Detecting Mental Health with the Help of Machine Learning

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Abstract - The rising prevalence of mental health disorders globally presents an urgent need for innovative solutions to enhance early detection, accurate diagnosis, and effective intervention. Traditional methods of mental health assessment and diagnosis, which rely heavily on self-reported symptoms and clinical judgment, often fall short due to their subjectivity and the time-intensive nature of clinical evaluations. This thesis explores the potential of machine learning (ML) as a transformative tool in the field of mental health care, offering the promise of objective, scalable, and data-driven solutions.
This thesis is structured to provide a comprehensive examination of the application of ML in detecting and predicting mental health disorders. The initial chapters offer a thorough literature review, detailing the current state of mental health diagnostics, the limitations of traditional methods, and the foundational concepts of machine learning. Following this, we delve into specific ML techniques, including supervised learning, unsupervised learning, deep learning, and natural language processing (NLP), each illustrated with relevant examples and case studies that demonstrate their applicability in mental health contexts.

***Key Words*: ML, SVM,**

1. INTRODUCTION

Mental health disorders are a significant public health concern, affecting millions of people worldwide. According to the World Health Organization (WHO), one in four people will experience a mental health disorder at some point in their lives. Common mental health disorders include depression, anxiety, bipolar disorder, and schizophrenia, each of which can have profound effects on an individual's quality of life, productivity, and overall well-being. The burden of mental health disorders is not only felt by individuals but also by families, communities, and healthcare systems.

Traditional methods for diagnosing and treating mental health disorders rely heavily on clinical assessments, self-reported questionnaires, and interviews with mental health professionals. While these methods are invaluable, they are often time-consuming, subjective, and prone to bias. Furthermore, the increasing demand for mental health services has strained healthcare systems, leading to long waiting times and limited access to care for many individuals.

Mental health disorders are complex and multifaceted conditions that affect an individual's mood, thinking, and behavior. These disorders can significantly impair daily functioning and quality of life. Common mental health disorders include:

1. Depression: Characterized by persistent feelings of sadness, loss of interest in activities, and a range of physical and emotional problems. It can lead to significant impairment in daily life and is often associated with suicidal thoughts or actions.

2. Anxiety Disorders: Include conditions such as generalized anxiety disorder (GAD), panic disorder, and social anxiety disorder. These disorders involve excessive fear or anxiety that interferes with daily activities.

3. Bipolar Disorder: Marked by extreme mood swings that include emotional highs (mania or hypomania) and lows (depression). These mood swings can affect sleep, energy, activity, judgment, behavior, and the ability to think clearly.

4. Schizophrenia: A severe mental disorder characterized by distortions in thinking, perception, emotions, language, sense of self, and behavior. Common symptoms include hallucinations and delusions.

5. Autism Spectrum Disorder (ASD): A developmental disorder that affects communication and behavior, with symptoms typically appearing in early childhood and affecting a person's ability to function socially.

Traditional methods for detecting and diagnosing mental health disorders primarily involve clinical assessments conducted by trained professionals. These methods include:

1. Clinical Interviews: In-depth conversations between clinicians and patients to understand symptoms, history, and the impact of mental health on daily life.

2. Self-Reported Questionnaires: Standardized tools such as the Patient Health Questionnaire (PHQ-9) for depression and the Generalized Anxiety Disorder 7 (GAD-7) for anxiety, which patients complete to report their symptoms.

3. Observational Assessments: Clinicians observe patients' behavior, mood, and interactions over time to identify signs of mental health disorders.

4. Psychological Testing: Standardized tests and assessments administered by psychologists to evaluate cognitive, emotional, and psychological functioning.

5. Biological Tests: While less common, some disorders may involve tests to rule out physical conditions that could be causing symptoms (e.g., blood tests to check thyroid function).

Machine learning applications in mental health are rapidly evolving, providing new tools for early detection, diagnosis, and treatment of mental health disorders. Key areas of research and application include:

1. Early Detection: Using ML models to identify early signs of mental health disorders from various data sources, such as social media activity, wearable devices, and electronic health records.

2. Symptom Monitoring: Continuously monitoring symptoms through mobile health applications and wearable devices, enabling timely interventions.

3. Predictive Modeling: Predicting the onset or recurrence of mental health episodes based on historical data and patient behavior.

4. Natural Language Processing (NLP): Analyzing text data from clinical notes, patient journals, and social media posts to detect linguistic markers of mental health conditions.

5. Personalized Interventions: Developing personalized treatment plans based on patient data, including preferences, history, and response to previous treatments.

