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# Mental Health Detection and Smart Recommendation System

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**ABSTRACT :** Early detection of mental health problems is important for psychiatrists to provide timely treatment and improve patients' quality of life. Depression is the leading cause of disability worldwide and is the focus of this article evaluating the use of machine learning in mental health care. This article explores the role of machine learning in mental health research and explores how it can aid clinical practice, while acknowledging its current limitations. It shows that one should be careful about mental health problems in children, which can lead to serious problems if left untreated. Use machine learning techniques to analyze medical data and use a selection process to simplify the data. The report compares the accuracy of various algorithms and presents the best results. But he emphasizes the importance of careful interpretation of the results and recommends continued efforts to close the gap between machine learning in psychology and its actual medical use.

**KEYWORDS :** Recommendation Systems, Feature Selection, Machine Learning, Psychiatric Diagnosis, Mental Health Disorders, Differential Diagnosis

## I. INTRODUCTION

We plan to launch a new initiative to support the development of mental health services: the Mental Health Detection and Smart Recommendation System (MHD&SRS). The system provides users with a secure and personal login that they can access by providing a variety of experiences. Users introspect by learning thinking-related behaviors as well as through carefully designed experiments [1]. At the heart of this innovation is powerful machine learning, which uses user feedback to provide better insights into mental health. In addition to pure screening, the system provides compassionate assistance to detect potential suicide or risky behavior to enable timely intervention. The system expands support to provide users with self-healing suggestions based on effective guidelines for improving mental health. But our passion for user health does not end with tests and recommendations. Aware of the importance of instant relaxation, the system includes interactive features such as guided meditation and meditation to support exercise according to the individual's needs. We also know the importance of fast service. That's why the system also includes the ability to find nearby hospitals or mental health centers to ensure users can get the support they need. This holistic, user-centered approach transcends the traditional boundaries of mental health technology. It not only wants to detect mental health issues, but also contributes to the health of its users, providing support and support to the community. In creating this revolutionary process, we envision a future where technology serves as a good friend on the journey to health and wellness.

## II. RELATED WORK

The current research in the area has proven that analysis of the social media data is a great factor that helps in diagnosis and monitoring of mental illnesses. Tracking the online behavior of the patients is the key to providing personalized healthcare to individuals. But not many systems have been implemented that use this research in assisting psychiatrists in early diagnosis of depression as well as in treating it. Mental Health Detection and Smart Recommendation System by using real life data such as mobile phones and wearable sensors and social media data from websites such as E-learning platforms.

**Table 1 Survey of Depression Detection**

Sr No.	Author	Title	Advantages	Limitations
1.	Sunil D Kale, Gaurav Rasal, Pratiksha Ganjave, Rushikesh Markad, Yash Kalekar[1] [2023]	Depression Detection and mental health tracker using machine learning	The machine learning techniques used in paper can be used to detect depression symptoms	Textual, audio, video or ECG signals can't be used together as a input
2.	Konda Vaishnavi[2] [2022]	Predicting Mental Health Illness using Machine Learning Algorithms	The accuracy of all the classifiers are above 79%	Large dataset is not used
3.	Manju Lata Joshi[3] [2022]	Depression detection using emotional artificial intelligent and machine learning : A closer review	Depression is detected, analysed and prevented through twitter sentiment analysis	Approaches aren't integrated into a vast system to clinically categorize patients suffering from depression on the basis of discovering their emotional profiles
4.	Jetli Chung and Jason Teo[4]	Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges	Many different techniques and algorithms had been introduced and proposed to test and solve the mental health problems.	As classifying the mental health data is generally a very challenging problem, the features used in the machine learning algorithms will significantly affect the performance of the classification
5.	Tianlin Zhang, Kailai Yang, Shaoxiong Ji, Sophia Ananiadou[5]	Emotion fusion for mental illness detection from social media: A survey	Its provided that comprehensive survey of how emotion fusion has been used to support this task	challenge of emotion fusion is still there



**Table 2 Datasheet Including Data Domain, Purpose and Description of the ML Application or Approach, Its Motivation, and Target Mental Health Symptom or Condition**

