International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Detection Of Mental Health Instability Using Machine Learning Models

Burramukku Ashutosh[1], Busavaly Dathrao[2], Yelamoni Chathurya[3], B Surekha[4]

[1] Computer Science and Engineering Guru Nanak Institutions Technical Campus Telangana, India ashutoshjamalpur8@gmail.com
[2] Computer Science and Engineering Guru Nanak Institutions Technical Campus Telangana, India anikethbusavale03@gmail.com
[3] Computer Science and Engineering Guru Nanak Institutions Technical Campus Telangana, India chathuryayelamoni06@gmail.com
[4] Asst. Professor Guru Nanak Institutions Technical Campus Telangana, India surekha.iotgnitc@gniindia.org

ABSTRACT –

In the current fast-paced environment, individuals increasingly encounter mounting pressures in both their personal and professional lives, leading to a rise in mental health issues such as stress and depression. If these issues remain unaddressed, they can have serious repercussions, including self-harm and a decline in overall quality of life. Bipolar disorder exemplifies a mental health condition that necessitates prompt diagnosis and treatment. This research investigates the identification of depressive indicators among working professionals using sophisticated machine learning methods. The study examined survey data that included various demographic and psychological elements, employing preprocessing and feature selection strategies. Among the different algorithms utilized, the Random Forest model recorded the highest accuracy at 87.02%. These results highlight the potential of machine learning to offer scalable, data-driven solutions for early detection and intervention of mental health issues in workplace settings.

Keywords -Bipolar Disorder, Mental Health Monitoring, Random Forest Algorithm, Machine Learning, Ensemble Methods, Feature Selection, SMOTE, PHQ-9, GAD-7.

I. Introduction :

Mental health plays a crucial role in overall well-being, significantly impacting an individual's daily experiences, relationships, and physical health. Unlike visible physical health issues, mental health disorders often go unnoticed and are underestimated, yet their effects are extensive, influencing productivity, personal satisfaction, and the fabric of society. In today's world, the rapid evolution of technology, combined with increasing societal and workplace pressures, has led to a surge in mental health difficulties, including stress, anxiety, and depression. If these issues remain unaddressed, they can result in severe consequences such as self-harm, reduced quality of life, and even death.

According to the World Health Organization (WHO), mental health disorders impact millions of people worldwide, with depression identified as a leading cause of disability. Suicide, frequently associated with untreated mental health issues, is a significant public health concern, particularly among the younger population. Despite the increasing recognition of these challenges, stigma, lack of resources, and insufficient awareness still obstruct effective diagnosis and treatment.

A variety of factors contribute to mental health issues. Modifiable factors, such as financial security, social support systems, and job status, significantly influence an individual's mental health. Non-modifiable factors, like age and gender, also play a role in vulnerability to mental health disorders. For example, older adults may struggle with loneliness and deteriorating health, while younger individuals often deal with societal pressures and uncertainties regarding their futures. These factors frequently intersect, leading to complicated situations that necessitate comprehensive approaches for resolution.

Conventional approaches to diagnosing and managing mental health conditions have mainly depended on clinical evaluations and self-reported information. However, these techniques have limitations, including their subjective nature and challenges in scaling for extensive populations. The emergence of technology, especially within data science and machine learning, has paved the way for innovative solutions to these obstacles. Machine learning algorithms can analyze large sets of data and uncover intricate patterns, providing effective means for early detection and intervention. By utilizing psychological assessments, demographic information, and behavioral data, machine learning models can yield insights that assist clinicians and policymakers in formulating targeted strategies.

This research centers on employing machine learning methods to detect depressive tendencies among working professionals, a group particularly at risk for mental health issues due to job-related stress and high expectations. The study highlights the significance of preprocessing, feature selection, and rigorous model evaluation to ensure accurate and dependable predictions. The results are intended to enrich the expanding field of mental health informatics, offering scalable and data-driven strategies to alleviate the burden of mental health disorders within society.

II. Related Work Area :

- Extensive studies have been conducted in the area of mental health detection using machine learning, highlighting its increasing potential in tackling psychological issues. Machine learning algorithms have shown their capacity to analyze intricate datasets and identify significant patterns, resulting in more precise diagnosis and intervention strategies.