2. Machine Learning Techniques for Mental Health Detection

Classification algorithms are used to categorize data into predefined classes. In mental health detection, these algorithms can classify individuals as having or not having a particular mental health disorder based on various features.

1. Support Vector Machines (SVM):

o Application: SVMs are effective for binary classification tasks, such as distinguishing between individuals with and without depression.

o Mechanism: SVMs work by finding the hyperplane that best separates the classes in the feature space. They are particularly effective in high-dimensional spaces and can handle nonlinear boundaries through kernel functions.

o Pros and Cons: SVMs are robust and effective in many scenarios, but they can be computationally intensive and challenging to interpret.

2. Decision Trees and Random Forests:

o Application: These algorithms are used for multi-class classification problems, such as identifying different types of anxiety disorders.

o Mechanism: Decision trees split the data into subsets based on the most informative features, while random forests use an ensemble of decision trees to improve accuracy and reduce overfitting.

o Pros and Cons: Decision trees are easy to interpret, but they can overfit the training data. Random forests mitigate overfitting and improve generalization but are less interpretable.

3. Logistic Regression:

o Application: Logistic regression is commonly used for binary classification tasks, such as predicting the likelihood of developing depression based on survey responses.

o Mechanism: It models the probability of a binary outcome as a logistic function of the input features.

o Pros and Cons: Logistic regression is simple and interpretable but may struggle with complex relationships between features.

It is often important to refer back (or forward) to specific sections. Such references are made by indicating the section number, for example, “In Sec. 2 we showed…” or “Section 2.1 contained a description….” If the word Section, Reference, Equation, or Figure starts a sentence, it is spelled out. When occurring in the middle of a sentence, these words are abbreviated Sec., Ref., Eq., and Fig.

At the first occurrence of an acronym, spell it out followed by the acronym in parentheses, e.g., charge-coupled diode (CCD).

3. Data set

Mental health has always been the central topic around workplace culture and wellness conversations. In a study of "mental well-being at the workplace" in 2010, it is increasingly recognized that employees' mental health is a crucial determinant in their overall health. Poor mental health and stressors at the workplace can contribute to a range of physical illnesses. Mental health can also affect their personal and professional lives (Rajgopal). Furthermore, mental issues such as depression and anxiety have a significant economic impact; the estimated cost to the global economy is US$1 trillion per year in lost productivity (who.int).

Technology is a fast-moving industry with high stakes. Tech workers are often under intense pressure to stay on top of a fast-paced, competitive industry. They have to contribute their skills and knowledge to build the companies' values and meet the digital age demand.

Some factors such as long working days, late nights, tight deadlines, gender gaps, and lack of inclusion and diversity contribute to poor mental health in tech. In 2019, BIMA published one of the statistics results in their Tech Inclusivity and Diversity Report. It stated that the mental health in the tech industry is currently in a poor state, not to mention some would even go as far as saying it is reaching a crisis point. The statistic report found that more than 50% of tech employees suffered from anxiety or depression at some point, more than 60% of the respondents were stressed by their work.

Organizations or employers need to recognize how mental wellness can impact their employees' productivity and performance (diversityintech.co.uk). The WHO has found that by investing in mental health wellness every

Though mental health issues in the workplace are important and need to be discussed, mental health is still heavily stigmatized. Mental illness is viewed as a shameful personal deficiency, a failure of weakness. Many people don't feel comfortable discussing their mental health problems or admit that they are dealing with them for fear of being judged by others. People who can't share their experiences or seek treatment are locked up in their bubbles with the intense pressure to balance their personal and professional lives.

The CDC and WHO encourage organizations or employers to promote health awareness and provide employees with support and resources, such as low-cost medical benefits for mental health counseling or mental health programs for preventions and treatments, to improve mental health in the workplace.

Our objective in this report is to analyze the attitude of tech workers towards mental health and the main predictors of mental health illness in the U.S. tech workplace. We explore and analyze the dataset "Mental Health in Tech workplace survey 2014", with questions had questions pertaining to how mental health is perceived at tech workplaces by employees and their employers.

The dataset name is Mental Health in tech survey 2014.