Reference	Data Domain	Purpose	ML Application/Approach (What)	Motivation (Why)	Mental Health Target
Chang et al. [6]	Audio	Detecting symptoms/condition	Development of an automatic mental-health monitor based on the human voice. Initial step: developing categorization of voice utterances for analysis of mental health symptoms.	To assist in the early diagnosis and longitudinal monitoring of mental illness symptoms in everyday speech conversation.	Depression
Mitra et al. [7]	Audio	Detecting symptoms/condition	Development of a depression-level recognizer based on a set of acoustic features in spoken audio.	To assist accurate diagnosis of depressive symptoms.	Depression
Frogner et al. [8]	Accelerometer	Detecting symptoms/condition	Development of multiple ML models to detect presence and level of depression from motor activity recordings.	To accurately detect depression from very easy to obtain motor activity.	Depression
DeMasi and Recht [9]	Mobile phone (GPS)	Detecting symptoms/condition	Modeling the relationship between user characteristics and algorithmic predictions of peoples' daily mental well-being from smartphone GPS data.	To explore if mental well-being can be inferred from smartphone behavioral data and automatically tracked over time.	Depression
Alam et al. [10]	Multiple (body)	Understanding/predicting risks	Development of a cloud-based system architecture for collecting and processing real-time body-sensor data as well as additional patient information for assessing suicide risks.	To effectively predict (normal, atypical, and suicidal) mental states of patients with mental health conditions to monitor suicide risk.	Suicide
Kavuluru et al. [11]	Social media: Reddit	Understanding mental health content	Development of identifiers of "helpful" comments posted within the Reddit community: Suicide Watch (SW), using varied text-mining techniques.	To assist human moderators who review online posts through indicating and/or prioritizing useful/helpful comments.	Suicide

Nguyen et al. [12]	Social media: Live Journal	Understanding mental health content	Application of text-mining to better understand linguistic features and topics related to mental health discussed within online communities on the Live Journal platform.	To improve understanding of mental illnesses.	Depression
Fatima et al. [13]	Social media: Live Journal	Detecting symptoms/condition	Development of three ML models for classifying depressive posts, communities and the degree of depression from online social media (Live Journaling posts).	To make use of user-generated content to identify depression and characterize its degree of severity.	Depression
Nobles et al. [14]	Messages (SMS)	Understanding/predicting risks	Development of a model that identifies periods of suicidality. Report on collection + analysis of text messages of individuals with a history of suicidal behaviors.	To identify subtle clues in text communication as indicators of heightened suicide risk for more effective prevention.	Suicide
Pestian et al. [15]	Suicide notes	Understanding/predicting risks	Development of a classifier for predicting suicide through natural language processing of written suicide notes.	To provide emergency departments with an evidence-based risk assessment tool for predicting repeated suicide attempts.	Suicide
Adamou et al. [16]	Medical notes (from Health record)	Understanding/predicting risks	Application of text-mining techniques of medical notes to improve accuracy of a predictive model of suicide risk within 3 or 6 months at point of referral to mental health services.	To increase accuracy of predictive model in efforts to provide a tool that could support clinical assessment of suicide risk.	Suicide

### III. METHODOLOGY

#### A. Data Collection and Pre-processing:

- Gather a diverse dataset that includes labelled examples of mental health conditions and relevant features.
- Pre-process the data, including handling missing values, removing duplicates, and ensuring the data is in a suitable format for analysis.
- Identify relevant features from the dataset that can be used to classify mental health conditions.
- Perform feature selection or engineering to enhance the predictive power of the features.
- Split the dataset into training and testing/validation sets to evaluate the models' performance.

#### B. Train an SVM model and Random forest Algorithm:

- Train an SVM model using the training data and selected features.
- Train a Random Forest model using the same training data and features.
- Evaluate the SVM and Random Forest models using the testing/validation dataset.
- Measure performance metrics such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC).
- Compare the performance of the SVM and Random Forest models based on the evaluation metrics.

#### C. Recommendation System:

- Based on the trained models, develop a recommendation system to suggest appropriate actions or interventions for individuals based on their mental health characteristics.
- Use the trained models to predict mental health conditions for new individuals and provide recommendations accordingly.
- Optimize the SVM and Random Forest models by adjusting hyper parameters to achieve better performance.
- Deploy the trained models and the recommendation system in a suitable environment, such as a web application or a mobile app, for real-time use.
- Continuously monitor the performance of the deployed models and recommendation system in a live environment, and update them as needed based on new data or changes in mental health knowledge.