- One notable study by Jadhav et al. (2019) applied a Decision Tree Classifier to the Mood Disorder Questionnaire (MDQ) dataset, concentrating on pinpointing essential features for detecting bipolar disorder. This method showcased the practicality of automated systems in efficiently screening mental health issues.
- Kumar et al. (2020) examined how physiological factors, like heart rate variability and sleep patterns, can be combined with ensemble methods such as Random Forests and Gradient Boosting. These models achieved accuracies between 78% and 85%, demonstrating the effectiveness of ensemble techniques in mental health contexts.
- Another important contribution came from Smith et al. (2022), who used self-reported workplace surveys and employed Random Forest models to forecast mental health problems. Their findings revealed that Random Forests surpassed other machine learning algorithms in accuracy and interpretability, reaching an accuracy of 84.5%. This is closely aligned with the results of the current study, where Random Forest attained an accuracy of 87.02%.
- Overall, these studies highlight the transformative impact of machine learning in the mental health field, laying the groundwork for scalable, data-driven methods for detection and intervention. The present research builds on these approaches by utilizing a comprehensive dataset designed for working professionals and refining preprocessing and model evaluation techniques to improve performance.

III. Methodology :

The research methodology employed in this study consisted of several comprehensive stages, ensuring accuracy and reliability in detecting depressive tendencies among working professionals. Each step was designed to optimize data quality and enhance model performance.

1. **Data Collection:** Data was gathered through structured surveys tailored to working professionals, covering a broad spectrum of information, including:
    - **Demographics:** Age, gender, profession, and geographic location.
    - **Psychological Assessments:** Standardized scales like PHQ-9 (Patient Health Questionnaire) and GAD-7 (Generalized Anxiety Disorder Scale) were employed to evaluate mental health conditions.
    - **Lifestyle Patterns:** Information on sleep hours, social interactions, and work stress levels was collected to gain holistic insights. This diverse dataset ensured a representative sample, enabling the identification of critical mental health indicators.
2. **Preprocessing:** To ensure data integrity and readiness for analysis, several preprocessing techniques were applied:
    - **Handling Missing Values:** Imputation methods, such as mean or median imputation for numerical fields, were utilized to address gaps in data.
    - **Categorical Encoding:** Categorical variables were transformed into numerical formats using techniques like one-hot encoding and label encoding.
    - **Feature Scaling:** Numerical features were normalized using Min-Max scaling to maintain consistency across variables.
    - **Class Balancing:** The Synthetic Minority Oversampling Technique (SMOTE) was employed to mitigate class imbalance, ensuring that minority-class instances were adequately represented in the dataset.
3. **Feature Selection:** Relevant features were identified through:
    - **Correlation Analysis:** Examined relationships between variables to eliminate redundancy.
    - **Mutual Information Evaluation:** Assessed the dependency of features on the target variable.
    - **Domain Expertise:** Incorporated expert knowledge to ensure the inclusion of critical attributes like psychological scores, sleep patterns, and stress levels. Feature selection reduced dimensionality, improving computational efficiency and model interpretability.
4. **Model Training:** A range of machine learning algorithms was implemented to determine the most effective model for mental health detection:
    - **Logistic Regression:** Used as a baseline for binary classification.
    - **Support Vector Machines (SVM):** Explored for its capability to classify high-dimensional data.
    - **Random Forest (RF):** An ensemble method known for its ability to handle non-linear data and avoid overfitting.
    - **Gradient Boosting Machines (GBM):** Utilized to capture complex feature interactions. Hyperparameter tuning was conducted using grid search, ensuring optimal performance for each model.
5. **Validation:** Model validation involved rigorous testing using:
    - **K-Fold Cross-Validation:** Divided the dataset into training and testing subsets to evaluate model generalizability.
    - **Performance Metrics:** Key metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, were calculated to assess model effectiveness.

The Random Forest algorithm emerged as the best-performing model, achieving an accuracy of 87.02%. This result underscores the effectiveness of ensemble methods in handling complex, multi-dimensional data.

IV. Analysis and Insights :

The analysis conducted in this study revealed that work stress levels, sleep patterns, and psychological scores were the most significant predictors of overall mental health outcomes among employees. These factors were identified as key indicators that directly influence the well-being of individuals in the workplace, highlighting the importance of addressing mental health concerns in professional environments.

In terms of algorithm performance, the Random Forest model demonstrated exceptional accuracy and efficiency. Its ensemble approach, which combines multiple decision trees to improve prediction accuracy, proved particularly effective in capturing complex, non-linear relationships within the data. This made it a valuable tool for understanding the intricate interactions between various factors that influence mental health, providing more robust predictions compared to simpler models.

From a practical standpoint, the findings underscore the critical need for scalable mental health monitoring systems in workplace settings. These systems should be able to continuously track key indicators such as stress levels, sleep patterns, and psychological health, offering timely interventions for employees who may be at risk. By integrating such systems into organizational frameworks, companies can foster a healthier work environment, mitigate the impact of mental health issues on productivity, and enhance overall employee satisfaction and performance.

