

Cloud-based wearable mental health tracking system with intelligent psychotherapy

Fengzhou Pan

McKelvey School of Engineering, Computer Science & Engineering Department,
Washington University in St. Louis, St. Louis, 63130, United States

panfengzhou@wustl.edu

Abstract. In order to provide mental healthcare services to people who do not have access to professional psychiatrists, a Cloud-based Wearable Mental Health Tracking System with Intelligent Psychotherapy is introduced with four major steps: multimodal data collection from various sources, mental health issue predictions from machine learning models, intelligent VR psychotherapy to solve mental disorders, and pacification effect monitoring and feedback sending to adjust the psychotherapy methodology. The solution incorporates multiple front-end technologies including Big Data, Cloud Computing, Machine Learning, IoT, VR, and Blockchain.

Keywords: Virtual Reality, Emotion Detection, IoT, Machine Learning, Psychotherapy, Intelligent System.

1. Introduction

Mental health problems, especially in the times of the Covid-19 pandemic when people are trapped indoors with fewer activities, have become increasingly critical globally. According to the WHO data [1], over 1 in every 8 people in the world live with a mental disorder. Although relatively mature psychotherapy methodologies, such as cognitive behavioral therapy, have been proven to work effectively in curing the most common mental diseases including depression and anxiety disorders, multiple barriers prevent patients from seeking to receive necessary treatment. For instance, most patients focus more on their dealing with their somatic symptoms and often leave the underlying mental disorder unrecognized and untreated. Even if the patients actively start the treatment, the lack of significant signs of complete healing may easily dissuade them from completing the whole treatment process, which leaves them with unresolved disorders and high possibilities of relapses. A private psychiatrist for each person who can sustainedly keep an eye on his or her health condition changes might be a solution to the circumstance, however, the number of professional psychiatrists is highly limited and hardly accessible to the population in underdeveloped regions.

Due to the fast development of cloud computing, an intelligent lightweight system that constantly monitors mental health and provides psychotherapies accordingly without supervision from any professionals is considered to have the potential to improve the above predicament. AIWAC [2] (Affective Interaction through Wearable Computing and Cloud Technology) has brought up a full-stack solution aiming at providing effective remote emotional healthcare assistance. The solution contains three major components - collaborative data collection via wearable devices, enhanced sentiment

analysis, and forecasting models, and controllable affective interactions. The first two components serve to detect emotional issues in the user, while the last component serves to pacify the user once emotional issues are detected. Remarkably, AIWAC has noticed the problem lies in the traditional remote healthcare system that patients are forced to wear uncomfortable devices for accurate physiological data collection, and creatively brought up the idea to lighten the data collection devices and focus on improving mental state prediction models based on multimodal data not only from the physiological data collection devices (i.e., the physical space) but also from video data that record user behaviors (i.e., the cyberspace) and interactive social contents (i.e., the social space). The combination of multiple data sources works not only to enhance the accuracy of mental problem detection but also to transfer the burdens from the patients to the backend models.

However, the solution provided by AIWAC has two major limitations. Firstly, the system starts operating at the moment with close to zero knowledge of the user basic information such as daily behavioral patterns, physiological thresholds, comfort, and non-comfort zones, and possible sources of emotional turbulences. In other words, it takes a relatively long period for the system to learn and adapt to the normal patterns of single users, which is necessary for effective detection of abnormalities. If, for instance, a user is born with lower-than-general pulses, his exceptional high pulses may fall in the range of normal pulses for the majority, which leaves his possible emotional problems undetected. Secondly, the system is mainly targeted at the empty-nested elders who are in huge need of companionship, so it is focused on providing basic living services such as playing music and making food, which is less effective for patients who really have serious mental disorders and are in need of proper treatments. Thus, a system that can provide much more professional psychotherapies is sure to benefit an even bigger group of population.

To address the two limitations mentioned above, a VR equipment is introduced into the system. The VR equipment mainly completes two tasks - collecting basic data for quickly setting up user profiles and providing complete VR psychotherapies.

