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Zenspace: A Machine Learning Model for Mental Health Tracker Application

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Abstract: Mental health is a critical concern in today's environment. The ability to adjust with maximum efficacy, happiness, satisfaction, socially responsible behavior, and the ability to face and accept reality are all regarded signs of mental health. Our paper aim to design a system architecture which is based on "Mental Health Tracker". This identifies the mental health of the user by asking few questions. Using this model, a person can use this model to overcome their mental illness and lead a happier life With the help of some chores or activities they can engage in to achieve their objectives or by recommending therapy.

Keywords: *Age, Anxiety, Depression, Gender, Mental Health, Mobile Application, Prediction*

1. Introduction

Mental health is an important issue in the world today. A person's adjustment with a maximum of efficacy, pleasure, happiness, socially responsible behaviour, and the capacity to face and accept reality are all considered indicators of their mental health [1]. According to the WHO, every sixth Indian needs mental health help and yet the treatment gap ranges between 70% and 92% for different mental health disorders. As such, it becomes important to track and remedy any problems before they get too serious. We are trying to achieve this by making an application for the same. By combining App Development with data science, we hope to create an application that will have a positive impact.

Many individuals struggle with managing and understanding their mental health, leading to difficulty in tracking symptoms and identifying patterns. This can make it challenging for individuals to communicate effectively with their healthcare providers and make informed decisions about their treatment. The goal of this app is to provide a convenient and user-friendly way for individuals to track their mental health symptoms and patterns over time, allowing them to better understand their condition and make more informed decisions about their treatment. Emotional wellness is among the most crucial components of mental health and wellbeing. It is difficult to track daily changes in emotional state over extended periods of time using standard methods. Giving mental health support is particularly difficult because only about one in two people who experience mental health problems seek professional assistance. A durable method of improving emotional self-management is provided by mobile phone technology by us.

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2. Benefits of Mental Health Tracker

Mental health apps have potentials in improving the monitoring and management of mental health symptoms or disorders [2]. The promotion of self-awareness, early problem diagnosis, and efficient management of mental health can all be achieved with the help of mental health tracking. If you're having mental health issues, you might want to look into your alternatives for tracking Some benefits of mental health tracking:

• Increased self-awareness: You can improve your awareness of your moods, feelings, and behaviors by keeping a mental health journal. You can have a better understanding of your mental health and make wise decisions about your wellbeing by recognizing trends and triggers.

• Early detection of mental health issues: You can spot potential mental health problems early on by keeping track of your mental health. Recognizing changes or swings in your mood will enable you to get assistance before the problem gets worse.

• Improves communication with mental health professionals: Maintaining a mental health journal might improve your interactions with mental health experts. You can give your doctor or therapist more accurate information by keeping a diary of your symptoms and experiences.

• Identification of effective coping strategies: You can find coping mechanisms that work for you by keeping track of your mental health. You can create a unique toolset for managing your mental health by experimenting with various methods and gauging their efficacy.

• Increased motivation: You can maintain your motivation to give your mental health and wellbeing a priority by tracking your mental health. A significant source of inspiration and motivation can come from observing progress over time.

3. Literature Review

Rickard N, Arjmand H, Bakker D, Seabrook E attempt to outline the creation of a mobile phone app that can track emotional changes in real time and in the course of normal daily activities. This research-based mobile phone software tracks emotional, mental, and overall health as well as connects to websites and other resources for mental health organizations. The software collects data using automated behavioral data collecting, experience sampling methodology (ESM), and self-report psychological questionnaires [3].

Kathleen M. Griffiths, Helen Christensen took two websites BluePages Depression Information and MoodGYM to find all controlled and uncontrolled studies of their effectiveness. They focused their review on publications that had been published, reports, dissertations, conference presentations, and articles that had been submitted or were being prepared. They derived a total of 12 papers and reports from nine separate studies of MoodGYM and BluePages[4]. They wanted to measure the outcomes which include levels of depressive and anxiety symptoms, dysfunctional thoughts, depression literacy, stigma, help seeking and cost-effectiveness.

