

Mental Health Analysis Using Machine Learning

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ABSTRACT

This study investigates the application of machine learning algorithms and image processing techniques for the early detection of mental health issues. The primary objective is to assess the effectiveness of these technologies in promptly identifying mental health problems, thereby facilitating timely medical intervention. A thorough review of existing literature and analysis of relevant datasets reveal that mental health issues are particularly prevalent among young adults and the working population. Our findings indicate that early detection through machine learning can significantly mitigate the negative effects of these conditions, improving diagnostic accuracy by up to X% and enabling individuals to receive timely medical assistance. The research underscores the potential of machine learning to enhance the precision of mental health diagnoses by analysing data and recognizing patterns indicative of underlying issues. Various methodologies, including Natural Language Processing (NLP), K-Nearest Neighbors (KNN), and OpenCV for image processing, were employed to enhance the analysis. In conclusion, the integration of machine learning algorithms presents a promising approach for the early detection and management of mental health problems. By aiding healthcare providers in diagnosing conditions more accurately and efficiently, this approach not only supports individuals in need but also enhances the overall effectiveness of mental health care delivery, ultimately contributing to improved health outcomes and better quality of life for patients.

Keywords: Machine Learning in Psychiatry, Mental Health Diagnosis, Sentiment Analysis, Mental Health Monitoring, NLP, KNN

INTRODUCTION

This review paper follows the standard process of the systematic literature review. First of all, this review paper begins with the planning phase where the research questions or objectives are investigated and determined. In the planning phase, the data sources are being selected, and then the terms that are related to the topic will be used for searching in the data sources. In conducting the review, several aspects need to be prioritized. For instance, publications of the research articles or papers are identified, the studies of the related topic will be selected, and studies that satisfy the research questions will be chosen. Besides that, the evaluation part will begin by extracting the data from the chosen research articles or papers. Further analysis will be carried on the data or evidence from the selected articles and papers. Trends of the research based on the topic will be discussed and investigated. Last part of the process is the discussion and conclusion. Limitations, drawbacks, or gaps of the research will be discussed and examined in this part. Besides that, future directions and potential areas of the research will be investigated and

determined. A conclusion will be provided based on the findings from the research.



Understanding Mental Health

Mental health, as defined by the World Health Organization (WHO), is a vital state of well-being that enables individuals to effectively manage life's stresses, recognize their potential, learn and work productively, and contribute positively to their community. It is a critical aspect of both individual and societal health, underpinning our capacity to make sound decisions, build meaningful

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relationships, and shape our personal and collective futures. Importantly, mental health is a fundamental human right, essential for personal, communal, and socio-economic advancement.

Mental health is a broad concept that goes beyond merely the absence of mental disorders; it exists along a complex continuum, experienced differently by each individual. This range includes varying levels of difficulty and distress that can manifest in distinct social and clinical outcomes. Mental health conditions encompass a variety of mental disorders and psychosocial disabilities as well as other states associated with significant distress, functional impairment, or self-harm risk. Individuals living with these conditions often report lower levels of mental well-being, although this is not universally the case. Given the pervasive impact of mental health on overall well-being, there is a pressing need for greater awareness, research, and systemic support for individuals affected by these conditions.

The Need for Addressing Mental Health in Society

Mental health has become an urgent concern across diverse demographics, affecting working professionals, students, individuals of varying marital statuses, and people of all ages and professions. The necessity of treating mental health with the same importance as physical illnesses is increasingly recognized. Mental health challenges, if left unaddressed, not only impact an individual's emotional and psychological state but can also lead to long-term physical health issues. Therefore, there is an increasing call to address mental health concerns with the same urgency and resources as physical diseases. Early detection and intervention can significantly improve outcomes, and with advances in technology, there are now new ways to support mental health care and diagnosis.

Leveraging Machine Learning for Mental Health Assessment

This research explores the potential of machine learning in supporting psychiatrists with early detection and assessment of depression, aiming to bridge gaps in access and provide timely intervention. The approach involves a multi-layered process, beginning with a *questionnaire* designed to estimate the level of mental illness in an individual. This preliminary assessment is then followed by a *linguistic analysis*, where individuals are asked to write a short passage, which will be examined for

language indicative of depressive thoughts. This method provides insights into the *cognitive* and *emotional state* of the individual.

Furthermore, *facial expression analysis* is conducted as the individual engages in daily activities. Facial expressions can reveal emotional states and, when analyzed over time, can serve as indicators of prolonged emotional distress. By combining these assessments, machine learning algorithms can help predict the likelihood and severity of depressive conditions. Based on the assessment's results, individuals may be offered tailored recommendations, ranging from self-help techniques to connections with mental health professionals in severe cases. By employing a data-driven approach, this project aims to enhance early detection, making mental health care more accessible and effective.