1.1. User Profile Setup

At the beginning of each usage phase for a new user, the system is required to set up a basic user profile with important physiological and behavioral data. In order to quickly collect necessary data, the VR machine is utilized to simulate different situations such as relaxing, doing exercises, or conversing with other people, and, during the simulation periods, the system records user reactions and physiological changes to determine a specific baseline, which eases future predictions of the user's mental problems.

1.2. VR Psychotherapy

VR psychotherapy methodology is considered one of the most effective psychotherapies for mental diseases such as anxiety disorders and phobias due to its possibility to expose and immerse users to scenes that are hard to monitor in real life [3]. However, most VR psychotherapies right now still rely entirely on the manipulation of trained psychiatrists, who have the final words on what to show to the patients, which extent of the contents should be shown, and when to have the follow-up treatment sessions. This system, however, is designed to calculate all these parameters in the VR scenes in the backend system, providing complete human-free mental healthcare services remotely.

2. Solution Design

The whole system is designed with four major components. Firstly, multimodal data, including both profile data set up at the very beginning and real-time data from multiple sources, are collected and arranged. Secondly, the arranged data are passed through a machine learning model on the cloud to detect any mental issues. Thirdly, once any mental issues are detected, the VR device is then to plan out the most suitable psychotherapy to pacify the patient. Fourthly, during the therapy, the sensor data are continuously collected to observe the effect of the pacification, according to which the VR device is to adjust the levels of the scenes or the methodologies. The four stages above form a closed loop for each

mental health problem detected in the user, and the circulation comes to an end whenever the mental health problem is considered to be solved.

2.1. *Big Data*

In AIWAC, data are set to be collected from the CPS-Spaces (i.e., the cyber, physical, and social spaces). Based on the idea, the following different types of data are mainly applied to the mental issue detection model.

- (1) **Demographic Data:** Demographic data (including both socio-demographic data including sex, age, education, and smoking, and community environmental factors including green space, facilities, and annual PM₁₀ level have been proved to be strongly correlated with mentality [4]. To better predict mental health status, profiled demographic data are collected by both user input on basic personal information and national or regional public datasets. It is widely accepted that mental health disorders are influenced by both genetics and environmental factors. As a result, to accurately predict the existence of mental disorders, it is beneficial to collect not only personal information of the user such as the gender, age, and family history of diseases, socio-economic status, but also environmental information, the regional prevalence of mental disorders, and population distributions on mental disorders. Important data can be achieved from official public healthcare websites.
- (2) **Physiological Data:** Research has shown that the emotion recognition algorithm is effective from multimodal physiological signals for emotion-aware healthcare systems [5]. In this system, both profiled, and real-time physiological data are collected by the wearables equipped on the users. Profiles of physiological data are collected with the assistance of VR scenes to record baseline physiological responses under natural scenes, while real-time physiological data are collected constantly under everyday situations. Quite a few research have attested to the possibility of emotion recognition based on various physiological data, including peripheral physiological responses (e.g., respiratory belt, plethysmograph, and fingertip temperature) and electrograms (e.g., EEG, EMG, and ECG). Even though due to the intent to reduce the discomforts of users by lightening the measuring equipment they are requested to wear, not all physiological data are proper to be considered in the metrics, some data are still qualified due to their low requirements on the measuring hardware.
- (3) **Behavioral Data:** Daily behavior patterns including in-person interactions and eating habits have provided insights into various disease detection including mental health problems [6]. Real-time behavioral data are collected by any interactive device installed with audio and video recording functions. In AIWAC, the interactive device is designed to be a robot with anthropomorphic appearances and human behavior patterns in order to maximize the pacification effects, but it can also be as simple as a smart speaker like Alexa given that it is used mainly to collect data and not on emotion pacification. Depressed facial expressions, sorrowful tones of speech, and anomalous sluggish or violent actions can all be considered signs of mental disorder predictions.
- (4) **Social Data:** Computational approaches are widely used by major social media platforms for suicidal detection, but research can now assess even more the presence of multiple mental disorders including eating disorders and schizophrenia, and related symptoms such as self-harm [7]. Real-time social data are collected from social media platforms. These data are mostly text-based but may also include images of which semantics can be interpreted.