Grist R, Porter J, Stallard P[5] looked between January 2008 and July 2016 for relevant publications in fifteen internet databases for use by children and teenagers under the age of 18. They included abstracts summarising mental health apps for electronic devices, mobile phone, or tablet. They incorporated theses, conference proceedings, case studies, RCTs, uncontrolled feasibility studies, qualitative research publications evaluating teen-targeted applications available in app stores and articles describing app design and implementation to make sure they were capturing current and developing evidence. Apps being tested include Crisis Care, Mobile Mood Diary and Copesmart.

Torous, J., Wisniewski, H., Bird, B examined the LAMP (Learn Assess Manage and Prevent) platform in this study as an example of how the platform and the app that supports it may be co-designed to suit the overlapping demands of the clinical/research and patient/consumer populations. They see LAMP as a sociotechnical system that depends on both technology and people [6], much like a learning healthcare system is also a sociotechnical system that relies on new technologies to help gather and analyse data and interdisciplinary teams to implement change. The healthcare system, technology, and app capabilities will all continue to change, but the point at which patient needs for digital mental health (such as trust, control, and community) and clinical research needs for digital mental health (such as transparent, data-driven, translational) converge is likely to stay the same.

Eisenstadt A, Liverpool S, Metaxa A, Ciuvat RM, Carlsson C performed mixed-method analysis of data to conclude their findings. They gathered anonymous real-world data on the user demographics and well-being as well as the usability and acceptance of the app using validated surveys and open-ended questions. Before completing the follow-up tasks, participants used the app for at least two weeks. It was possible to track the degree of app engagement using Google Analytics [7]. Quantitative data were analysed using chi-square and two-tailed t tests, and qualitative data were analysed thematically.

App being reviewed: the Paradym app

Miranda Olff's methodology entails gathering information on numerous mobile health applications designed to treat particular diseases and evaluating their efficacy in a test group. Who has access to the data and who owns the data are other crucial queries when using data gathered by mobile apps to advise health professionals or policy makers[8].

David Bakker, Nikki Rickard followed this methodology: Participants completed in-app evaluations at the beginning of use and once more 30 days later after downloading the MoodPrism app from the iOS and Android app stores. The results raise the possibility that additional important mediators were not taken into account, and subsequent research could use alternate methodologies—for example, comparison with a control group [9]—to confirm the results.

The safety and efficacy of mobile mental health apps for treating psychological conditions like depression, anxiety, and addiction was studied by 42 statistical analyses and systematic reviews in the study. K. Wang, D. S. Varma, and M. Prosperi discovered that using mobile mental health apps as a supplement to conventional treatment can significantly improve mental health results[10]. The study did, however, also point out a number of drawbacks and hazards relating to mobile mental health apps, such as problems with data security and privacy, an inadequate degree of restrictions, and the potential to worsen pre-existing gaps in access to services related to mental health.

According to Miriam Cabrita, Monique Tabak and Miriam Vollenbroek-Hutten, a mobile app-based mental health tracker has the potential to be a useful tool in the management of depression and could assist people with mental health disorders live better lives. They do, however, also note that more study is required to confirm these results and examine the potential of the mental health tracker in various settings and demographics[11].

The mobile app-based depression seriousness score, according to the J. Koh, G. Y. Q. Tng, and A. Hartanto, has the potential to be a useful tool for depression treatment and early detection. They propose incorporating the app into standard clinical practise to aid medical professionals in the identification and therapy of depression, as well as to raise the standard of care for individuals who are depressed[12]. They do admit that additional study is required to confirm these results in broader and more diverse populations.

