected and based on the results recommends intervention to users based on their interests. This application is divided into 2 main parts:

1. Collecting social media data through browser extension and performing sentimental analysis on it.
2. To recommend user-liked activities to uplift their mood.

"How was your day?", "How are you feeling right now?", "Is anything bothering you?" and other topics are all acceptable for users to post about. After that, this textis examined, and the user's input is subjected to sentiment analysis to forecast their mood. The chrome extension is used by this application to gather user social media data from YouTube, Twitter, and Gmail service. When a user watches a YouTube video, sends an email, or updates a Twitter post, the extension scrapes the data. Sentiment analysis is then applied to the scraped data and this acts as an input tothe application to forecast the user's mood.

The application also provided a graphically organized summary of the user's most recent seven days of mood analysis. The general mood of the day is determined bythe intensity of the day's emotions. Users can view all of the application's analysis for the full time they were active, as well as for the previous three, seven, and fourteen days. According to the counselor's advice, if unpleasant emotions persist for longer than 7 to 12 days, the person should pay closer attention to their mental health. A notification is delivered to the user regarding unpleasant feelings if they persist for more than 14 days.

The application also recommends interventions to users if the user is found to be ina negative state of mind. These interventions can help them boost their mood which can help to improve the mental state of users.

This application uses a machine learning model to detect users' emotions. This modelis trained using Bi-direction LSTM (Long Short-Term Memory) algorithm. To train this model, the dataset was used from Kaggle. The dataset has 2 columns- text andemotion. The text column contains the input text and the emotion column contains the actual emotion associated with the text. This application uses Support Vector Machine which makes use of a Sigmoid Kernel to find best-suited activities for usersto uplift their mood.

The section below describes the implementation of the 2nd part of the application. Based on the proposed system flow diagram, following are the implementation details.

IV a. Profile

Fig. 2 User's Profile page

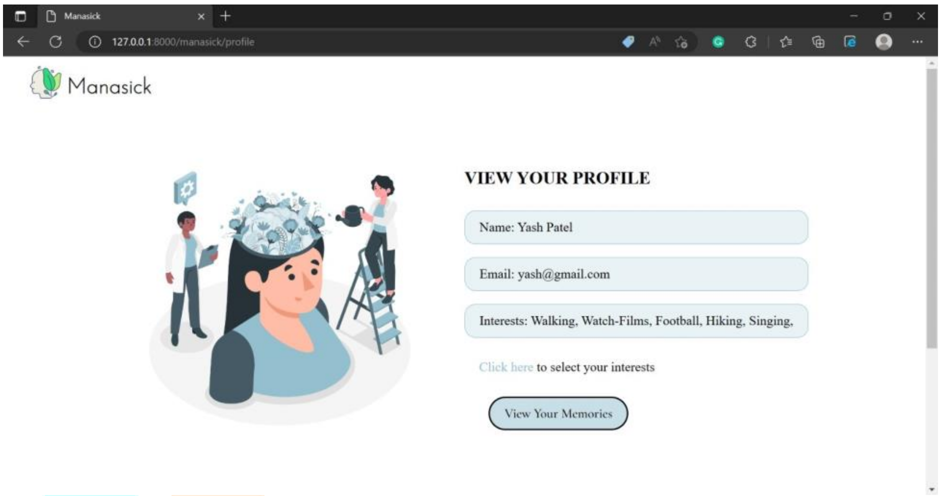


Figure 2 represents the profile of the user. It displays the personal information of the user such as Name and Email ID. It also displays the selected interests of the user.It contains a button for the user to go to the Select Categories page to select activities of interest which will be displayed on the user's profile page. It also contains a button named 'View your memories' which redirects the user to the Memories display page.

IV b. Recommendation

Figure 3 shows a wide choice of categories from which the user can choose his/her activities of interest. The categories are as follows - Art, Sports, Music, Movies, Fitness,Games, Craft, Literature, Educational, Theatre, Adventure, Cooking, Entertainment, Travel and Collection.