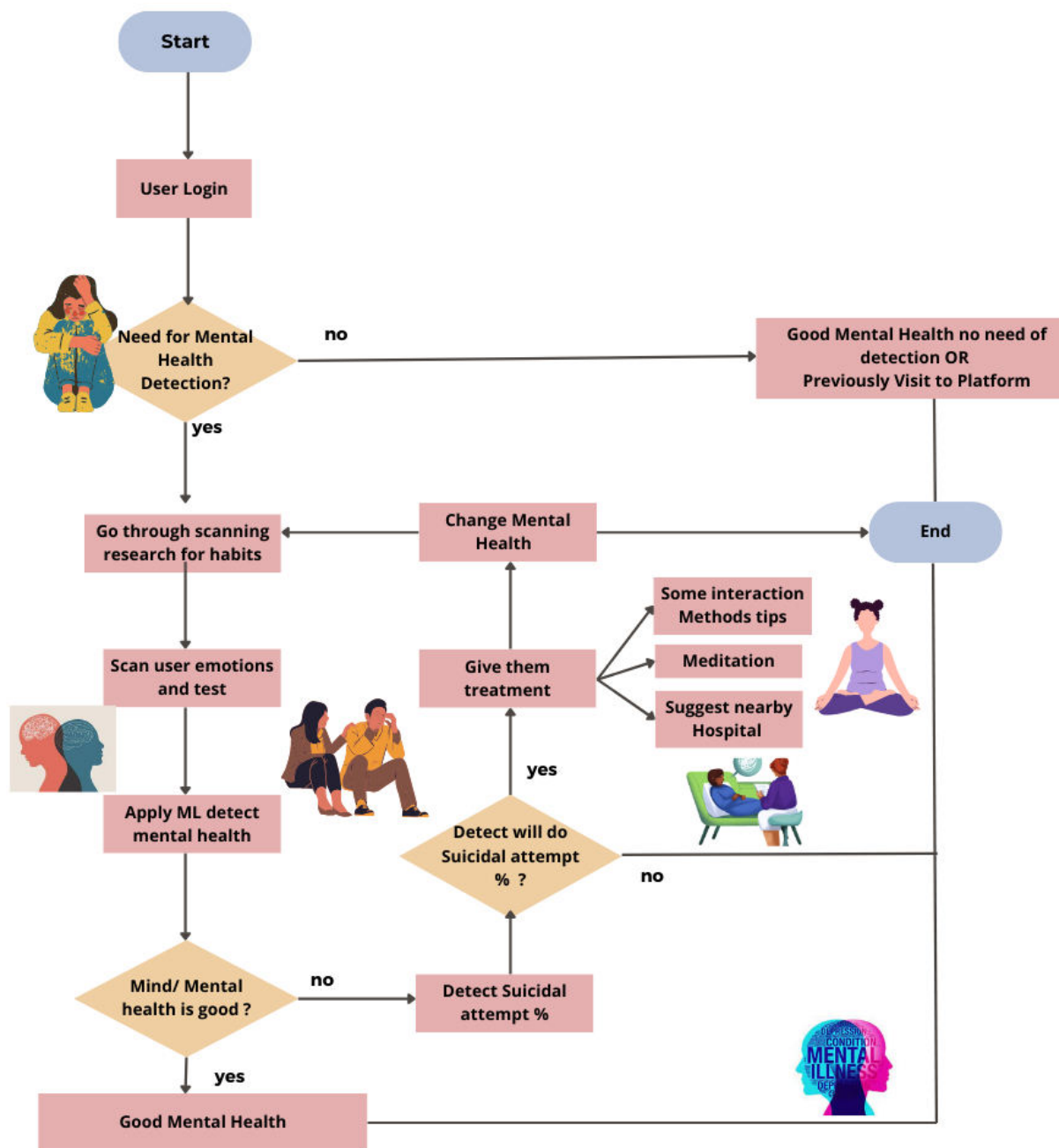
### IV. FLOWCHART

Mental Health Detection and Smart Recommendation System(MHD&SRS) which incorporates data from various sources like Medical Linked Open Data along with Electronic Health Records (EHR), IoT sensors (wearable and environmental), social data of a person to suggest a personalized course of action to cure a disease are used in recording different types of readings of a person. This data is semantically annotated to represent it abstractly. So, that no domain expertise is required to understand it. Meaningful information regarding mental state is extracted from the social data using Lexicon. All this information will be saved in the PHKG to make it more personalized and contextualized The general architecture of MHD&SRS system is presented in figure 1.

