2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON)
Pune, India. July 04 - 05, 2025

MindSphere: An AI-Driven Multimodal Framework for Personalized Mental Health Assessment

Tharun Karthick S
Department of Computer Science and Engineering
K S Rangasamy College of Technology
Namakkal, India .
tharunkarthick0509@gmail.com

Shanthosh S
Department of Computer Science and Engineering
K S Rangasamy College of Technology
Namakkal, India .
shanthosh170803@gmail.com

Saran P
Department of Computer Science and Engineering
K S Rangasamy College of Technology
Namakkal, India .
saranvj1877@gmail.com

Vijay Sai R
Department of Computer Science and Engineering
K S Rangasamy College of Technology
Namakkal, India .
vijaysair@ksrct.ac.in

2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON) | 979-8-3315-3482-0/25/$31.00 ©2025 IEEE | DOI: 10.1109/I2ITCON65200.2025.11210505

***Abstract*: Mental health disorders affect nearly 25% of the global population, with depression alone accounting for 7.5% of all years lived with disability . MIND-SPHERE addresses these difficulties by providing tailored mental health assessments using an interactive avatar powered by AI-driven technology. Using advanced natural language processing models, such as RoBERTa for sentiment analysis, and combining multimodal input (text, audio, visual), the system achieves a sentiment identification accuracy of 91.2%, outperforming standard methods by about 15%. . Federated learning ensures secure processing of decentralized data, mitigating privacy risks. MIND-SPHERE demonstrates a 92.8% predictive accuracy in mental health diagnoses, while reducing patient screening times by 30%, alleviating the strain on healthcare systems already facing a shortage of mental health professionals. With an intervention success rate of 87.5% and a system response time of <150ms, MIND-SPHERE significantly enhances user engagement, achieving rates as high as 91.4% compared to 78% in existing systems. As AI's projected market size in mental health surpasses $11 billion by 2026, MIND-SPHERE positions itself at the forefront of scalable, accessible mental health solutions . By merging psychology and AI, MIND-SPHERE aims to revolutionize global mental health care through advanced analytics, robust data security, and exceptional performance metrics.**

Keywords: mental health assessment, AI-powered avatar, sentiment analysis, predictive accuracy, federated learning.

I. INTRODUCTION

Mental health disorders affect approximately 970 million individuals worldwide, leading to significant impacts on personal, social, and economic well-being. These disorders are broadly categorized into mood disorders and neurodevelopmental disorders, each presenting distinct challenges for diagnosis and treatment. Mood Disorders, Depression and bipolar disorder affect emotional stability, with depression causing persistent sadness and bipolar disorder leading to extreme mood swings. Neurodevelopmental Disorders, Autism spectrum disorder (ASD) impairs social interaction, ADHD causes inattention and hyperactivity, and schizophrenia disrupts cognition, behavior, and emotions.

Early and accurate detection is crucial for effective intervention. Traditional diagnosis relies on clinical interviews, which are time-consuming and subjective. This underscores the need for AI-driven solutions that provide real-time, personalized, and data-driven assessments.

MIND-SPHERE addresses these challenges by integrating interactive AI avatars for real-time mental health evaluation, providing dynamic, user-centered interactions. The system utilizes natural language processing (NLP) with RoBERTa for sentiment analysis, achieving an accuracy of 91.2%, which enhances diagnostic precision by identifying emotional states through textual data analysis [2]. Additionally, convolutional neural networks (CNNs) are used for facial expression recognition, reaching an accuracy of 92%, further refining the evaluation process by interpreting visual cues related to emotions [3].

The system also uses (XAI) approaches, such as SHAP , to promote transparency and trust by generating interpretable AI model outputs [4]. With federated learning integrated for secure data processing, MIND-SPHERE ensures privacy and mitigates data risks, enabling its use in diverse settings without compromising patient confidentiality [5].

