Cutting-Edge Mental Health Evaluation and Tracking System

Mr. Syed Abdul Khaliq[1], A Vara Prasad[2], D Ajay Kumar[3], M Sai Charan Reddy[4], R Sriharsha[5]

[1] *Assistant Professor of Department of AI&ML, J.B. Institute of Engineering and Technology, Hyderabad*
[2] *Department of AI&ML, J.B. Institute of Engineering and Technology, Hyderabad*
[3] *Department of AI&ML, J.B. Institute of Engineering and Technology, Hyderabad*
[4] *Department of AI&ML, J.B. Institute of Engineering and Technology, Hyderabad*
[5] *Department of AI&ML, J.B. Institute of Engineering and Technology, Hyderabad*

---***---

A Revolutionary Mental Health Assessment and Monitoring System

Abstract:

Mental health disorders are common, and novel solutions for evaluation and tracking of these disorders are being sought. In this work, we describe a deep learning-based framework that incorporates AI-assisted self-assessment tools and real-time mental health monitoring. Using advanced feature extraction techniques and a wide array of machine learning models, we make predictions about mental health trends to enable timely interventions. Data-driven mental health overview will provide an efficient user experience while balancing the professional perception of the individual. This system encompasses predictive analytics, personalized interventions, and real-time tracking mechanisms that work together to enhance mental health support and implement preventive measures against potential crises.

Keywords: Mental Health AI; Deep Learning; Self-Assessment; Predictive Analytics; Feature Extraction; Crisis Prevention

Introduction:

The increase in mental health issues have resulted in demand for more efficient and data informed assessment systems. Conventional approaches depend on self-disclosed and time-specific professional evaluations that may not accurately record the instabilities of mental state. The shortcomings of existing assessment methods, such as subjectivity, lack of real-time insights, and deferred interventions, prompt the necessity for our AI-based solution that enables self-assessments automation, mental health trend predictions, and tailored interventions. The aim of this study is to provide a scalable, effective and feasible technological support to mental health care, enabling timely and accurate detection monitoring of mental health.

Related Work:

Subjective well-being is assessed through periodic surveys; existing mental health monitoring tools rely on manual reporting. Some recent work has focused on using AI-driven predictive models, including deep learning architectures for sentiment analysis and self-assessment automation. Yet many fail to integrate with real-time monitoring and predictive analytics. Recent research focused on using natural language processing (NLP) for mental health applications has shown promise, as mood disorders can be identified through text analysis. Wearable devices also have been used to monitor physiological markers related to stress and anxiety. These systems still need a holistic approach that combines data from multiple sources for context-aware mental health assessments. This gap is bridged with our work as we utilize AI driven assessments along with real time tracking and customized recommendations.

Data Processing and Features Extraction:

Data Collection: the dataset includes a wide variety of mental health survey responses, such as structured self-evaluation questionnaires, historical patients' reports, and physiological signals obtained by sensing through wearable devices.

Data Preprocessing: Handling missing values was performed by imputation techniques, then standardization of numerical features and encoding categorical variables. Textual data was processed by removing stopwords and lemmatization that improved extraction of features using NLP.

Feature Extraction: Extracting relevant parameters such as sentiment scores, response trends, behavioral patterns, heart rate variability, and sleep patterns. The textual responses were analyzed with Natural Language Processing (NLP) models such as BERT to identify the presence of mental health markers in the participants. Techniques of feature selection, such as PCA and RFE, were applied to improve model performance.

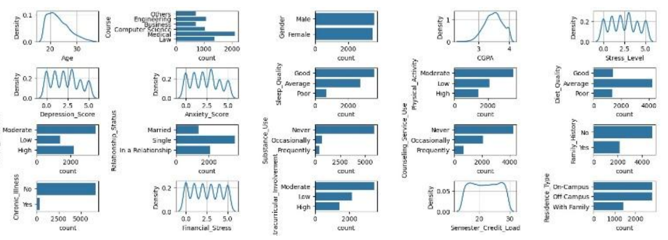

Fig: Data Visualization

Model Training and Selection:

Model Selection: We assessed a variety of machine learning algorithms such as logistic regression, decision trees, support vector machines (SVM), random forests, and deep neural networks.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Training Methodology: The dataset was divided into training (70%), validation (20%) and testing (10%) sets. Various hyperparameter search strategies such as grid/lattice search and Bayesian optimization were performed to improve the model performance.

