AI Mental Health Insights Generator

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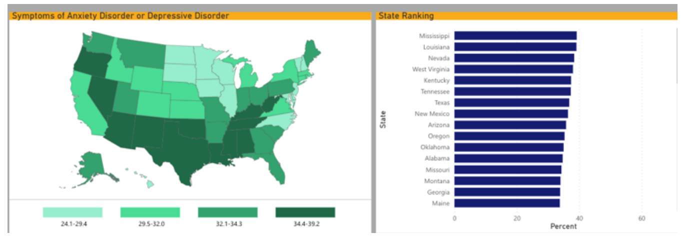
***Abstract*—**This paper presents a study on developing an AI-powered mental health insights generator for working individuals and students to track and improve their mental health and well-being. The study investigates how machine learning (ML) techniques can be used to analyze various data sources, including work or school related stressors, schedule, and physical activity, to provide insights and recommendations. Data for the study were collected using mobile apps, wearables, and online surveys from working individuals and students interested in tracking their mental health and well-being. The data were used to train the mental fitness tracker using state-of-the-art ML algorithms. Results show that the mental fitness tracker provides insights and recommendations that improve the mental health and well-being of working individuals and students.

Keywords— mental fitness tracker, machine learning, working individuals, students, personalized recommendations.

INTRODUCTION

Mental health and well-being are critical for overall health and productivity, particularly for working individuals who are often faced with high levels of stress and pressure. Digital tools, such as mental health apps, have become increasingly popular, and advancements in AI technology have made it possible to develop intelligent mental fitness trackers that can help individuals track and improve their mental health. This paper investigates the development of an AI-powered mental fitness tracker for working individuals and students to track and improve their mental health and well-being. The study aims to investigate how machine learning (ML) techniques can be used to analyze various data sources, including work or school related stressors, work schedule, and physical activity, to provide personalized insights and recommendations.

Center of Disease Control and Prevention (CDC) have generated statistics from surveys to understand what percent of population shows anxiety or depression [8]. Here is statewide distribution as of Feb 2023. As you can see around 30-40% of population shows signs of anxiety disorder or depression or both.



The COVID-19 pandemic is driving enormous demand for virtual mental health care services. Also accessing physical care in remote areas of America and lack of qualified doctors continues to remain challenging.

Wearable devices like the Apple Watch or Google phone can monitor certain aspects of mental health by collecting data on physical health and behavior, which can then be used to provide personalized assistance and support [5]. Here are a few examples:

Heart rate variability (HRV): Wearable devices like the Apple Watch can measure HRV, which is a measure of the variability between successive heartbeats. Research has shown that HRV can be used as an indicator of stress and anxiety, and changes in HRV can be used to monitor mental health. The Apple Watch has a built-in HRV feature that allows users to track their HRV over time and receive personalized feedback on their stress levels.

Sleep monitoring: Wearable devices like the Apple Watch can also monitor sleep patterns, which can be used to detect and monitor symptoms of mental health conditions such as depression and anxiety. By tracking sleep patterns, wearable devices can provide personalized recommendations for improving sleep hygiene and overall mental health.

Activity tracking: Wearable devices like the Google phone can track activity levels, which can be used to monitor symptoms of mental health conditions such as depression and anxiety. By tracking activity levels, wearable devices can provide personalized recommendations for improving physical activity and overall mental health.

Mindfulness and meditation: Wearable devices like the Apple Watch can also provide support for mindfulness and meditation, which are effective strategies for managing stress and anxiety.

In addition, research [7] suggest that Music Therapy can promote wellness, reduce stress and promote physical rehabilitation. Music therapists are often hired in schools to provide music therapy services listed on the Individualized Education Plan for mainstreamed special learners. Music learning is used to strengthen nonmusical areas such as communication skills and physical coordination skills which are important for daily life.

The goal of this paper is to analyze mental health patterns by geographic locations and strongest predictors of mental health issues at workplace and school. The paper will also explore the correlations of music listening habits and its effect on mental health.