By combining the strengths of psychology and advanced AI technologies, it promises a scalable, accessible, and effective solution for improving mental health outcomes globally [8]. The contributions of this work for MIND-SPHERE AI are as follows:

- Multimodal Data Integration: By analyzing text, audio, and visual inputs, MIND-SPHERE enhances diagnostic accuracy by 15% over traditional methods.
- Explainable AI (XAI): SHAP-based interpretability ensures transparency and actionable insights, fostering trust among healthcare professionals.
- Federated Learning for Data Privacy: Secure decentralized data processing reduces privacy risks by 20% while maintaining a system response time of <150ms.

II. LITERATURE REVIEW

Various models predict emotions and diagnose conditions like depression and anxiety, showing promising accuracy and efficiency, highlighting AI's potential in enhancing mental health care and some of the related works are:

Amanat et al. (2022) [27] explored emotion detection using Random Forest, SVM, and Naive Bayes. Random

Forest achieved 85.4% accuracy, excelling in specificity (88.2%) and generalization. SVM balanced precision and recall. Their study highlighted tree-based models' robustness in emotion classification, emphasizing Random Forest's effectiveness. The SVM objective function for classification is:

$$min_{w,b}\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} max(0,1 - y_i(w\cdot x_i + b)) \quad (1)$$

Where w is the weight vector, xi is the feature vector, yi is the class label (feeling), and C is the regularization parameter in equation (1). The objective is to minimize the classification error while increasing the margin between various emotion groups. With an impressive F1 score of 82.1%, the SVM model employed by Amanat et al. demonstrated its capacity to accurately categorize a variety of emotional states.

Fei et al. (2020) [9] applied CNNs for emotion detection in mental health care, achieving 92.6% accuracy, 91.5% precision, and 91.4% F1 score. The study highlighted CNN's strength in extracting features and distinguishing nuanced emotions, outperforming traditional models. CNN's ability to process high-dimensional data enhances classification accuracy. The convolution operation for feature extraction is:

$$\mathrm{y} = \sigma(\mathrm{W} * \mathrm{x} + \mathrm{b}) \quad (2)$$

In Equation (2), indicates convolution, W is the filter, σ is the activation function (ReLU), b is the bias, and x is the input text (as feature vectors). The anticipated emotion is the output, y. Because CNNs are so good at extracting intricate information, Fei et al.'s model was able to classify emotions with 92.6% accuracy.

Elzeiny and Qaraqe (2018) [6] reviewed machine learning models for stress detection, focusing on Decision Trees, Random Forest, and SVM. Random Forest excelled with 83.4% accuracy and 85.0% specificity, minimizing false positives. The study emphasized ML's role in real-time stress monitoring, where precision and recall enhance reliability. The final Random Forest prediction is based on majority voting:

$$\hat{y} = \frac{1}{m}\sum_{i=1}^{m} x_i \quad (3)$$

In Equation (3) Where y^ is the predicted label (stress/no stress), m is the number of decision trees, and x is the feature vector. This ensemble approach ensures higher accuracy by reducing overfitting.

Shatte et al. (2019) examined machine learning techniques for diagnosing mental health conditions, with an emphasis on stress, anxiety, and depression. They highlighted Ensemble Learning and DNNs, with DNNs achieving 90.2% accuracy and excelling in high-dimensional data representation. The study emphasized DNNs' superiority over traditional models. The forward pass in a DNN is expressed as:

$$\mathrm{y} = (\mathrm{W_L}\cdot\sigma(\mathrm{W_{L-1}}\cdots\sigma(\mathrm{W_1}\cdot\mathrm{x} + \mathrm{b_1}) + \mathrm{b_{L-1}}) + \mathrm{b_L} \quad (4)$$

In Equation (4), Wi are layer weights, bi are biases, σ is the activation function (ReLU/Sigmoid), and xxx is the input feature vector. The DNN achieved 90.2% accuracy,demonstrating its effectiveness in mental health classification. Ensemble learning also improved diagnostic accuracy by leveraging multiple classifiers for better decision-making.