#### A. Input Types

For providing smart mental healthcare, inputs from various Some of the systems take single Input (only IoT data, only Social data) and some takes a combination of inputs (like IoT +Social Media + LOD). These inputs are discussed below:

- 1) **Internet of things (IoT)** Data from wearable and environmental Sensors: The wearable sensors record a persons' physiological activities (sleep, walk, etc.), which gives useful information to infer his health condition and this helps in personalization of a patient diagnosis. The environmental sensors provide data about surroundings (weather, location, temperature of surrounding etc.) and provides context to the patient data.



2) **Electronic Health Records of Patient:** Medical history of a patient helps in understanding a patient's current health condition and diagnosis in a better way. E.g. If he/she suffered with the same or related problem in the past, what precautions and prescriptions were applied at that time, etc.

3) **Social Media Data:** In modern times, social media content is a good source to predict the nature of a person, as people share almost every feeling or life events on social media platforms. Facebook, Twitter, Reddit, web forums etc. are the largest platforms used by the public to share their feelings. By analyzing this content of a particular person, we can easily determine his mental health condition. Also, analysis of social media content helps in determining if the user's behavior is according to the prescribed course of action or it's not working.

4) **Medical Linked Open Data:** The medical knowledge available on the web in various forms like ontology's or medical guidelines etc. It is useful in inferring causes, symptoms from the patients' data and selecting the course of actions to cure. E.g. Pub Med, various medical ontology's.

## B. Use Cases

Smart mental health treatments can benefit many actors, from doctors to patients and their relatives, to prevent or treat diseases. SMH can be used to predict whether a person will develop disease in the future based on their current performance in physical activities and health. SMH can diagnose whether a person has a mental disorder. SMH may also recommend surgery to treat the disease. Various benefits of smart brain therapy are discussed below:

- 1) Prediction:** Early detection/prediction of disease helps prevent or treat it quickly when prevention is not possible. This suits their current culture. This process is difficult because it can be predicted before the mental patient whose words do not contain words that directly refer to the content in the language of mental illness. Sadness, fatigue etc. It is thought to cause mental illnesses [Thorstad R., et., 2019]. Other features in this report (such as the frequency of certain words used in the ad, time and frequency of the ad, etc.) are used to obtain important information regarding consumer health.
- 2) Diagnosis:** This term is often used to check whether a person has a disease when they are actually sick. This is easier because the patient's words often contain words directly related to mental illness. For example. "Diagnosed with depression," "mental illness," etc.
- 3) Recommendation:** This is the step of creating an action for prevention or treatment based on the symptoms (disease). Some warnings or messages containing what needs to be done (abstract information) can be sent to doctors or patients.

## V.CONCLUSION

In recent years, the use of social media in autism diagnosis has received increasing attention. In this article we provide a general analysis of how fusion theory can be used to support this task. After analyzing related studies, we first divided mixed methods into aesthetic architectural techniques and deep learning. For the former method, we introduce different machine learning methods and various feature extraction tools to support feature fusion. Steps in using SVM and random forest algorithms to generate mental health diagnoses and recommendations include data collection and prioritization, model elimination, model training (SVM and random forest), evaluation, model comparison, recommended development, fine-tuning, and deployment. and regularly monitor for updates and improvements.