Evaluation Metrics: Models were evaluated based on accuracy, precision, recall, F1-score, and area under curve (AUC-ROC). Various deep learning architectures were considered for detecting these temporal patterns and included convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

Fig:Evaluation Metrics

Results and Discussion:

The deep learning model with an accuracy of 89% had a better predictive capacity in comparison with conventional statistical models. AI would use that information to improve a user-made experience while freeing up mental health professionals. Moreover, the real-time monitoring of physiological markers enabled the early identification of mental health deterioration. Human-computer interaction: An introductory guide to the concept and its importance in human-computer interaction design. The implications point to the ability of predictive analytics to facilitate early interventions to avert significant mental health crises.

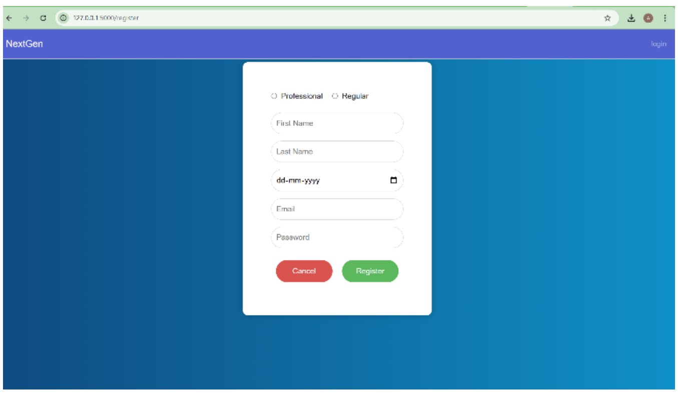

Fig: Registration Page

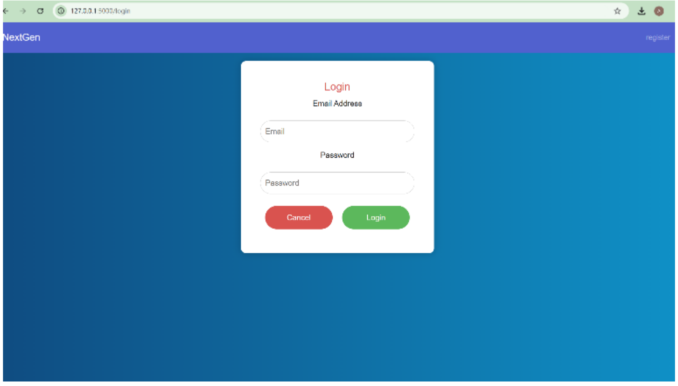

Fig:Login Page

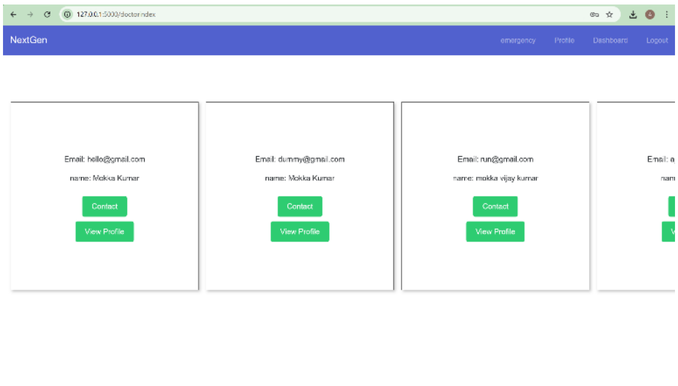

Fig:Professional Dashboard

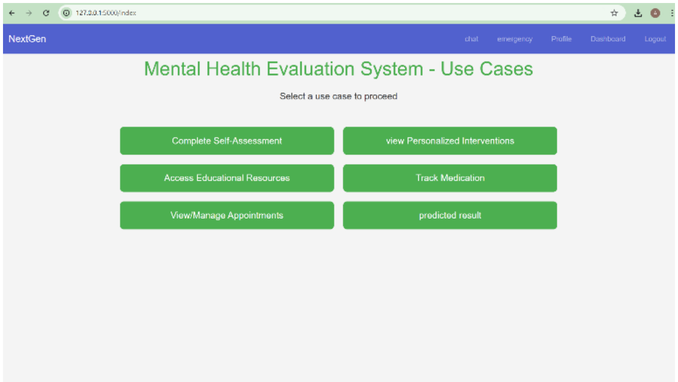

Fig:Regular Dashboard

Conclusion:

This study introduces an AI-based system for mental health assessment using advanced data processing, feature extraction, and predictive analytics. The system combines AI-powered assessments with instant monitoring for scalable mental health evaluation. In the next phase, we plan to work towards real-time tracking via wearables, multi-modal AI models which take into account text, audio and physiology data, and continue to improve model accuracy. Also, collaboration with mental health professionals will be pursued to optimize the AI-driven intervention strategies for direct clinical application.