The apps' functionality and usability varied, M. E. Larsen, J. Nicholas, and H. Christensen discovered, and only a small number had undergone thorough testing for efficacy. Some of the applications, however, showed promise in terms of their capacity to offer assistance and resources to those who are at risk of suicide as well as their potential to help medical professionals diagnose and treat suicidality[13].

J. Torous, J. Nicholas, M. E. Larsen, J. Firth, and H. Christensen[14] come to the conclusion that although there is potential for mobile phone apps to play a significant role in the management and prevention of suicidality, further study is required to confirm this potential and to pinpoint the optimum methods for their development.

If we want to create apps that the target demographic will use and adopt, it's essential to understand what they think. F. Alqahtani and R. Orji used thematic analysis to find the main themes in a qualitative study we conducted on 106 mental health apps available on the Apple App Store and Google Play[15]. They specifically found the features and attributes of the apps that users enjoyed, disliked, and suggested improvements to in order to generate insights into the strengths and shortcomings of the available mental health apps. This review adds to the body of research by highlighting the features of mental health apps that consumers value most and that developers should take into account.

S. M. Schueller, M. Neary, J. Lai, and D. A. Epstein was to identify the participants' perceptions of the advantages and restrictions of mood-tracking applications. Benefits included better emotional control, more self-awareness, and facilitated contact with mental health professionals[16]. Concerns regarding privacy and security, challenges with regular and prolonged usage, and possible detrimental effects on mental health, such as increased anxiety or reliance on the app, were some of the limitations. In order to fully understand the benefits of mood-tracking applications, customisation possibilities, and integration with other mental health therapies, further study is required, as the paper's conclusion emphasises. The results of this study offer important new understandings into the reasons, experiences, and viewpoints of people who use mood-tracking applications, and they may guide the creation and enhancement of such apps to better serve users.

For creating highly effective mobile apps for mental health, P. Chandrashekar offers suggestions. These suggestions include evidence-based interventions, guaranteeing user-friendliness and ease of use, personalization based on user needs, including mechanisms for monitoring and feedback, addressing privacy and security issues, and integrating with current mental health care systems[17].

Yu Chen and the other authors analyse the features and user testimonials of mobile apps made for tracking mood. The study looks at the different features that these applications have to offer and analyses user feedback to determine how effective and popular they are. The writers look into the features of mood-tracking apps and examine user comments to find recurring themes and trends[18]. In addition to outlining areas for improvement and prospective prospects for more research and development in this area, the article offers insights into the advantages and disadvantages of the already available mood tracking apps.

A useful methodology for rating health apps was presented by Philip Henson, Gary David, Karen Albright, and John Torous. The authors draw attention to the rising demand for health apps and the necessity of a standardised evaluation procedure to guarantee their efficacy[19]. The architecture is made to be thorough yet useful, taking into account the particular characteristics of health apps. It includes the following four important aspects: therapeutic effectiveness, usability, security and privacy, and engagement. The authors also stress the value of including pertinent parties in the evaluation process, such as clinicians, patients, and app developers. The suggested framework intends to offer a systematic method for assessing health apps and promoting their secure and efficient use in healthcare environments.

With a focus on compelling design concepts, Kong Saoane Thach and Thi Phuong Nam Phan present a qualitative examination of user ratings of mental health apps [20]. Based on user reviews, the authors investigate how users assess the persuasive design components of mental health apps, such as feedback, reminders, social impact, and personalisation. The report highlights major themes in the user reviews and offers user-perspective insights regarding the efficacy of persuasive design concepts in mental health apps. Overall, the report clarifies the crucial part persuasive design concepts have in influencing how users interact with and view mental health apps.

Kyriaki G. Giota and George Kleftaras explore the innovations, dangers, and ethical issues surrounding the current crop of mhealth apps. The authors emphasise the potential advantages of mental health apps, such as greater monitoring and self-management, decreased stigma, and improved availability of mental health care[21]. They also draw attention to dangers such the absence of evidence-based methods, the possibility of misinformation, and problems with data privacy and security. Also included are moral concerns including informed permission, privacy, and the value of human contact in the treatment of mental illness. In order to ensure the responsible and efficient use of mental health applications in clinical practice, the study emphasises the need for additional research, regulation, and ethical norms.