2.2. *Machine Learning*

The machine learning model continuously receives and integrates data from all the above sources to generate the best predictions on the current mental states of the user. There are two major tasks for the model in this stage - predicting what, if any, types of disorders the user has at the moment, and predicting what the severity levels are for the disorders.

- (5) **Disorder Type Recognition:** This is a classification task. Based on the standard medical diagnosis metrics of mental disorders and the data collected from the user, the model is to predict what types of disorders the user is suffering from.
- (6) **Disorder Severity Measuring:** This is a regression task. Based on the levels and values of the data collected from the user, the model is to predict what extent the disorders are to the user.

2.3. *IoT*

There are three major IoT devices in the whole system - a wearable device, a behavioral interactive device, and a VR device. The prior two devices are primarily utilized for data collection from the user, while the last device is used in both the data collection phase and the service delivery phase.

- (7) **Wearable Device:** The wearable device is designed to be lightweight which is convenient for daily wearing but should be capable of monitoring necessary physiological data in real time. An example wearable device is the iWatch but is equipped with more physiological monitoring functions.
- (8) **Behavioral Interactive Device:** The behavioral interactive device is designed to be a “digital human” which can converse with the user and keep track of his or her facial expressions and speech tones. An advanced version of the “digital human” can be, as introduced in AIWAC, a robot with anthropomorphic appearances and human behavior patterns, but a primitive version can also be an Alexa smart speaker with a camera on it.
- (9) **VR Device:** The VR device is dually used for both eliciting baseline physiological responses for the initial profiling and providing VR psychotherapy scenes to the user.
 - (a) **VR Profiling:** In order to quickly set up a normal physiological response range from calmness to excitement, the VR device can help immerse the user into different scenes from quiet libraries to raucous clubs to examine his or her general patterns.
 - (b) **VR Psychotherapy:** VR has been proven as highly effective in treating various types of mental disorders. Existing VR psychotherapy methods include VR Meditation (creating an absolute private quiet space for self or guided meditation during depressed periods), VR Avatar Therapy (creating virtual avatars and externalizing auditory verbal hallucinations to the avatars), and VR Exposure Therapy (exposing the patient to his or her source of fear from mild and abstract levels to intense and concrete levels at a gradual pace to desensitize the patient from anxiety). Traditional VR psychotherapy requires a trained psychiatrist to control and adjust the VR scenes shown to the patient - for instance, the psychiatrist needs to make sure the patient is fully adapting to one level of his or her source of fear and then decides to move to the next more intense level. In the intelligent system, however, the user’s physiological data are constantly analyzed during the whole process of VR psychotherapy, and the analyzed results are applied to automatically make adjustments to the VR scenes regarding what levels should be shown at what time.

2.4. *Blockchain*

The development of decentralized technology has enabled the applications of blockchain in healthcare to secure patient medical records [8]. Similarly, mental health records can benefit from high data security and convenient data sharing with blockchain applications. With blockchain, the intelligent system can trustworthily record every user’s mental disorder history, and the information can be transparently shared with other physical healthcare providers, which facilitates the treatments of other disorders and prevent any medical contraindications.

3. **Solution Implementation**

In order to test out the feasibility of the intelligent system, a minimum viable product is designed and built for demonstration. For this specific product, the purpose is to provide a VR exposure therapy to a patient with social anxiety. The minimum viable product contains two major parts - a stress recognition machine learning model and a multilevel VR psychotherapy scene.

3.1. Stress Recognition

The model is implemented based on a stress detector API based on OpenCV from CodeChef [9], which continuously scanning the facial expressions of the user through the camera and analyzing whether the user is in a state of stress or not and, if is in stress, what level of stress the user is experiencing (as shown in Figure 1). The output of the stress detector is a value indicating the stress level from 1 to 3, where stress level 1 suggests high stress of the user, while stress level 3 suggests low stress. The model is active during the whole process of the VR psychotherapy, providing feedback on the user's comfort levels toward the scenes shown in the VR.