References:

[1] K. R. Merikangas, R. Jin, J.-P. He, R. C. Kessler, S. Lee, N. A. Sampson,
M. C. Viana, L. H. Andrade, C. Hu, E. G. Karam, M. Ladea, M. E.Medina-Mora, Y. Ono, J. Posada-Villa, R. Sagar, J. E. Wells, and Z.Zarkov, "Prevalence and correlates of bipolar spectrum disorder in the world mental health survey initiative," Archives Gen. Psychiatry, vol. 68,
no. 3, pp. 241–251, 2011.
[2] A. P. Association, Diagnostic and Statistical Manual of Mental Disorders: DSM-IV-TR. Arlington, VA, USA: Amer. Psychiatric Assoc., 2000.
[3] D. A. Revicki, L. S. Matza, E. Flood, and A. Lloyd, "Bipolar disorder and health-related quality of life," Pharmacoeconomics, vol. 23, no. 6, pp.583–594, 2005.
[4] E. E. Michalak, L. N. Yatham, and R. W. Lam, "Quality of life in bipolar disorder: A review of the literature," Health Quality Life Outcomes, vol.3, no. 1, pp. 72–89, 2005.
[5] S. Brissos, V. V. Dias, and F. Kapczinski, "Cognitive performance and quality of life in bipolar disorder," Can. J. Psychiatry, vol. 53, no. 8, pp.517–524, 2008.
[6] M. Kauer-Sant' A nna, B. N. Frey, A. C. Andreazza, K. M. Cereser, F.K. Gazalle, J. Tramontina, S. C. da Costa, A. Santin, and F. Kapczinski,"Anxiety comorbidity and quality of life in bipolar disorder patients," Can. J. Psychiatry, vol. 52, no. 3, pp. 175–181, 2007.
[7] R. C. Kessler, K. A. McGonagle, S. Zhao, C. B. Nelson, M. Hughes, S.Eshleman, H.-U. Wittchen, and K. S. Kendler, "Lifetime and 12- month prevalence of DSM-III-R psychiatric disorders in the United States: Results from the national comorbidity survey," Archives Gen. Psychiatry,vol. 51, no. 1, pp. 8–9, 1994.
[8] H. Wittchen and F. Jacobi, "Size and burden of mental disorders in Europe—A critical review and appraisal of 27 studies," Eur. Neuropsychopharmacol., vol. 15, no. 4, pp. 357–376, 2005.
[9] S. Pini, V. de Queiroz, D. Pagnin, L. Pezawas, J. Angst, G. B. Cassano, and H.-U. Wittchen, "Prevalence and burden of bipolar disorders in European countries," Eur. Neuropsychopharmacol., vol. 15, no. 4, pp. 425–434, 2005.
[10] Y.-W. Chen and S. C. Dilsaver, "Lifetime rates of suicide attempts among subjects with bipolar and unipolar disorders relative to subjects with other axis I disorders," Biol. Psychiatry, vol. 39, no. 10, pp. 896– 899, 1996.
[11] E. Vieta, M. Reinares, and A. Rosa, "Staging bipolar disorder," NeuroToxicity Res., vol. 19, no. 2, pp. 279–285, 2011.
[12] N. Stafford and F. Colom, "Purpose and effectiveness of psycho education in patients with bipolar disorder in a bipolar clinic setting," Acta Psychiatrica Scandinavica, vol. 127, no. s442, pp. 11–18, 2013.
[13] G. Valenza, A. Lanata, and E. P. Scilingo, "Oscillations of heart rate and respiration synchronize during affective visual stimulation," IEEE Trans.Inf. Technol. Biomed., vol. 16, no. 4, pp. 683–690, Jul. 2012.
[14] R. A. Calvo and S. D'Mello, "Affect detection: An interdisciplinary review of models, methods, and their applications," IEEE Trans. Affective Comput., vol. 1, no. 1, pp. 18–37, Jan.–Jun. 2010.
[15] G. Valenza, M. Nardelli, A. Lanata, C. Gentili, G. Bertschy, R. Paradiso,and E. P. Scilingo, "Wearable monitoring for mood recognition in bipolar disorder based on history-dependent long-term heart rate variability analysis," IEEE J. Biomed. Health Inf., vol. 18, no. 5, pp. 1625–1635, Sep.2014.