Til Wykes, Jessica Lipshitz, and Stephen M. Schueller talk on the necessity of moral guidelines for the diverse applications of digital psychological wellness. The authors draw attention to the potential advantages of digital mental health interventions, such as their enhanced accessibility and scalability, but they also express concern over any potential moral dilemmas, such as those related to confidentiality, data security, equity, and informed permission. The authors put up a framework that incorporates values like openness, equity, responsibility, and inclusivity for ethical issues in digital mental health[22]. They urge interdisciplinary cooperation between interested parties, such as researchers, practitioners, policymakers, and users, in order to establish moral guidelines that guarantee the moral and responsible application of mental wellness innovations.

Jamie M. Marshall, Debra A. Dunstan, and Warren Bartik discuss the use and efficacy of hand-held emotional wellness apps for people experiencing anxiety and depression. The authors look at the advantages of utilising mobile apps, such as convenience, stigma reduction, and easier access to medical care. They also draw attention to issues with data privacy and security, the possibility of false information, and the shortage of scientific backing for many apps' efficacy[23]. In order to assess the clinical efficacy and safety of mobile mental health apps, the report emphasises the necessity for thorough research and evaluation. The authors underline the importance of evidence-based methods and the necessity for regulation and instructions in order to ensure the responsible use of mobile apps in the treatment of anxiety and depression.

A thorough analysis of the usage of smartphones in the field of mental health is provided by Michael Bauer, Tasha Glenn, and Peter C. Whybrow. The authors go over the historical context around the widespread usage of cell phones, as well as some of their potential advantages, like improved access to mental health resources, self-monitoring, and customised interventions. They also draw attention to the difficulties, such as worries over data privacy and problems with the dependability, accuracy, and integrity of mental health apps[24]. They also stress how crucial it is to involve consumers, healthcare professionals, and other stakeholders in the development and implementation of smartphone therapies.

4. Methodology

This study aimed to develop a mental health detector that can classify people based on 21 features into one of three classes: 'therapy', 'no therapy', or 'recommend self-help tasks'. To achieve this, a list of questions related to the mental health of an individual, were framed for a survey under the guidance of a licensed therapist. The survey was distributed online via various social media platforms and email to reach a diverse range of participants. The survey consisted of 21 questions related to mental health, including questions related to anxiety, depression, stress, sleeping habits, and physical activity. In total, we received 260 responses, which were then used as our dataset.

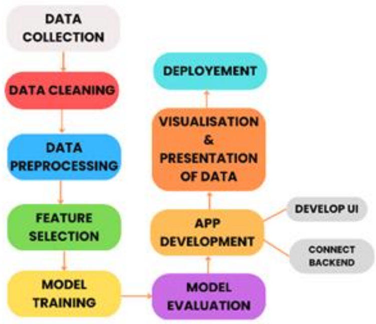

Fig. 1. Block Diagram of the Data Processing

To ensure data quality, we cleaned the dataset by removing missing values and duplicates. After cleaning, we had an analytical base table ready for analysis. We analysed the data using visualizations to understand the relationship between each feature and the target variable. The target variable was the mental health classification of each participant, which was based on their responses to the survey questions. We used various visualization techniques such as histograms, scatter plots, and correlation matrices to explore the relationship between the features and the target variable.

After analysing the data, we developed a classification model using various machine learning algorithms such as Decision Tree, Random Forest, Bagging, AdaBoost, LightGBM, Gradient Boosting, XGBoost, and SVM. We selected the Random Forest algorithm for our final model, which had an accuracy of 76% and an F1 score of 74% after hyperparameter tuning. We also developed a graphical user interface (GUI) that takes in the input and predicts the output in real-time. The GUI was developed using Gradio library and can be accessed from any desktop or laptop computer with an internet connection.