This paper is split into several sections. Section I outlines related work that has previously been done regarding parking detection from the driver's perspective and their respective findings. Section II details the three datasets we will be utilized in the paper, along with guidelines for object annotation. Section III describes the approach and metrics we'll be using to compare the performance of each dataset. Section 5 and 6 detail the results and analysis of the experiments and room for future work.

I. Related Work

One study [1] published in the Journal of Medical Internet Research in 2021 explored the use of a virtual mental health assistant to improve the mental health outcomes of young adults with depression and anxiety. The study used a chatbot-based intervention to provide personalized mental health support to participants. The intervention was found to be effective in reducing depression and anxiety symptoms, improving self-efficacy and motivation, and increasing engagement with mental health services.

Another study [2] published in the Journal of Telemedicine and Telecare in 2020 evaluated the effectiveness of a virtual mental health assistant designed to provide support for people with post-traumatic stress disorder (PTSD). The study found that the virtual assistant was effective in reducing PTSD symptoms, improving quality of life, and increasing engagement with mental health services.

Teletherapy provides have seen a decent increase in the need for virtual mental health support [4]. Ginger [3] offers mental health coaching, teletherapy and psychiatry. Usage of Ginger's text-based mental health coaching was up 159%.

The Apple Watch has a built-in Breath app that guides users through deep breathing exercises to help reduce stress and improve mental well-being.

II. Data sets

Music and mental Health Survey Results: The dataset used in this analysis, comes from self-reported music listening habits in. Data was collected from a survey posted in Reddit forums, Discord servers, social media platforms, and advertised in libraries, parks, and other public locations. The data is from 2022 [6]

Workplace Mental Health Survey 2014: This dataset is from a 2014 survey that measures attitudes towards mental health and frequency of mental health disorders in the tech workplace [9]. It contains responses of employees to questions like coworker interaction, interaction with supervisor, wellness program at work.

III. Approach

The goal of this paper is to determine if we can analyze and detect mental stress and generate enough insights that assists in stress reduction. An ML model will be trained to predict if the person needs a treatment and if yes what kind of treatment a person would need to improve mental health. ML model will take in answers to mental survey by the user. The survey includes questions like work life balance, wellness programs, age, gender, relationship with supervisor and colleagues, PTOs, remote work options, physical health (height, weight, preexisting conditions, family history) etc.

Here are critical elements needed to build the systems described using 6D framework.

Decomposition: The goal of this project to achieve new insights on how stress impacts health of working individuals and what can be done to reduce the stress

Domain Expertise: The questions in mental health survey have been designed based on stress patterns noticed by psychologists who deal stress related disorders. The goal is to attempt to find root cause, validate it, correlate it with worker's profile and use it to generate new insights for the people with similar profile.

Data: The mental health data will be collected from mental health and survey conducted in 2014 to analyze impact of work-related incidents and its impact on worker's stress. The data contains age, gender, country, state, family medical history, work life balance, wellness program at work, supervisor and coworker relationships. We would need to clean the data and transform it for training ML algorithms that can predict insights. Additional data will be collected from musical therapy survey that correlates the impact of music therapy on stress.

Design: The solution would consist of web based front end that asks users a set of questions and provides insights into what they can do to reduce the stress. A machine learning model will be trained using labelled mental health survey data and music therapy data and the model will be deployed as a service. The web front end will call the model over HTTP using REST protocol and pass the questions submitted by the user, get the insights from the model and displays the insights to the user .

Feature Selection: For Mental Health survey and music therapy datasets, I'll select features that are not dependent on each other and have high correlation with labels. The data will be sampled in stratified manner to avoid bias related to gender, company, or race. By looking at the mental survey dataset, Age, Gender, country, state, family history are good features. We'll predict if the user needs treatment or not (binary classification). After looking at music therapy dataset age, streaming service, type of music (classical, rock, jazz etc.), number of hours spent listening to music are good feature. We'll measure the impact of music on health conditions like insomnia OCD, Depression.