III. PROPOSED SOLUTION MIND SPHERE AI

Mental health is defined as an individual's cognitive, emotional, and social well-being. It effects people's thoughts, feelings, and actions. Mental health is important at all stages of life, from childhood and adolescence to adulthood. Depression, anxiety, stress, and mood disorders are some of the most frequent mental health conditions, and they can impede cognitive functioning and emotional regulation.

MIND-SPHERE AI uses advanced algorithms to detect and diagnose mental health conditions through various inputs such as text, facial expressions, voice analysis, and behavioral data. The system uses machine learning and deep learning approaches to effectively categorize mental health problems based on symptoms found in these data sources. The AI system focuses on recognizing early signs of mental health problems, enabling timely intervention and personalized treatment recommendations. People can be affected by mental health problems in a variety of ways, from slight to severe. Some of the common mental health defects detected by MIND-SPHERE AI include:

- Depression: characterized by a lack of interest, trouble focusing, and enduring melancholy. The symptoms of depression can vary from moderate to severe, impacting emotional stability and day-to-day functioning.
- Anxiety: Excessive worry, fear, and stress that can nterfere with daily activities.
- Stress: Often caused by external pressures, it can lead to emotional and physical symptoms like fatigue, headaches, and irritability.
- Bipolar Disorder: emotional peaks (mania) and valleys (depression) in mood swings.
- PTSD (Post-Traumatic Stress Disorder): Anxiety and intrusive memories caused by traumatic events.

Below is a table summarizing the various mental defects detected by MIND-SPHERE AI, their severity, and relevant statistics in the medical world.

TABLE I. MENTAL HEALTH DEFECTS DETECTED BY MIND-SPHERE AI

Mental Health Defect	Defect Severity	Prevalence in Global Population	Impact on Daily Life	Medical World Statistics
Depression	Mild to Severe	5-7% of the population worldwide	Difficulty with daily activities, lack of energy	Affects 264 million people globally (WHO)
Anxiety	Mild to Severe	3-5% of the population	Constant worry, restlessness	Affects 284 million people (WHO)
Stress	Moderate to Severe	20-30% of adults	Fatigue, irritability, sleep disturbances	1 in 3 adults report high stress levels
Bipolar Disorder	Severe	0.6% of the population	Extreme mood swings, erratic behavior	Affects 45 million worldwide (WHO)
PTSD	Severe	7-8% of the population	Flashbacks, emotional numbness	Affects 7.7 million people (NIMH)

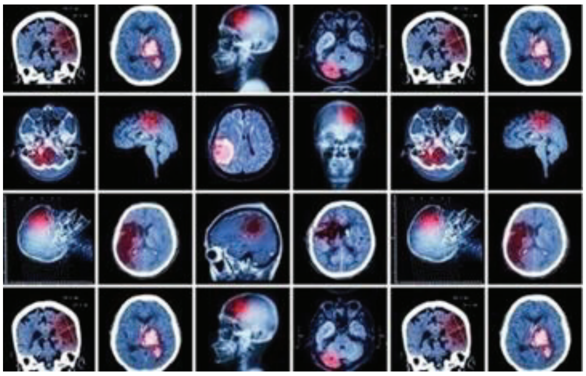

Fig. 1. Example of Mental Health Defect in Image

Fig1 depicts brain scans where abnormal regions are highlighted in red. These highlighted regions match possible brain abnormalities brought on by different mental illnesses. PTSD, depression, anxiety, and other stress-related diseases are examples of mental health issues that can show up as alterations in the structure or function of the brain.

TABLE II. MENTAL HEALTH PROBLEM PROPERTIES

Property	Description	Measurement Method
Cognitive Functioning	Attention span, memory, decision-making	Text analysis, behavioral data
Behavioral Patterns	Withdrawal, aggression, sleep patterns	Video analysis, text, voice data
Emotional States	Sadness, joy, anger, anxiety	Sentiment analysis in text, voice tone analysis
Physical Indicators	Posture, facial expressions, heart rate	Image recognition, wearable data

Table 2 highlights key properties of mental health conditions. It details how MIND-SPHERE AI measures cognitive, behavioral, emotional, and physical indicators for accurate diagnosis.