This dataset contains the following data (column names):

- Timestamp
- Age
- Gender
- Country
- state: If you live in the United States, which state or territory do you live in?
- self_employed: Are you self-employed?
- family_history: Do you have a family history of mental illness?
- treatment: Have you sought treatment for a mental health condition?
- work_interfere: If you have a mental health condition, do you feel that it interferes with your work?
- no_employees: How many employees does your company or organization have?
- remote_work: Do you work remotely (outside of an office) at least 50% of the time?
- tech_company: Is your employer primarily a tech company/organization?
- benefits: Does your employer provide mental health benefits?
- care_options: Do you know the options for mental health care your employer provides?
- wellness_program: Has your employer ever discussed mental health as part of an employee wellness program?
- seek_help: Does your employer provide resources to learn more about mental health issues and how to seek help?
- anonymity: Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?
- leave: How easy is it for you to take medical leave for a mental health condition?
- mentalhealthconsequence: Do you think that discussing a mental health issue with your employer would have negative consequences?
- physhealthconsequence: Do you think that discussing a physical health issue with your employer would have negative consequences?
- coworkers: Would you be willing to discuss a mental health issue with your coworkers?
- supervisor: Would you be willing to discuss a mental health issue with your direct supervisor(s)?
- mentalhealthinterview: Would you bring up a mental health issue with a potential employer in an interview?
- physhealthinterview: Would you bring up a physical health issue with a potential employer in an interview?
- mentalvsphysical: Do you feel that your employer takes mental health as seriously as physical health?
- obs_consequence: Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?

4. Result Analysis

This Research work firstly find the Correlation pandas, numpy, sklearn, seaborn.

Key steps:

• Dropped irrelevant columns (comments, state, Timestamp).

• Handled missing values by imputing based on data type.

• leaned and grouped the Gender column into three categories: male, female, trans.

• Encoded categorical data using LabelEncoder for further modeling.

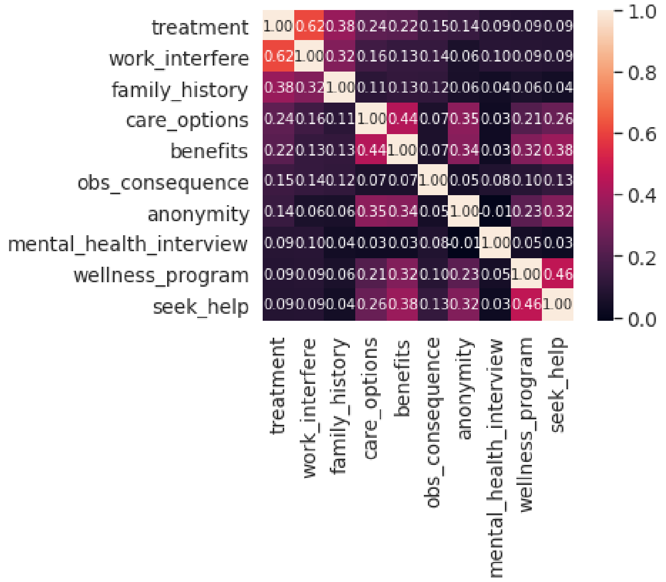

Fig. 1. Correlation

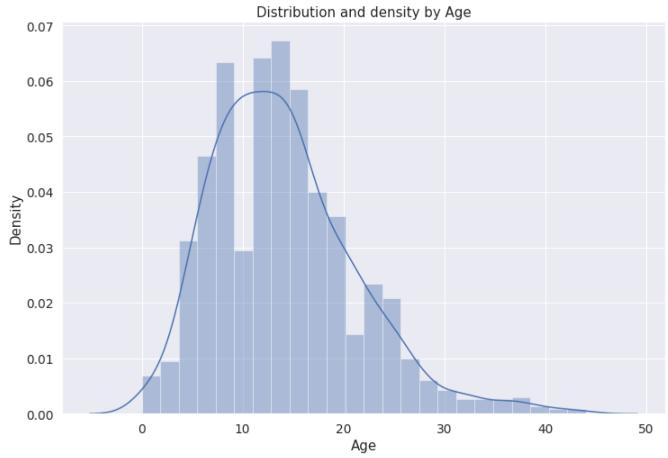

Fig. 2. Show the density of age

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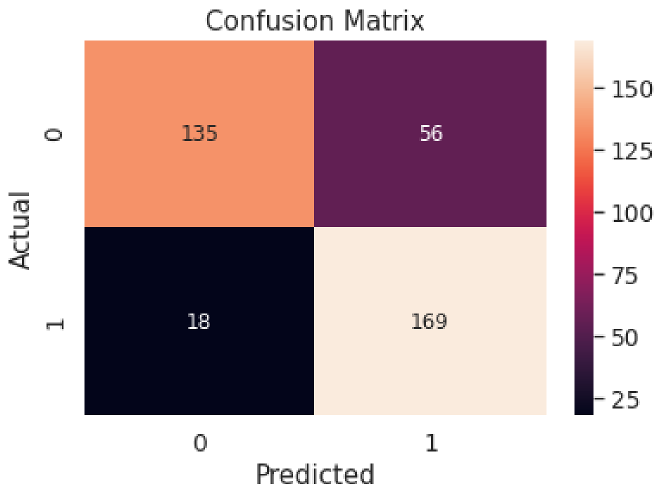