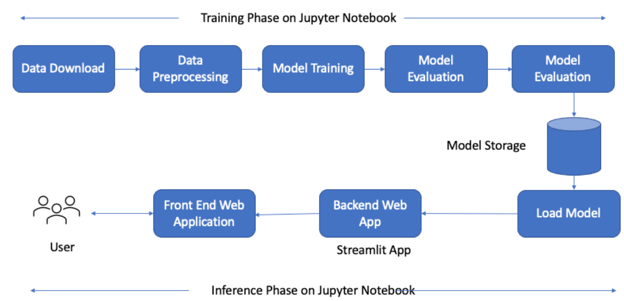
Model Selection: Few supervised algorithms mentioned below will be experimented. I'll evaluate all o thee models like accuracy, Confusion Matrix and select the model that gives best results.

- Random Forests
- KNN

IV. Experiments

The mental health survey dataset was obtained from Kaggle. The survey was measures attitudes towards mental health and frequency of health disorders. The data includes survey on well ness program at work, supervisor and coworker relations, family medical history. The data is first cleaned by removing null values and unnecessary features. The data distributions is then explored to find correlations among data. The data is then normalized to bring it in the same range. 'treatment' has been selected as label that we would like model to predict. Age, family history, wellness program at work, Coworker and supervisor relationships as features. We divided the sample dataset into train and test (70%: 30%) and then trained a model using KNN and Random forest. We evaluated accuracy and confusion matrix. We fine tuned the model using Grid Search method. We persisted the model the disk. The model has the ability to predict on new set of questions. The entire Jupyter notebook that does feature selection, data normalization and model training is available here

V. Architecture



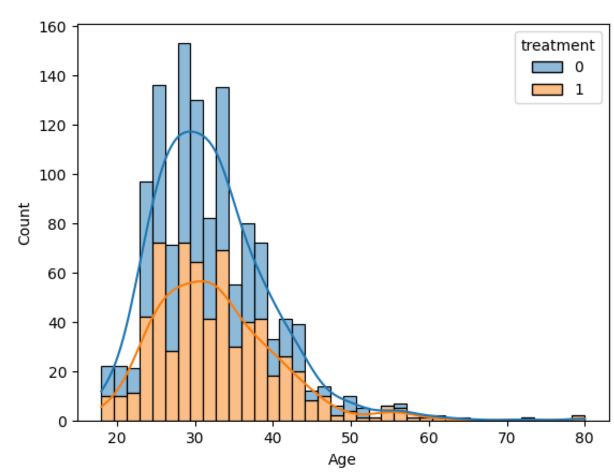
A backend was developed with a Jupyter notebook that downloads training data, trains a model and evaluates its performance and serializes the model to the disk .

A front end was developed using Streamlit interface. The model is loaded the from the disk. The front end asks the user questions similar to the ones in the survey. User's answers are then process by the model to answer I the person needs a treatment or not. A video demonstration of the model is available here

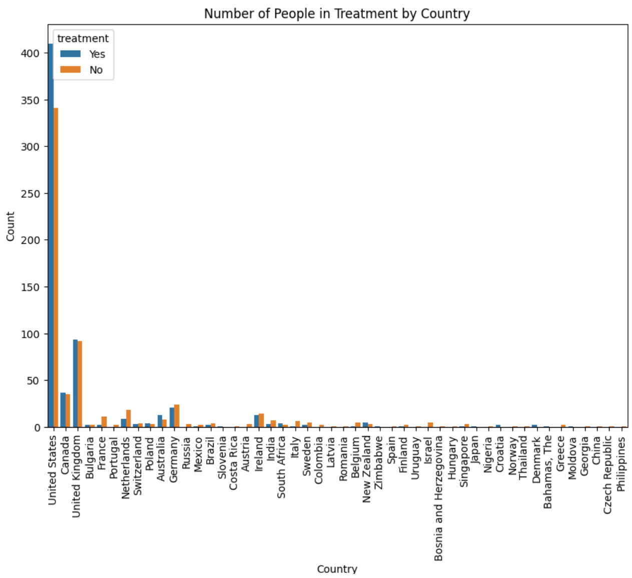
VI. Findings

The data had columns like timestamp and state which were not relevant. Such columns have been removed from the data. Categorical values have been converted into numerical buckets. Age was bucketized into 4 buckets.