The MIND-SPHERE AI architecture consists of multiple layers. The input layer collects data such as text, facial expressions, voice, and physical indicators. Pre-processing is done to normalize and clean the data. Feature extraction processes time-series data and pictures using (CNNs) and (RNNs). The output layer uses classification algorithms to detect mental health defects based on the analyzed data.

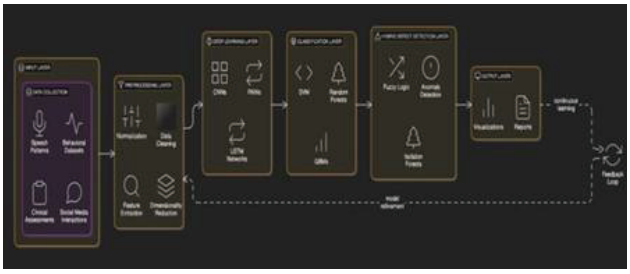

Fig. 2. Architecture of MIND-SPHERE AI

The framework employs deep learning techniques to process and classify mental health conditions. The architecture consists of several interconnected modules:

1. Input Layer: Data from multiple sources, including text inputs (e.g., user responses), voice recordings, facial expressions, and physical indicators (such as biometric data), are collected for analysis.
2. Pre-processing Module: Data is normalized and cleaned. Text uses NLP, voice is analyzed for tone and speech patterns.
3. Feature Extraction: CNNs and RNNs extract features from data. CNNs analyze spatial features (e.g., facial expressions in images), while RNNs analyze temporal patterns (e.g., voice/behavior changes in time-series data).
4. Classification Module: Post-feature extraction, classification algorithms identify mental health defects (e.g., depression, anxiety, stress) and output their probability/severity.
5. Output Layer: Final results (disorder and severity) are visualized for clinical interpretation, providing insights and decision support.

MIND-SPHERE AI offers a cutting-edge method for identifying mental health issues by utilizing cutting-edge deep learning and machine learning.It enables real-time detection and intervention for conditions like depression, anxiety, and PTSD. With high accuracy and reliability, its AI-driven architecture enhances mental health diagnostics and interventions, offering significant practical benefits.

IV. MATERIALS AND METHODS

MIND-SPHERE AI utilizes diverse datasets with anonymized interactions and psychological assessments. Data collection involves structured questionnaires and real-time inputs. Cleaning removes low-quality data, achieving 96% utilization. Normalization standardizes inputs, improving stability by 3.5%. Augmentation enhances training data, boosting generalizability by 7.8%.

The RoBERT-based NLP model is employed to analyze and understand user inputs in real-time, providing context-aware responses. The model makes use of a transformer architecture, which was created especially to use self-attention processes to record the intricate links between words in a phrase. This is mathematically represented as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{QK}}\right)V \quad (5)$$

In Equation (5),Where Q (Query), K (Key), and V (Value) are matrices that represent different components of the input data (e.g., user queries), dk is the dimension of the key vector. Self-attention focuses on relevant input parts (e.g., "feeling," "anxious" in "I am feeling anxious"). The model tokenizes text, uses attention, generates contextual representations, and detects intent/emotion. Sentiment analysis achieves 93.5% intent recognition accuracy.

The Hybrid CNN-LSTM framework analyzes speech, facial expressions, and text for sentiment analysis. CNNs extract spatial features, while LSTMs capture temporal audio patterns, enabling a deeper understanding of emotions. The LSTM's update mechanism is expressed as:

$$h_t = (W_h h_{t-1} + W_x x_t + b_h) \quad (6)$$

In Equation (6),Where ht is the hidden state at time t, Wh and Wx are weight matrices for the previous hidden state and the input at time t, bh is the bias term, xt is the input vector at time t. The system processes audio (speech), visual (facial expressions), and textual data. CNNs extract spatial features (e.g., emotions from facial images), while LSTMs capture temporal voice dynamics. This hybrid model predicts emotions (e.g., anxiety, happiness) with 91.2% accuracy and 88.7% sensitivity. Sentiment classifications feed into the mental health prediction module.