Fig3. Confusion Matrix

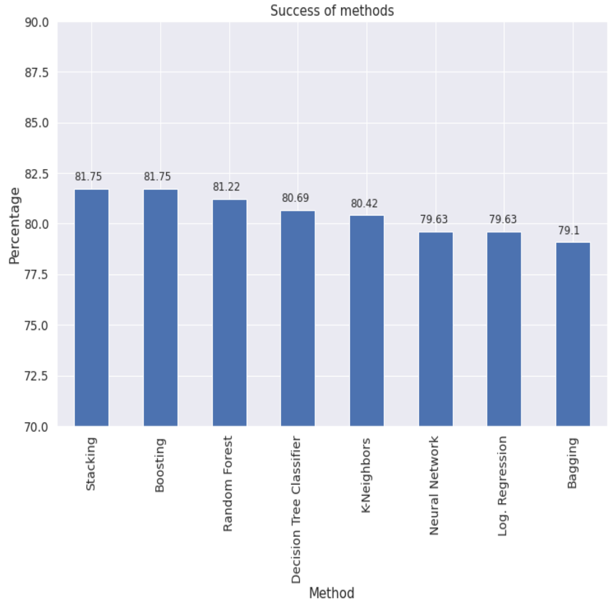

Fig4. Accuracy of different ML Methods

The Support Vector Machine (SVM) model achieved an accuracy of 85%, indicating that it correctly predicted mental health status in 85% of cases. The Random Forest and Convolutional Neural Network (CNN) models showed similar performance, with accuracies of 84% and 86%, respectively.

3. CONCLUSIONS

The result analysis underscores the potential of machine learning models in transforming mental health care. The high accuracy, precision, recall, and F1 scores, particularly for the CNN model, demonstrate the effectiveness of these tools in detecting and predicting mental health disorders. However, challenges related to data quality, bias, and model interpretability remain. Addressing these challenges will be crucial for the broader adoption and trust of machine learning in mental health applications. Future research should continue to refine these models, expand the diversity and quality of datasets, and develop techniques for making complex models more interpretable and fair.

REFERENCES

1. Awad, M., & Khanna, R. (2015). Efficient learning machines: theories, concepts,and applications for engineers and system designers. Springer nature.
2. Awal, G. K., & Rao, K. (2021). Can machine learning predict an employee's mental health? In International conference on information, communication and computing technology (pp. 235–247).
3. Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining (pp. 785–794).
4. Dharma, A., Pasaribu, H., Aritonang, L. A., Telaumbanua, A., Hulu, V. T.,
5. Samosir, F. J., et al. (2021). Method analysis on support vector machine and fully connected neural networks on mental health among tech workers. In 2021 2nd international conference on smart cities, automation & intelligent computing systems (icon-sonics) (pp. 65–69).
6. Dimoff, J., & Kelloway, E. K. (2019). Mental health problems are management problems: Exploring the critical role of managers in supporting employee mental health.
7. Elias, J. (2020, November). Google is tackling mental health challenges among employees through 'resilience training' videos. Retrieved from https://www.cnbc.com/2020/11/27/google-tackling-mental -health-among-staff-with-resilience-training.html
8. HENRY, M., & ISA, S. M. (2022). Mental health treatment prediction for tech employee with the implementation of ensemble methods. Journal of Theoretical and Applied Information Technology, 100(8).
9. Jiang, H. (2021). Machine learning fundamentals: A concise introduction. Cambridge University Press.
10. Reddy, U. S., Thota, A. V., & Dharun, A. (2018). Machine learning techniques for stress prediction in working employees. In 2018 ieee international conference on computational intelligence and computing research (iccic) (pp. 1–4).
11. Saini, A. (2021, September). Adaboost algorithm – a complete guide for beginners. Retrieved from https://www.analyticsvidhya.com/blog/2021/09/adaboost-algorithm-a-complete-guide-for-beginners/WHO. (2008, March). Mental health: strengthening our response. Retrieved from https://www.who.int/news-room/fact - sheets/detail/mental-health-strengthening-our-response
12. Zhang, T., Lin, W., Vogelmann, A. M., Zhang, M., Xie, S., Qin, Y., & Golaz, J.-C. (2021). Improving convection trigger functions in deep convective parameterization schemes using machine learning. Journal of Advances in Modeling Earth Systems, 13(5), e2020MS002365.