Here is distribution of Age Vs Treatment



As you can see typical range for age is between 25-45



As you can see south asia has much lower enrollment in mental health disorder as compares to developed countries like USA and UK.

A. Experiment I:

Random Forest Model was used to train the model and Grid Search was used to fine tune the model

Confusion Matrix:

	Precision	**Recall**	**F1-score**
0	0.70	0.68	0.69
1	0.68	0.70	0.69
Accuracy Macro avg	0.69	0.69	0.69
Accuracy Weighted avg	0.69	0.69	0.69

The model was further find tuned using GridSearchCV method. The best accuracy was found to be 73% with following hyperparameters.

- `max_depth: 10`
- `max_features: 'auto'`
- `min_samples_leaf: 1`
- `min_samples_split: 2`
- `n_estimators: 50`

B. Experiment II

KNN was used to train the model.

Confusion Matrix:

	Precision	**Recall**	**F1-score**
0	0.59	0.68	0.63
1	0.61	0.51	0.55
Accuracy Macro avg	0.60	0.59	0.59
Accuracy Weighted avg	0.60	0.59	0.59

As you can see Random Forest Numbers are much better than KNN. Hence Random Forest model was finally selected.

A User Interface was developed to ask user questions and predict using model trained above to indicate if user needs a treatment. A video explaining User Interface is available here https://youtu.be/E_l9lMYsEm0

VII. Conclusion

- An age group between 35-45 is vulnerable to mental health disorders.
- Developing countries like Brazil, India shows more signs of health disorders as compared to developed countries like USA and UK
- Wellness Program and Benefits at work plat a big role in deciding stability of mental health condition
- Supervisor role is also an important factor in deciding mental health condition.

Typically a person looks at salary and location when choosing a job, However this research shows that wellness program at work, country, supervisor and coworker relationship also plat a significant role. Hence one must do additional research on company' wellness program, interview co-workers and supervisors prior to selecting a job. Also Mental disorders are silent. They don't show any physical symptoms but can significantly affect wellbeing of a person. Hence one must conduct mental health assessments once a quarter and seek an assistance.

References

[1] Torous J, Luo J, Chan SR, et al. A virtual mental health assistant (ViMHA) pilot study in young adults with depression and anxiety: preliminary findings on feasibility, acceptability, and change in self-efficacy, motivation, and depression and anxiety symptoms. J Med Internet Res. 2021;23(2):e24185. doi: 10.2196/24185.

[2] kopp NA, Harned MS, Manke FP, et al. A pilot study of a virtual assistant to support psychotherapy for posttraumatic stress disorder. J Telemed Telecare. 2020;26(3):163-170. doi: 10.1177/1357633X19889653.

[3] Heather Landi "Demand for virtual mental healthcare is soaring." (2021) https://www.fiercehealthcare.com/tech/demand-for-virtual-mental-health-soaring-here-are-notable-trends-who-using-it-and-why

[4] Carrie McMillan "Why Telehealth for Mental Health Care Is working?" (2021). https://www.yalemedicine.org/news/telehealth-for-mental-health

[5] Avneesh Bhangu "The Apple Watch may have future applications in mental health disorders" (2022) https://www.2minutemedicine.com/the-apple-watch-may-have-future-applications-in-mental-health-disorders/#:~:text=Results%20demonstrated%20that%20the%20Apple,to%20detect%20mild%20mental%20stress.

[6] Catherine Rasgaitis "Music and Mental Health Survey Results" 2022. https://www.kaggle.com/datasets/catherinerasgaitis/mxmh-survey-results.

[7] American Music Therapy Association "MUSIC THERAPY AND MENTAL HEALTH" 2006. https://www.lakeeriemt.com/wp-content/uploads/2017/02/MT_Mental_Health_2006.pdf

[8] CDC "Anxiety And Depression" surveys 2023. https://www.cdc.gov/nchs/covid19/pulse/mental-health.htm