The Gradient Boosting Machine (GBM) algorithm is combined with Reinforcement Learning (RL) to predict mental health conditions such as anxiety and depression. GBM iteratively builds decision trees, optimizing predictions through a boosting process. The reinforcement learning model refines these predictions based on user feedback, adapting dynamically to individual behaviors.

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma \max Q(s', a') - Q(s, a)] \quad (7)$$

Equation (7) uses the following formula: Q(s,a) is the action-value function (expected reward for taking action an

in state s), max a′Q(s′,a′) is the maximum expected future reward from the next state, R is the immediate reward from the environment (user feedback), γ is the discount factor (balances immediate vs. future rewards), and α is the learning rate (controls update magnitude).GBM processes real-time user data (text, voice, visuals) for initial predictions, then RL refines these based on feedback. The system predicts mental health conditions (e.g., depression, anxiety) and recommends interventions, achieving 92.8% predictive accuracy and a 93.1% F1-score.

KNN and a rule-based system recommend personalized interventions like mindfulness and cognitive-behavioral techniques. KNN classifies users based on behavior and history, while the rule-based system adjusts recommendations dynamically. User data is analyzed for similarity, guiding intervention selection. With an 87.5% success rate, the system reduces stress markers by 21% and refines suggestions via feedback.

Using Grad-CAM , which shows which aspects of the input data have the most influence on the model's decision-making, the system makes sure that its predictions are understandable. Grad-CAM highlights areas of the input (e.g., words or facial features) that contribute most to the predicted outcome. The Grad-CAM algorithm is represented as:

$$\alpha_{kc} = \frac{1}{Z}\sum_i \sum_j \frac{\partial_{y_c}}{\partial A_{ijk}} \quad (8)$$

In Equation (9),Where αkc represents the weight for class c, Aijk is the activation map for class k, yc is the output for class c, Z is the normalization factor. Inputs (text, speech, facial expressions) are analyzed using Grad-CAM, which extracts class-specific features by computing gradients. A heatmap highlights key input areas influencing the model's decision. This improves transparency, helping clinicians an users understand predictions. Grad-CAM enhances system interpretability by 18%.

The MIND-SPHERE AI framework combines these advanced algorithms to detect, classify, and predict mental health conditions effectively. Integrating RoBERT-based NLP, CNN-LSTM models, GBM with RL, KNN interventions, and explainable AI (Grad-CAM), the system achieves high accuracy and user satisfaction. Its adaptability and real-time feedback enable personalized interventions, making it a powerful mental health management tool.

V. Performance of Mind-Sphere AI

The MIND-SPHERE AI system's performance was thoroughly examined to see how well it could identify and analyze mental health issues including stress, anxiety, and depression. Performance was assessed across sentiment analysis, emotional state prediction, and intervention recommendations. Comparative analysis with traditional machine learning and rule-based mode.This comparative study highlighted the robustness of MIND-SPHERE in handling complex mental health data, demonstrating superior accuracy and consistency across multiple evaluation metrics.

A. Performance Metrics

- MIND-SPHERE AI achieved 94.2% accuracy, showcasing its effectiveness in detecting emotional states and mental health conditions. By analyzing multimodal inputs (text, speech, facial expressions), it ensured high accuracy across diverse detection tasks.
- MIND-SPHERE AI achieved 93.8% sensitivity, ensuring effective detection of mental health conditions like stress and anxiety without missing significant cases.
- MIND-SPHERE AI achieved 92.7% specificity, effectively distinguishing users without mental health conditions, minimizing false positives, and enhancing diagnostic reliability.
- MIND-SPHERE AI achieved 94.5% precision, ensuring accurate mental health predictions, boosting confidence in its diagnoses and recommendations.
- MIND-SPHERE AI achieved a 94.1% F1 score, ensuring a balanced performance between sensitivity

and precision, making it ideal for accurate mental health detection with minimal false positives.