Factors Influencing Mental Health

Mental health conditions are influenced by an interplay of various factors, broadly categorized into biological, social, and environmental domains. Recognizing these factors is crucial for a holistic approach to mental health.

1. Biological Factors:

a. Genetic predisposition and brain chemistry play a significant role in mental health. Common disorders such as depression, anxiety, bipolar disorder, eating disorders, and schizophrenia often result from a combination of genetic variations and environmental experiences. While most genetic variations do not directly cause mental disorders, rare gene variants can increase susceptibility to these conditions. For instance, mood disorders and neurodevelopmental disorders like autism spectrum disorder have genetic links, and these variations affect how genes function, impacting overall mental well-being. Recognizing genetic risk factors allows for targeted prevention and personalized treatment approaches.

2. Life Experiences:

a. Trauma and adverse experiences have a profound impact on mental health. Traumatic events, such as accidents, violence, or natural disasters, can cause long-lasting psychological effects, including post-traumatic stress disorder (PTSD). Chronic stress, abuse, bullying, and even pandemics can leave individuals vulnerable to mental health challenges. Trauma can disrupt

everyday functioning, affect personal relationships, and lead to coping mechanisms that may include substance misuse or self-harm. Addressing trauma is essential for mental health recovery and involves both individual and community-level interventions.

3. Family History of Mental Health Issues:

- a. A family history of mental health issues increases the likelihood of an individual developing similar conditions. Although mental disorders may run in families, they typically involve a mix of genetic and environmental factors rather than following clear-cut patterns of inheritance. This multifactorial nature of mental disorders means that individuals with a family history of these conditions may experience different symptoms or severity levels, necessitating a tailored approach to prevention and treatment.

Social and Environmental Influences on Mental Health

Mental health is also shaped by broader social and environmental factors. Social interactions play a significant role, as relationships with family, friends, and communities contribute to emotional support and resilience. Social connectivity, especially among students and young adults, fosters a sense of belonging and can be a protective factor against mental health issues. Supportive friendships and positive social networks encourage personal growth and can help buffer the effects of life's challenges.

Parenting and upbringing further influence mental health. Parents who foster independence and decision-making in their children contribute to their self-confidence and ability to cope with stress. Moreover, substance abuse, such as prolonged alcohol or drug use, has detrimental effects on mental health, contributing to emotional instability, social isolation, and strained relationships. Addressing these social and environmental aspects is essential for building supportive systems that promote mental well-being.

CONCLUSION

Mental health is a multifaceted and critical component of overall well-being, deeply influenced by biological, social, and environmental factors. As mental health issues become more visible and better understood, there is a growing responsibility to integrate innovative approaches, such as machine learning, to enhance early detection and personalized intervention. The project outlined in this research

aims to offer a comprehensive and proactive approach to mental health assessment, leveraging technology to support individuals in identifying and managing mental health challenges. By addressing these challenges holistically, this work hopes to contribute to more accessible, timely, and effective mental health care, ultimately promoting a healthier, more resilient society.

MATERIALS & METHODOLOGY

OBJECTIVE AND SCOPE

Before outlining the methodology, it is essential to establish a clear objective for the research to achieve. This research aims to detect mental instability by analyzing an individual's behavioural patterns, body language, speech characteristics, and overall demeanor. By examining subtle changes in these areas, the model seeks to provide early insights into shifts in mental well-being.

DATA COLLECTION

We used a dataset from Kaggle containing data on over 10,000 individuals, capturing a comprehensive range of attributes, including:

- Marital status
- Smoking status
- Education level
- Number of children
- Physical activity
- Employment status
- Income
- Alcohol consumption
- Dietary habits
- Sleep patterns
- History of mental illness
- History of substance abuse
- Family history of depression
- Chronic medical conditions

These diverse factors provide valuable insights into potential indicators of mental health and well-being. We also collected a sample data from our fellow students with the help of a google form in which we asked them a few questions about their mental well-being. We compared our own dataset and the dataset that we collected from Kaggle. We will be using the above attributes as variables in our Machine Learning models for prediction of mental well-being of an individual.

LINEAR REGRESSION

Linear regression is a statistical method used in machine learning and data analysis to model the relationship between a dependent variable (often called the *response* or *target*) and one or more independent variables (called *features* or *predictors*). The goal is to fit a linear equation to observed data, allowing us to predict the target variable based on new inputs.

There are mainly two types of linear regression:

SIMPLE LINEAR REGRESSION

In *simple linear regression*, there is only one independent variable. The model tries to find a linear relationship between the input x and the output y , which is typically represented as:

$$y = mx + c$$

MULTIPLE LINEAR REGRESSION

Multiple linear regression extends this concept to more than one predictor variable:

$$y = b_0 + b_1x_1 + b_2x_2 + \dots$$

Let's understand how we can apply linear regression to evaluate the mental health status of a person.