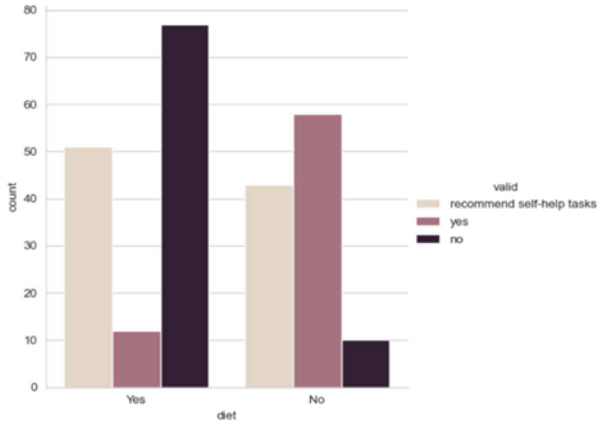

Fig. 2. Relationship between mental health and diet

The importance of maintaining a healthy diet for physical health has long been recognized, but its impact on mental health has received increasing attention in recent years. In this exploratory data analysis, we found that there is a significant relationship between diet and mental health. As shown in Figure 1, people who have a healthy diet are mentally seen to be healthier. The graph indicates that out of the 39 people who were recommended therapy, 32 did not have a healthy diet, while only 7 of them did. This finding suggests that promoting a healthy diet may be an effective way to improve mental health. Further research is needed to investigate the causal relationship between diet and mental health and to determine the most effective ways to promote a healthy diet for improved mental health outcomes. Nonetheless, our results provide preliminary evidence that dietary interventions could be a promising strategy to enhance mental health.

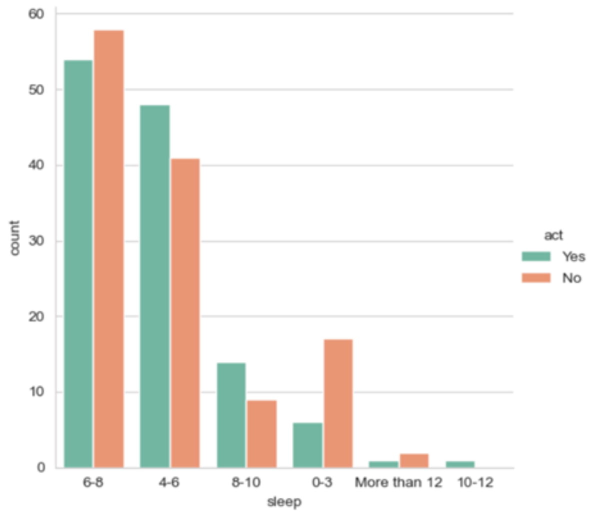

Fig. 3. Relationship between Physical Exercise and Sleep

Figure 2 presents a visualization of the relationship between sleep duration and daily activity levels. The data shows that individuals who sleep between 4 and 6 hours per night can maintain a higher level of activity during the day compared to those who sleep less or more than this range. This suggests that 4-6 hours of sleep may be an optimal range for individuals seeking to balance their sleep needs with their daily activities. Further research is required to understand the underlying mechanisms for this effect and to investigate whether other factors, such as sleep quality or timing, may also play a role in determining the relationship between sleep and daily activity. Nevertheless, this insight can potentially inform interventions aimed at improving individuals' mental health by encouraging them to adopt healthy sleep habits and prioritize adequate sleep duration within this optimal range.