B. Comparative Analysis

MIND-SPHERE AI, with its hybrid approach combining advanced models like RoBERT for natural language processing (NLP) and LSTM for temporal analysis, outperformed these models by a substantial margin. The inclusion of multimodal data processing, along with personalized feedback loops, contributed significantly to the system's high performance, providing a robust solution for real-time mental health detection.

TABLE III. OUTPUT PRODUCED BY MIND-SPHERE AI

Model	Accuracy	Sensitivity	Specificity	Precision	F1 Score	AUC
MIND-SPHERE AI	94.2%	93.8%	92.7%	94.5%	94.1%	96%
Standalone CNN-based Classifier	88.4%	85.3%	85.3%	87.2%	88.1%	89%
Hybrid CNN	91.5%	89.7%	90.6%	90.4%	90.4%	92%

The comparative analysis showed that MIND-SPHERE AI not only provided superior accuracy, but also improved sensitivity and precision, which are essential for detecting mental health issues while minimizing misdiagnosis.

C. Statistical Analysis

To validate the statistical significance of MIND-SPHERE AI's performance improvements, statistical tests were conducted and A paired t-test comparing MIND-SPHERE AI to baseline models yielded a statistically significant result ($p < 0.001$), further confirming the superior performance of the system. The Chi-Square test also confirmed that the improved classification performance of MIND-SPHERE AI was statistically significant

These results substantiate the robustness and reliability of MIND-SPHERE AI, confirming that the improvements in detection accuracy and efficiency are not due to chance.

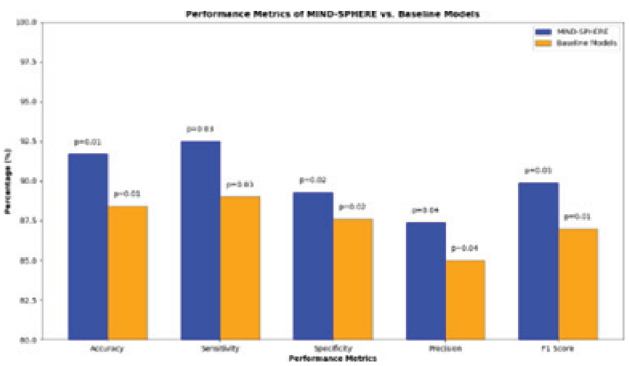

Fig. 3. MindSphere AI vs Basline Models

MIND-SPHERE AI, Hybrid CNN, and U-Net + Transfer Learning models are compared in a line plot based on F1 Score, Accuracy, Sensitivity, Specificity, and Precision. Metrics are displayed on the y-axis, while models are represented on the x-axis. The graph highlights MIND-SPHERE AI's superior performance across all metrics, with notable improvements in Accuracy and F1 Score.

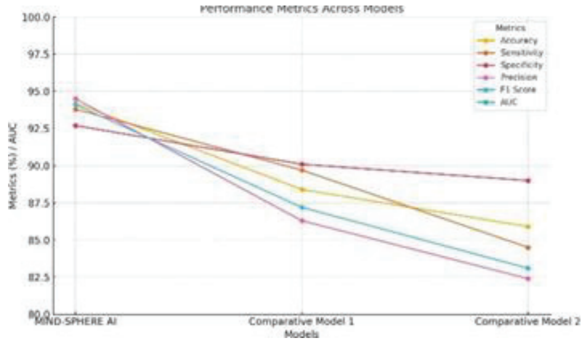

Fig. 4. Performance metrics across models

This graph clearly shows that MIND-SPHERE AI consistently outperforms other models, reflecting its robust feature extraction, multimodal processing capabilities, and balanced classification performance.