Fig. 3 Select Categories Page

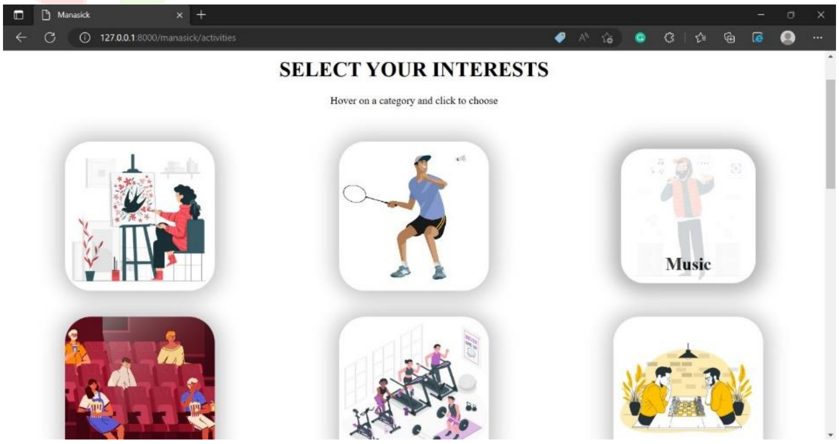


Fig. 4 Activity selection in given category

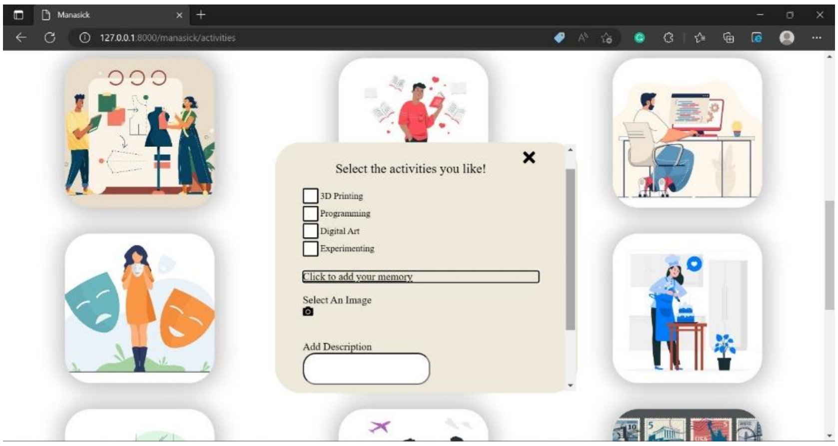
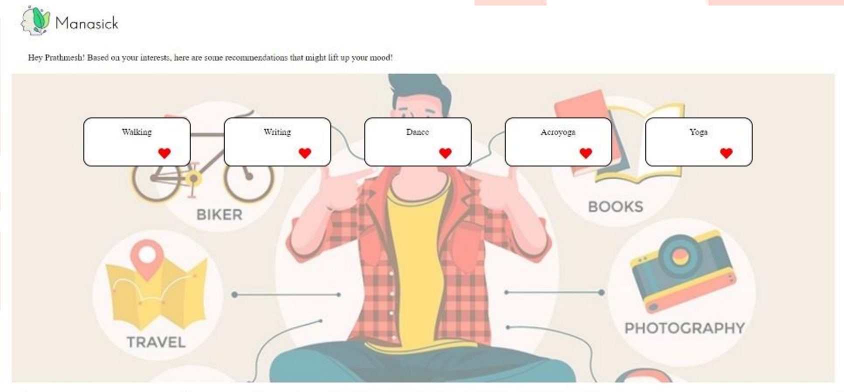


Figure 4 shows a popup for a given category. It lists all the activities that fall under the given category and the user can select multiple activities at a time. On the popup, the user is given the option to upload pictures of them pursuing their hobbies with a description that can be viewed by the user at a later time as happy memories. Figure 5 shows a list of interventions recommended to the user based on the user's profile and liked activities. More weightage is given to the user's selected activities as compared to the non-selected activities. Moreover, the weightage increases as the user likes an intervention recommended to him/her. Hence, the recommended interventions are ordered according to their resulting weightage. If a smaller number of interests are selected by the user from the Select Categories page, then the interventions are recommended based on similar activities to that of the selected interests of the user. Similar activities are found using an approach named Sigmoid Kernel.

Fig. 5 Recommendations Page



IV c. User's memories

Fig. 6 Page to display user's fond memories

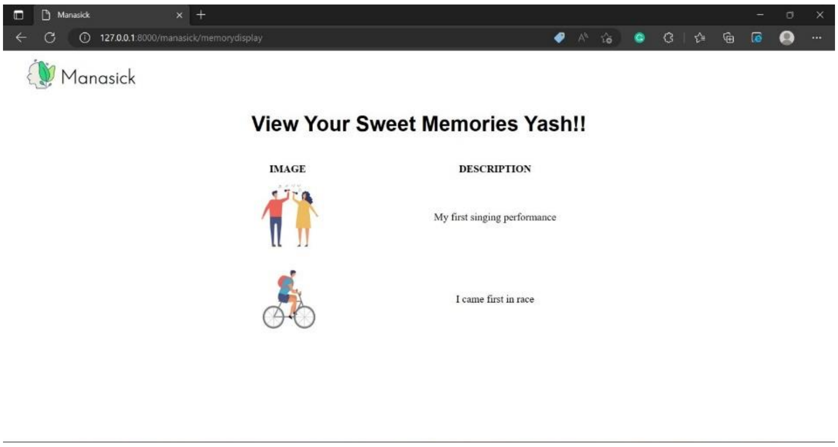


Figure 6 represents the Memory display page where the images uploaded by the user are shown along with their descriptions. Here users can view pictures of him/her pursuing his/her hobbies.