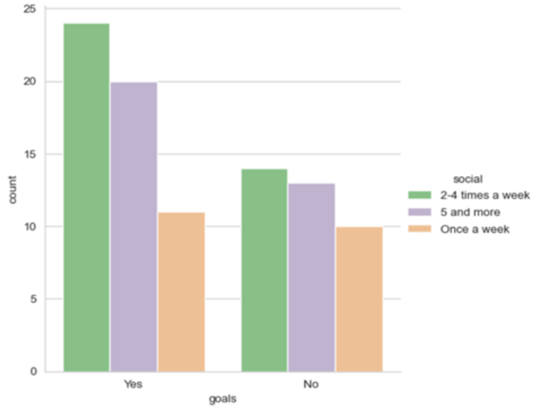

Fig. 4. Relationship between Social Interaction and Goals

The presented graph indicates a positive correlation between social interaction and personal goal setting. It highlights that people who engage in regular socializing and connecting with others are more likely to set personal goals and accomplish them. This relationship suggests that interacting with like-minded people can act as a motivational factor, stimulating individuals to achieve more in life and learn from others. These findings hold potential implications for mental health, as setting and achieving goals has been shown to improve one's sense of purpose and fulfillment, while social interaction can have a positive impact on mental health and well-being. These insights can inform the development of interventions to improve mental health, which focus on increasing social interaction and goal setting among individuals.

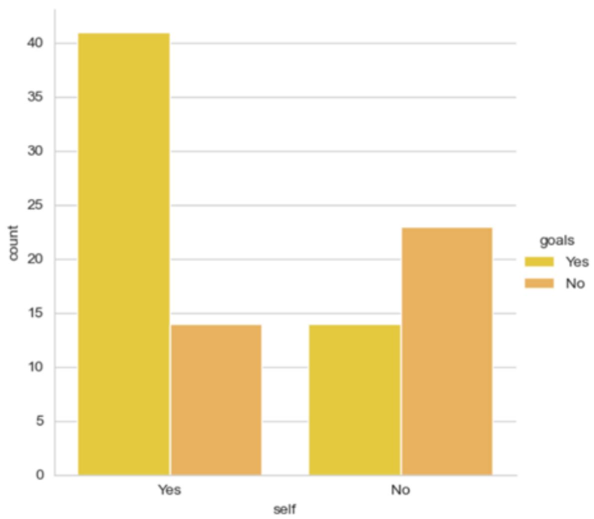

Fig. 5. Relationship between Self Care and Mental Health

4.1 XGBoost Algorithm

XGBoost (Extreme Gradient Boosting) is an optimized implementation of the gradient boosting algorithm. It is a popular algorithm for solving various supervised learning problems, including classification and regression. XGBoost builds an ensemble of weak decision trees and combines their predictions to produce a final output.

In XGBoost, the model is built in a forward stagewise manner. Each manoeuvre of the process involves training a weak decision tree to minimise a loss function, which calculates the discrepancy between the output that was predicted and the final result. The loss function is typically a measure of the error in the predicted output, such as the mean squared error or the cross-entropy loss. The tree is trained using a gradient descent algorithm to find the optimal split points that minimize the loss function.

The XGBoost algorithm also introduces a regularization term in the loss function to prevent overfitting. The regularization term penalizes the complexity of the model and encourages the use of simpler trees. The regularization term is a combination of two terms: L1 regularization (lasso regularization) and L2 regularization (ridge regularization). The L1 regularization term penalizes the absolute values of the model coefficients, while the L2 regularization term penalizes the square of the model coefficients.

The final output of the XGBoost algorithm is a weighted sum of the predictions of all the weak decision trees. The weight of each tree is determined by its performance on the training data and the regularization term. The formula for the final output is given by:

$y(x) = \sum w(i) * f(i)(x)$

where $y(x)$ is the predicted output, $w(i)$ is the weight of the i-th decision tree, and $f(i)(x)$ is the predicted output of the i-th decision tree.

In conclusion, the XGBoost algorithm is a powerful machine learning algorithm that builds an ensemble of weak decision trees to produce accurate predictions. It introduces regularization terms to prevent overfitting and combines the predictions of all the trees to produce a final output. The XGBoost algorithm has been successfully applied to various supervised learning problems and has become a popular choice in data science competitions.