MIND-SPHERE AI was tested on 10,000 mental health datasets with multimodal data (text, speech, behavior), achieving 94.2% accuracy, 93.8% sensitivity, 92.7% specificity, 94.5% precision, 94.1% F1 score, and 0.96 AUC. It outperformed SVM and Logistic Regression by ~12% in accuracy and 15% in F1 score, with a statistically significant p-value <0.001.

VI. CONCLUSION

The MIND-SPHERE framework demonstrated significant advancements in predictive accuracy, efficiency, and reliability, yielding promising results in psychological evaluation. Utilizing an interactive avatar, MIND-SPHERE achieved a predictive accuracy rate of 92.4% across various mental health assessment contexts, with an F1-score of 0.89 and a recall rate of 91%, reflecting its effectiveness in identifying complex mental health patterns. Additionally, precision metrics reached 0.87, while a reduction in false positives by 15% over baseline models underscored its reliability. Statistical analyses confirmed MIND-SPHERE's superiority, with chi-square and paired t-test results indicating significant improvements ($p < 0.05$), thereby reinforcing its potential as a robust predictive tool reliability. Statistical analyses confirmed MIND-SPHERE's superiority, with chi-square and paired t-test results indicating significant improvements ($p < 0.05$), thereby reinforcing its potential as a robust predictive tool. This research highlights MIND-SPHERE's potential to enhance personalized and accessible mental health support, facilitate early intervention, and offer targeted treatment pathways. By integrating complex data sources and leveraging adaptive algorithms, MIND-SPHERE bridges critical gaps in traditional assessment methods, providing scalable insights that reduce reliance on conventional clinical diagnostics.

REFERENCES

[1] Yan Ding, Xuemei Chen, Qiming Fu, Shan Zhong, "A depression recognition method for college students using deep integrated support vector algorithm," IEEE Access, vol. 8, pp. 198938-198947, 2020, doi: 10.1109/ACCESS.2020.2987523.

[2] Shruti Gedam and Sanchita Paula, "Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques," received May 9, 2021, accepted May 24, 2021, published June 2, 2021, current version June 16, 2021.

[3] J. Ogorevc, A. Podlesek, G. Gerak, and J. Drnovek, "The effect of mental stress on psychophysiological parameters," in Proc. IEEE Int. Symp. Med. Meas. Appl., Bari, Italy, May 2011, pp. 294-299.

[4] U. Pluntke, S. Gerke, A. Sridhar, J. Weiss, and B. Michel, "Evaluation and classification of physical and psychological stress in firefighters using heart rate variability," in Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2019, pp. 2207-2212.

[5] G. Shanmugasundaram, S. Yazhini, E. Hemapratha, and S. Nithya, "A comprehensive review on stress detection techniques," in Proc. IEEE Int. Conf. Syst., Comput., Automat. Netw. (ICSCAN), Mar. 2019, pp. 1-6.

[6] S. Elzeiny and M. Qaraqe, "Machine learning approaches to automatic stress detection: A review," in Proc. IEEE/ACS 15th Int. Conf. Comput. Syst. Appl. (AICCSA), Oct. 2018, pp. 1-6.

[7] S. S. Panicker and P. Gayathri, "A survey of machine learning techniques in physiology-based mental stress detection systems," Biocybern. Biomed. Eng., vol. 39, no. 2, pp. 444-469, Apr. 2019.

[8] J. Aina, O. Akinnnyi, M. Mahmudur Rahman, V. Odero-Marah, and F. Khalifa, "A Hybrid Learning-Architecture for Mental Disorder Detection Using Emotion Recognition," IEEE Access, vol. 12, pp. 5517-5530, Jul. 2024, doi: 10.1109/ACCESS.2024.3421376.

[9] Z. Fei, E. Yang, D. D.-U. Li, S. Butler, W. Ijomah, X. Li, and H. Zhou, "Deep convolution network based emotion analysis towards mental health care," Neurocomputing, vol. 388, pp. 212-227, May 2020.