V. Conclusion and Future Scope :

This research underscores the efficacy of machine learning, particularly the Random Forest algorithm, in effectively identifying mental health issues. The model's capacity to manage intricate data and provide high accuracy highlights its promise in recognizing early indicators of mental health challenges among people. The triumph of Random Forest in this area paves the way for additional progress in mental health detection via machine learning strategies. Looking forward, upcoming studies might concentrate on incorporating more sophisticated deep learning models, like neural networks, to enhance prediction accuracy and dependability. These frameworks, with their capability to discern complex patterns from extensive datasets, may yield even more accurate evaluations of mental health disorders. By leveraging the capabilities of deep learning, future solutions could offer more detailed insights and forecasts, facilitating earlier and more effective interventions.

In the end, these initiatives aspire to construct resilient, adaptable systems for practical applications in mental health monitoring. Such developments could transform the methods of detecting and addressing mental health issues across various settings, from workplaces to healthcare environments, resulting in improved outcomes for both individuals and organizations.

REFERENCES :

[1] R. Jadhav, V. Chellwani, S. Deshmukh and H. Sachdev, "Mental Disorder Detection : Bipolar Disorder Scrutinization Using Machine Learning," *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, 2019, pp. 304-308, doi: 10.1109/CONFLUENCE.2019.8776913.

[2] Intelligent data mining and machine learning for mental health using genetic algorithm Azar, Ghassan &Gloster, Clay & El-Bathy, Naser &Yu, Su&Neela,Rajasree&Alothman,Israa.(2015).Intelligent data mining and machine learning for mental health diagnosis using genetic algorithm. 201-206. 10.1109/EIT.2015.7293425

[3] A Framework for Classifying Online Mental Health-Related Communities With an Interest in Depression B. Saha, T. Nguyen, D. Phung and S. Venkatesh, "A Framework for Classifying Online Mental Health-Related Communities With an Interest in Depression," in IEEE Journal of Biomedical and Health Informatics, vol. 20, no. 4, pp. 1008-1015, July 2016.

[4] Detecting Cognitive Distortions Through Machine Learning Text Analytics T. Simms, C. Ramstedt, M. Rich, M. Richards, T. Martinez and C. Giraud-Carrier, "Detecting Cognitive Distortions Through Machine Learning Text Analytics," 2017 IEEE International Conference on Healthcare Informatics (ICHI), Park City, UT, 2017, pp. 508-512.

[5] Machine Learning Framework for the Detection of Mental Stress at Multiple Levels Subhani, Ahmad & Mumtaz, Wajid & MOHAMAD SAAD, MOHAMAD NAUFAL & Kamel, Nidal& Malik, Aamir. (2017). Machine Learning Framework for the Detection of Mental Stress at Multiple Levels. IEEE Access. PP. 1-1. 10.1109/ACCESS.2017.2723622.

[6] Prediction of Mental Health Problems Among Children Using Machine Learning Techniques Sumathi, Ms & B., Dr. (2016). Prediction of Mental Health Problems Among Children Using Machine Learning Techniques. International of Advanced Computer Science and Applications. 10.14569/IJACSA.2016.070176.

[7] F. Lederbogen, P. Kirsch, L. Haddad, F. Streit, H. Tost, P. Schuch, et al., "City living and urban upbringing affect neural social stress processing in humans," Nature, vol. 474, pp. 498-501, 2011.

[8] A. P. Allen, P. J. Kennedy, J. F. Cryan, T. G. Dinan, and G. Clarke, "Biological and psychological markers of stress in humans: Focus on the Trier Social Stress Test," Neuroscience and Biobehavioral Reviews, vol. 38, pp. 94-124, 2014.

[9] H. Ursin and H. Eriksen, "The cognitive activation theory of stress," Psychoneuroendocrinology, vol. 29, pp. 567-592, 2004.

[10] N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition and classification: A survey," Computer Methods and Programs in Biomedicine, vol. 108, pp. 1287-1301, 2012.

[11] J. T.-y. Wang, "Pupil dilation and eye tracking," A handbook of process tracing methods for decision research: A critical review and user's guide, pp. 185-204, 2011.

[12] F. Al-Shargie, M. Kiguchi, N. Badruddin, S. C. Dass, A. F. M. Hani, and T. B. Tang, "Mental stress assessment using simultaneous measurement of EEG and fNIRS," Biomedical Optics Express, vol. 7, pp. 3882-3898, 2016.

[13] S. Gowrisankaran, N. K. Nahar, J. R. Hayes, and J. E. Sheedy, "Asthenopia and blink rate under visual and cognitive loads," Optometry & Vision Science, vol. 89, pp. 97-104, 2012.

[14] F. Al-shargie, T. B. Tang, N. Badruddin, and M. Kiguchi, "Mental Stress Quantification Using EEG Signals," in International Conference for Innovation in Biomedical Engineering and Life Sciences, 2015, pp. 15-19.