## REFERENCES

- [1] Sunil D Kale, Gaurav Rasal, Pratiksha Ganjave, Rushikesh Markad, Yash Kalekar, "Depression Detection and Mental Health Tracker Using Machine Learning", *International Research Journal of Modernization in Engineering Technology and Science*, ISSN: 2582-5208, Volume:05/Issue:04/April-2023.
- [2] K Vaishnavi, UN Kamath, BA Rao, NVS Reddy, "Predicting Mental Health Illness using Machine Learning Algorithms", *Published under licence by IOP Publishing Ltd Journal of Physics: Conference Series*, Volume 2161, 1st International Conference on Artificial Intelligence, Computational Electronics and Communication System (AICECS 2021) 28-30 October 2021.
- [3] Manju Lata Joshi<sup>a</sup>, Nehal Kanoongo, "Depression detection using emotional artificial intelligence and machine learning: A closer review" *International School of Informatics & Management, Jaipur 302020, India*, Volume 58, Part 1, 2022.
- [4] Jetli Chung<sup>1</sup> and Jason Teo, "Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges", *Applied Computational Intelligence and Soft Computing*, Volume 2022 | Article ID 9970363.
- [5] Tianlin Zhang, Kailai Yang<sup>a</sup>, Shaoxiong Ji, Sophia Ananiadou, "Emotion fusion for mental illness detection from social media: A survey", *Information Fusion*, Volume 92, April 2023, Pages 231-246.
- [6] Keng-hao Chang, Matthew K. Chan, and John Canny. 2011. AnalyzeThis: Unobtrusive mental health monitoring by voice. In *Proceedings of the CHI'11 Extended Abstracts on Human Factors in Computing Systems (CHI EA '11)*. ACM, 1951–1956.
- [7] Vikramjit Mitra, Elizabeth Shriberg, Mitchell McLaren, Andreas Kathol, Colleen Richey, Dimitra Vergyri, and Martin Graciarena. 2014. The SRI AVEC-2014 evaluation system. In *Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge (AVEC'14)*. ACM, 93–101.
- [8] Joakim Ihle Frogner, Farzan Majeed Noori, Pål Halvorsen, Steven Alexander Hicks, Enrique Garcia-Ceja, Jim Torresen, and Michael Alexander Riegler. 2019. One-dimensional convolutional neural networks on motor activity measurements in detection of depression. In *Proceedings of the 4th International Workshop on Multimedia for Personal Health & Health Care (HealthMedia'19)*. ACM, 9–15.



- [9] Orianna DeMasi and Benjamin Recht. 2017. A step towards quantifying when an algorithm can and cannot predict an individual's wellbeing. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*. 763–771.
- [10]Md. Golam Rabiul Alam, Eung Jun Cho, Eui-Nam Huh, and Choong Seon Hong. 2014. Cloud based mental state monitoring system for suicide risk reconnaissance using wearable bio-sensors. In *Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication (ICUIMC'14)*. ACM, Paper 56, 6 pages.
- [11]Deepali J. Joshi, Mohit Makhija, Yash Nabar, Ninad Nehete, and Manasi S. Patwardhan. 2018. Mental health analysis using deep learning for feature extraction. In *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data (CoDS-COMAD'18)*. 356–359.
- [12]Thin Nguyen, Bridianne O'Dea, Mark Larsen, Dinh Phung, Svetha Venkatesh, and Helen Christensen. 2017. Using linguistic and topic analysis to classify sub-groups of online depression communities. *Multimedia Tools and Applications* 76, 8 (2017), 10653–10676.
- [13]Iram Fatima, Hamid Mukhtar, Hafiz Farooq Ahmad, and Kashif Rajpoot. 2018. Analysis of user-generated content from online social communities to characterise and predict depression degree. *Journal of Information Science* 44, 5 (October 2018), 683–695.
- [14]Alicia L. Nobles, Jeffrey J. Glenn, Kamran Kowsari, Bethany A. Teachman, and Laura E. Barnes. 2018. Identification of imminent suicide risk among young adults using text messages. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI'18)*. ACM, Paper 413, 11 pages.
- [15]John P. Pestian, Pawel Matykiewicz, and Jacqueline Grupp-Phelan. 2008. Using natural language processing to classify suicide notes. In *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing (BioNLP'08)*. ACM, Stroudsburg, PA, 96–97.
- [16]Marios Adamou, Grigoris Antoniou, Elissavet Greasidou, Vincenzo Lagani, Paulos Charonyktakis, and Ioannis Tsamardinos. 2018. Mining free-text medical notes for suicide risk assessment. In *Proceedings of the 10th Hellenic Conference on Artificial Intelligence (SETN'18)*. ACM, Paper 47, 8 pages.



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