4.2 Random Forest

Random Forest is a popular ensemble learning method for classification, regression, and other tasks. It builds a collection of decision trees, where each tree is trained on a random subset of the training data and a random subset of the features. The predictions of all the trees are combined to produce a final output.

In Random Forest, the decision trees are trained using the CART (Classification and Regression Trees) algorithm. CART builds binary trees by recursively partitioning the data into smaller and smaller subsets, based on the values of the input features. The partitioning is done by selecting the feature that best separates the data based on some criterion, such as the Gini index or the information gain.

The Random Forest algorithm introduces two main sources of randomness to the decision tree construction process: bootstrapping and feature sampling. Bootstrapping involves randomly sampling the training data with replacement to create a new subset for each tree. Feature sampling involves randomly selecting a subset of the features at each split point in the tree.

The final output of Random Forest is a weighted average of the predictions of all the decision trees. The weight of each tree is determined by its performance on the out-of-bag (OOB) data, which is the data that is not included in the bootstrapped subset for that tree. The formula for the final output is given by:

$y(x) = \sum w(i) * f(i)(x)$

where $y(x)$ is the predicted output, $w(i)$ is the weight of the i-th decision tree, and $f(i)(x)$ is the predicted output of the i-th decision tree.

In conclusion, the Random Forest algorithm is a powerful ensemble learning method that builds a collection of decision trees by randomly sampling the training data and the features. It produces accurate predictions by combining the predictions of all the trees. The Random Forest algorithm has been successfully applied to various machine learning problems and has become a popular choice in industry and academia.

5. User Interface

In the first phase of our project, we made a Graphical User Interface. A graphical user interface is a form of user interface that uses visual components like buttons, windows, and icons rather than text-based commands to let users interact with digital devices like computers and mobile phones. GUIs are intended to improve the usability and intuitiveness of digital devices.

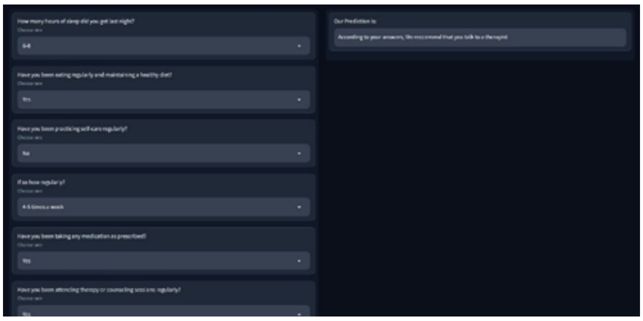

Fig. 6. GUI of the form with the questions

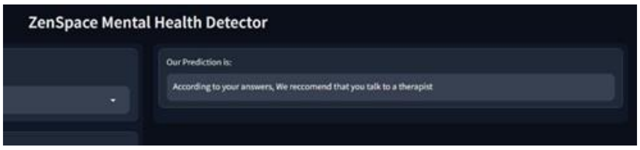

Fig. 7. GUI with the final submit button

Our Graphical User Interface accepts the answers for the questionnaire and predicts the output using the data science model. Gradio is being used for the creation of Graphical User Interface.