V. RESULTS

The Machine Learning model used for recommending interventions based on the user's preferred activities was able to achieve an accuracy of 85% against a testing dataset. After developing the web application, testing was conducted across 20 users. The data was collected from all of these users regularly over the course of 2 months. This data included the current mood as registered by the users themselves. For users suffering from low mood, interventions were recommended after taking into consideration the individual interests of the users. The users submitted feedback immediately after per- forming the interventions which were recorded as well. The feedback was included to record how satisfied the user was, on a scale of 1 to 5, with respect to the recommendation provided by the Machine Learning model for their current low mood. After analyzing the responses of the users from the feedback, it was found that the recommendation system was able to achieve an Average User Satisfaction score of 3.9 outof a maximum value of 5.

The table 1 presents a comparison of the developed application with a few other applications already available in the market considering a number of features. The table compares the proposed system features and also specifies what alternativefeatures are present in the rest of the applications mentioned in the table.

Table 1. Table showing a comparison between the proposed application and 2 applications available in the market

Features	Manasick (our proposed application)	Happify (Mood boosting app)	MoodKit (Mood improvement app)
Scientifically proven activities	Yes	Yes	Yes
Interventions are automatically recommended during low mood	Yes	No	No
User personalization in activities	Yes	Yes	Yes
Range of categories to choose from	15 categories	60+ tracks	5 categories
Guiding material for performing activities	No	AI coach	Examples and some tips provided
Storing happy memories	Yes	No	No
Community participation	No	Forums	Progress sharing

Both of the above-mentioned applications, Happify [20] and MoodKit [21], are some of the leading applications in the market in the mental health category and include using interventions for users' mental well-being as a major feature in them. As given in table 1, the first feature considered for comparison is whether the applications use scientifically proven interventions to enhance the mood of the user and it is true for Happify, MoodKit and our proposed system. The second feature for comparison is whether the interventions for users are being recommended by the system itself. Our proposed system uses Machine Learning to recommend these interventions to the user whereas, in Happify and MoodKit, the users are expected to choose an intervention for themselves. The third feature for comparison is whether the users have the ability to choose interventions that align with their interests. Our proposed system asks the users to choose hobbies from the given categories and recommends interventions that align with their choice. Similarly, in Happify and MoodKit, the users have the freedom to choose interventions aligning with their interests. The fourth feature for comparison is the available range of categories to choose from. Our proposed system provides enough categories for the users to choose their interests from as compared to Happify and MoodKit. The fifth feature for comparison is whether some guiding material is being provided for assisting users with their interventions. Our proposed system does not provide any guiding material whereas some helpful material is being provided for users in Happify and MoodKit. The sixth feature is whether the users are given a feature to store happy memories from them performing their interventions or not. Our proposed system provides this feature so that the users can store their happy memories and look back at them for motivation and to track progress. This feature is not a part of the Happify and MoodKit apps. The seventh feature for comparison is whether the users can actively participate in the community or not. Our proposed system does not include a feature for users to participate in the community but Happify and MoodKit include ways for users to actively participate by posting on forums and sharing their progress with other participants respectively. Our proposed system has a scope in the above-mentioned areas to improve in the future.

VI. CONCLUSION

In this project, primarily we devised a method to take users' interests as data and use it to recommend interventions when users are suffering from low mood. As stated earlier, there are many people who neglect their mental health and any concerning symptoms that might indicate mental illness. The proposed system makes it easier for users to include activities in their lifestyle to deal with negative moods easily.

The application is successfully able to collect data regarding users' interests through the user profile and store it for later use. The application is successfully able to run the machine learning model and the recommendation algorithm to recommend interventions to the users. This application is also successfully able to store images of happy memories uploaded by users for encouraging users to engage in their liked activity and to help users track their progress. The application is also able to record the likings of users for particular activities suggested to them and adjust the recommendations based on the users' inputs.

The system can be of great use to anyone trying to inculcate the habit of releasing their anxiety and negative thoughts and thus uplift their mood in a healthy manner. The future scope for the web application includes detecting the levels of stress, loneliness, and anxiety that the user goes through from their social media data and helping the user with connecting to the nearest mental health support professional or counselling services.

VII. ACKNOWLEDGEMENT.

All authors contributed significantly to the work detailed in the publication under the supervision of Dr. Nataasha Raul and Prof. Meghana N. (e.g., building the application, providing technical assistance, assisting with writing and editing, general support).

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