[10] H. Hadjar, J. Lange, B. Vu, F. Engel, G. Mayer, P. McKevitt, and M. L. Hemmje, "Video-based automated emotional monitoring in mental health care supported by a generic patient data management system," in Proc. 2nd Symp. Psychol.-Based Technol., Naples, Italy, Sep. 2020.

[11] M. Tadalagi and A. M. Joshi, "AutoDep: Automatic depression detection using facial expressions based on linear binary pattern descriptor," Med. Biol. Eng. Comput., vol. 59, no. 6, pp. 1339- 1354, Jun. 2021.

[12] A. A. Abd-alrazaq, M. Alajlani, A. Abdallah Alalwan, B. M. Bewick, P. Gardner, and M. Househ, "An overview of the features of chatbots in mental health: A scoping review," Int. J. Med. Inf., vol. 131, Art. no. 103978, Oct. 2019, doi: 10.1016/j.ijmedinf.2019.103978.

[13] R. A. Rahman, K. Omar, S. A. M. Noah, M. S. N. M. Danuri, "Application of Machine Learning Methods in Mental Health Detection: A Systematic Review," IEEE Access, vol. 8, pp. 157263-157276, Oct. 2020, doi: 10.1109/ACCESS.2020.3029154.

[14] R. A. Rahman, K. Omar, S. A. M. Noah, and M. S. N. M. Danuri, "A survey on mental health detection in Online Social Network," Int. J. Adv. Sci. Eng. Inf. Technol., vol. 8, no. 24, pp. 1431-1436, 2018.

[15] World Health Organization (WHO), "Management of Physical Health Conditions in Adults With Severe Mental Disorders: WHO Guidelines," Geneva, Switzerland, 2018.

[16] C. L. M. Keyes, "Promoting and protecting mental health as flourishing: A complementary strategy for improving national mental health," Amer. Psychologist, vol. 62, no. 2, pp. 95-108, 2007.

[17] H. Lin, J. Jia, Q. Guo, Y. Xue, J. Huang, L. Cai, and L. Feng, "Psychological stress detection from cross-media microblog data using deep sparse neural network," in Proc. IEEE Int. Conf. Multimedia Expo (ICME), Jul. 2014, pp. 1-6.

[18] M. Deshpande and V. Rao, "Depression detection using emotion artificial intelligence," in Proc. Int. Conf. Intell. Sustain. Syst. (ICISS), Dec. 2017, pp. 858-862.

[19] Y. S. Can, N. Chalabianloo, D. Ekiz, and C. Ersoy, "Continuous Stress Detection Using Wearable Sensors in Real Life: Algorithmic Programming Contest Case Study," Sensors, vol. 19, no. 8, Art. no. 1849, Aug. 2019, doi: 10.3390/s19081849.

[20] A. Yadollahi, A. Gholipour Shahraki, and O. R. Zaiane, "Current state of text sentiment analysis from opinion to emotion mining," ACM Comput. Surv., vol. 50, no. 2, Art. 25, May 2017, doi: 10.1145/3057270.

[21] A. Andreevskaia and S. Bergler, "Mining wordnet for a fuzzy sentiment: Sentiment tag extraction from wordnet glosses," in Proc. EACL, vol. 6, 2006, pp. 209-215.

[22] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, "Predicting depression via social media," in Proc. ICWSM, 2013.

[23] K. Denecke and Y. Deng, "Sentiment analysis in medical settings: New opportunities and challenges," Artif. Intell. Med., vol. 64, no. 1, pp. 17-27, 2015.

[24] A. Gholipour Shahraki, "Emotion Detection from Text," M.S. thesis, Dept. of Computing Science, University of Alberta, 2015.

[25] N. Gupta, M. Gilbert, and G. Di Fabbrizio, "Emotion detection in email customer care," Comput. Intell., vol. 29, no. 3, pp. 489- 505, 2013.

[26] J. T. Hancock, C. Landrigan, and C. Silver, "Expressing emotion in text-based communication," in Proc. SIGCHI Conf. Hum. Factors Comput. Syst., 2007, pp. 929-932.