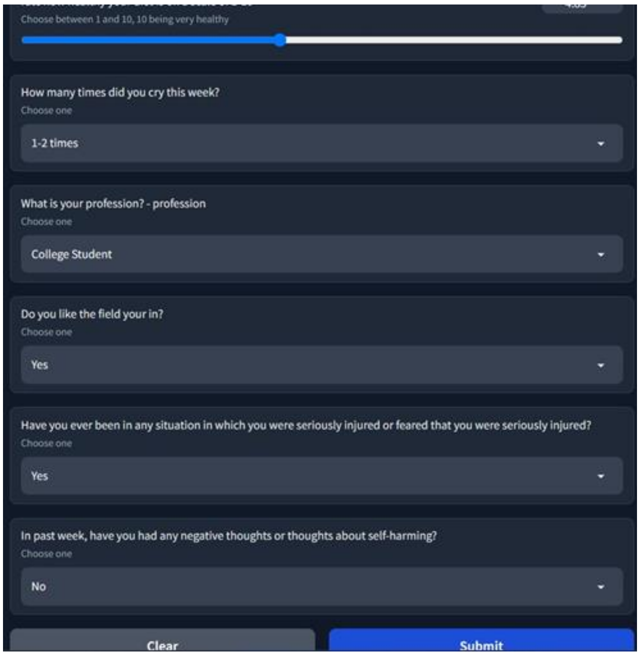

Fig. 8. Frame in which the diagnosis given by our model will be displayed

The answers given by the user through the GUI will be fed to the prediction model which will give the diagnosis/ recommendation.

6. Ethical Considerations

The aim, usage, and potential risks of recording mental health data should all be made explicit and understandable in the app. To participate in the tracking, users must give their informed consent, which they should be able to change at any moment. To preserve users' privacy, the app shall maintain the secrecy and security of any personal information it collects. The app should make sure to comply with all applicable data protection laws, including the GDPR, and explicitly state its data privacy policy. To ensure the accuracy of the data gathered, the app should track mental health data using trustworthy and tested methods. The software shouldn't stigmatise or categorise users based on their state of mental health. The wording used in the app should be tactful and refrain from supporting stereotypes or unfavourable viewpoints towards mental health conditions. The app should be created to guard against any potential harm to the user, such as distressing them or increasing their symptoms. If a user needs more help, the app should offer resources and assistance.

All users, including those with impairments or poor technological skill, should be able to access and utilise the app. The funding sources, alliances, and any potential conflicts of interest that might affect the creation or usage of the app should all be disclosed by the app creators.

7. Results and Discussion

The Graphical User Interface takes inputs from the user and predicts the output with help of the data science model. The users have to answer the questionnaire and the Graphical User Interface will predict the output. The output will tell the users whether they need therapy or not, or they just need some self-help tasks. The future of the project would be to make an interactive application for this model where users can get a better interface and experience.

8. Conclusion

In conclusion, we have successfully developed a mental health detector that can classify people based on 21 features into one of three classes: 'therapy', 'no therapy', or 'recommend self-help tasks'. Our study used first-hand data collected through a survey, which was then cleaned and analyzed using various visualization techniques and machine learning algorithms. We developed a Random Forest classification model with an accuracy of 76% and an F1 score of 74% after hyperparameter tuning, which outperformed other models developed in this study.

The advantages of our model include its high accuracy and F1 score, which can help healthcare professionals identify individuals who may require therapy or self-help tasks to improve their mental health. Additionally, our model can help in early intervention, which can lead to better mental health outcomes for individuals. The ability to recognise patterns, triggers, and progress over time might help users become more self-aware and achieve better mental health results. It's crucial to remember that a mental health tracker should never take the place of expert medical advice or treatment and that it should only ever be utilised in conjunction with the necessary therapeutic care.

However, there is scope for improvement in this study. The dataset used in this study is limited to a small sample size of 260 participants, which may not be representative of the wider population. Future studies can focus on collecting data from a larger sample size to improve the generalizability of the model. Additionally, incorporating other factors such as social and economic factors can further improve the accuracy of the model. Nevertheless, our study provides a promising foundation for further research on mental health detection and classification.This research was supported/partially supported by [Name of Foundation, Grant maker, Donor]. We thank our colleagues from [Name

of the supporting institution] who provided insight and expertise that greatly assisted the research, although they may not agree with all of the interpretations/conclusions of this paper. We thank [Name Surname, title] for assistance with [particular technique, methodology], and [Name Surname, position, institution name] for comments that greatly improved the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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