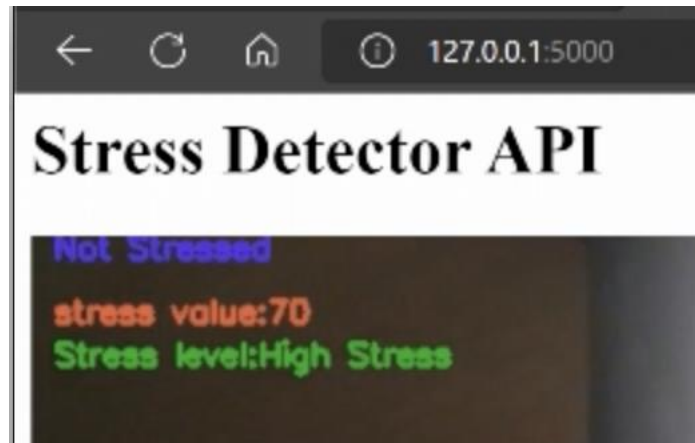


Figure 1. The stress detection API continuously provides stress level prediction based on facial expressions of the user.

3.2. VR Psychotherapy

The VR scene, inspired from Agora-VR [10], is composed of a large open space with a group of people. There are three levels of the scene, with increasing number of people appearing in the scene as the level goes up. The VR scene constantly receives information of the current user stress level from the stress recognition model, and accordingly adjusts the level of the scene to keep the user in a relatively comfortably exposing status. There are 3 levels of VR scenes in the minimum viable product, which corresponds to the 3 stress levels output from the stress recognition API – if the user is in stress level 1 (high stress), then the level 1 VR scene is shown where humans are relatively sparse and far away to pacify the stress; if the user is in stress level 3 (low stress), then the level 3 VR scene is shown where humans are more close by and crowded to expose the user to a more intense level for treatment purpose (as shown in Figure 2).

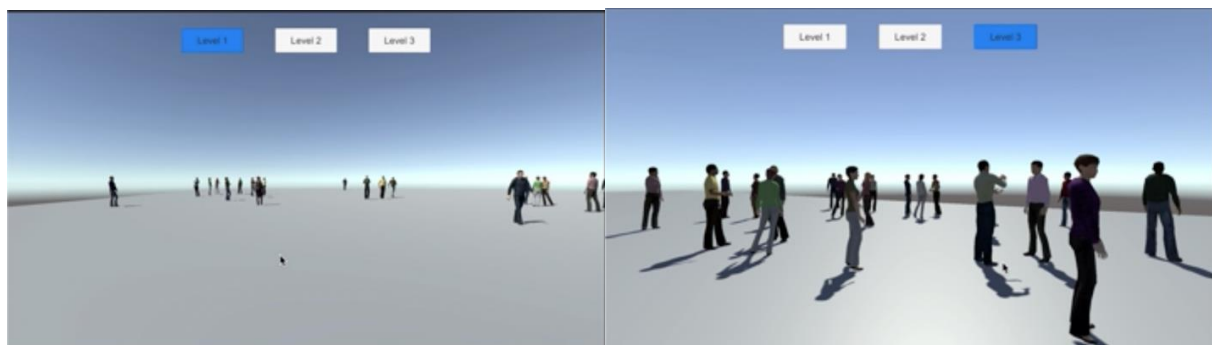


Figure 2. The implemented VR scenes in level 1 (far away and sparse) and 3 (close by and crowded) which is automatically adjusted according to the output from the stress recognition API.

The minimum viable product is an oversimplified version of the intelligent psychotherapy system. For an effective version, multiple sources of data are used to measure the status of the user, and more complicated scenes are shown to immerse the users under different occasions on different mental disorders.

4. Next Steps

The Cloud-based Wearable Mental Health Tracking System with Intelligent Psychotherapy provides a remote automatic solution for mental disorder detection and treatment with no human interference, which can largely benefit patients with limited access to professional psychiatrists. In order to improve the quality of services provided by the system, further steps of research in numerous regions are still in need.

4.1. Mental Disorder Detection Algorithms

Most current algorithms used in mental disorder detection, video-based or physiological-based, are in essence emotion detection. In other words, these algorithms implicitly assume that negative emotions are somehow equivalent to mental disorders. However, such assumption is questionable given that some types of mental disorders might be hidden under the appearance of calmness or emotionlessness. Thus, better algorithms are required to accurately detect various types of mental disorders.

4.2. VR Short-Term Solution

VR psychotherapy is especially effective for long-term planned-out treatment, where the patient can gradually get out of the woods at a proper pace. However, VR is not good at handling mental health emergencies, such as sudden manic episodes.

4.3. VR on More Mental Disorders

Currently, VR is examined to be effective and applied to a relatively limited types of mental disorders such as anxiety and depression, due to its capability of bringing patients to face up to their mental dilemmas as if they are tangible and force out reconciliations with the dilemmas. However, the potential of VR for treating other uncommon mental disorders has not yet been exploited or evaluated.

5. Conclusion

In this article, the idea of a Cloud-based Wearable Mental Health Tracking System with Intelligent Psychotherapy is introduced as a solution to remote mental health monitor and treatment. The system is equipped with a wearable device for physiological data collection, a behavioral interactive device for behavioral data collection, and a VR device for initial data profiling and psychotherapy production. The workflow of the system starts from collecting data from multiple sources, and then the data are sent to the backend machine learning model for real-time mental disorder detection. Once the mental disorders are detected, VR psychotherapy is provided to the user, and simultaneously user data during the treatment are sent back to the VR device for therapy adjustments. A minimum viable product with a stress recognition model connected to a VR scene is built to demonstrate the possibility of the intelligent system, and future research directions are brought up on both mental health prediction machine learning models and VR psychotherapy.

References

- [1] *Mental disorders*. (2022, June 8). Mental Disorders. <https://www.who.int/news-room/fact-sheets/detail/mental-disorders>
- [2] Chen, M., Zhang, Y., Li, Y., Hassan, M., & Alamri, A. (2015). AIWAC: Affective interaction through wearable computing and cloud technology. *IEEE Wireless Communications*, 22(1), 20–27. <https://doi.org/10.1109/mwc.2015.7054715>
- [3] Riva, G. (2005). Virtual Reality in Psychotherapy: Review. *CyberPsychology & Behavior*, 8(3), 220–230. <https://doi.org/10.1089/cpb.2005.8.220>

- [4] Kim, J., & Kim, H. (2017). Demographic and Environmental Factors Associated with Mental Health: A Cross-Sectional Study. *International Journal of Environmental Research and Public Health*, 14(4), 431. <https://doi.org/10.3390/ijerph14040431>
- [5] Ayata, D., Yaslan, Y., & Kamasak, M. E. (2020). Emotion Recognition from Multimodal Physiological Signals for Emotion Aware Healthcare Systems. *Journal of Medical and Biological Engineering*, 40(2), 149–157. <https://doi.org/10.1007/s40846-019-00505-7>
- [6] T.Sajana, M. G. (2021). Human Behavior Prediction and Analysis Using Machine Learning-A Review. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12(5), 870–876. <https://doi.org/10.17762/turcomat.v12i5.1499>
- [7] Chancellor, S., & de Choudhury, M. (2020). Methods in predictive techniques for mental health status on social media: a critical review. *Npj Digital Medicine*, 3(1). <https://doi.org/10.1038/s41746-020-0233-7>
- [8] Hasselgren, A., Kravlevska, K., Gligoroski, D., Pedersen, S. A., & Faxvaag, A. (2020). Blockchain in healthcare and health sciences—A scoping review. *International Journal of Medical Informatics*, 134, 104040. <https://doi.org/10.1016/j.ijmedinf.2019.104040>
- [9] Raju, H. (2021). GitHub - CodeChefVIT/Stress-Detector: API to detect if user is stressed or not using ML. GitHub. <https://github.com/CodeChefVIT/Stress-Detector>
- [10] Nguyen, D. (2020). GitHub - Agora-VR/Agora-VR: Agoraphobia Virtual Reality Therapy Solution. GitHub. <https://github.com/Agora-VR/Agora-VR>