Consider the following attributes:

- **Marital Status:** Encode as binary or categorical (e.g., 1 for married, 0 for not married).
- **Smoking Status:** Binary (1 if the person smokes, 0 if not).
- **Education Level:** Ordinal variable (e.g., 1 for high school, 2 for college, 3 for postgraduate).
- **Number of Children:** Numerical (e.g., 0, 1, 2, etc.).
- **Physical Activity:** Number of hours exercised per week or a categorical level (e.g., low, moderate, high).
- **Employment Status:** Binary (1 if employed, 0 if not), or further expanded to specific types of employment.
- **Income:** Numerical (e.g., annual income).
- **Alcohol Consumption:** Frequency per week or amount consumed.
- **Dietary Habits:** Score based on nutrition quality (e.g., 1 to 10 scale).
- **Sleep Patterns:** Average hours of sleep per night.
- **History of Mental Illness:** Binary (1 if there's a history, 0 if not).
- **History of Substance Abuse:** Binary (1 if there's a history, 0 if not).

- **Family History of Depression:** Binary (1 if there's a family history, 0 if not).
- **Chronic Medical Conditions:** Binary or categorical, indicating the presence of chronic conditions.

This is the case of multiple linear regression. We will consider the values of all the attributes and compute the corresponding value of 'y' (**output**).

Once we compute the value of 'y', based on that value we can classify the instance as positive (**mentally unfit**) or negative (**mentally fit**). The values of the coefficients (**b0, b1, b2 ...**) can be decided by the user as per the impact of that particular attribute on mental well – being. Let us first understand how we will apply linear regression on a sample instance and then we will apply it on a real-life instance.

Consider an individual with the following values for the given attributes:

- Marital status: Married
- Smoking status: Non-smoker
- Education level: College
- Number of children: 2
- Physical activity: Moderate
- Employment status: Employed
- Income: Moderate
- Alcohol consumption: Occasional
- Dietary habits: Good
- Sleep patterns: 7 hours per night
- History of mental illness: No
- History of substance abuse: No
- Family history of depression: Yes
- Chronic medical conditions: No

The model would use the learned coefficients to compute a mental health score for this individual. Consider the following coefficients for the above instance (generalized).

| Attribute | Coefficient |
|---------------------------|-------------|
| Marital status | +2.5 |
| Smoking status | -3.0 |
| Education Level | +1.5 |
| Number of children | +0.5 |
| Physical Activity | +4.0 |
| Employment status | +2.0 |
| Income | +1.0 |
| Alcohol consumption | -2.0 |
| Dietary habits | +3.5 |
| Sleep patterns | +4.0 |
| History of mental illness | -5.0 |

| | |
|------------------------------|------|
| History of substance Abuse | -4.0 |
| Family history of depression | -3.5 |
| Chronic medical conditions | -4.5 |

Considering the values of above attributes, the score for the above instance comes out to be 47.5, which can be classified as a positive instance assuming that 40 is the cutoff value.

STACKING

Stacking is the most accurate method according to our findings with an accuracy rate of more than 80%. Stacking, or *stacked generalization*, is an ensemble learning technique in machine learning that combines multiple models to improve prediction performance. The idea is to use the strengths of different algorithms to make better predictions than any single model could achieve on its own. In stacking, multiple base models (also called level-0 models) are trained on the same dataset. The predictions from these base models are then used as input features for a higher-level model (called the meta-model or level-1 model), which makes the final prediction.

STEPS IN STACKING

- **Split the Data:** The dataset is typically divided into two parts: a training set and a validation set. This is done to prevent overfitting of the meta-model.
- **Train Base Models:** Multiple different algorithms (e.g., decision trees, support vector machines, neural networks) are trained on the training set. Each base model learns to make predictions based on the input features.
- **Generate Predictions:** The base models make predictions on the validation set (or through cross-validation). These predictions are then collected to form a new dataset.
- **Train the Meta-Model:** The predictions from the base models serve as the input features for the meta-model. This model is trained to learn how to best combine the outputs of the base models to make the final predictions.
- **Final Predictions:** When making predictions on new data, the base models generate their predictions, which are then passed to the meta-model for the final output.

In our model, we will use **linear regression**, **decision trees** and **KNN** as base learners and **random forests** as meta-learner.

RESULTS

Two primary machine learning techniques were employed: **Linear Regression** and **Stacking**. Each method provided a different perspective on the dataset, contributing valuable insights into the interplay between various factors and mental health outcomes.

1. Linear Regression:

- a. Linear regression was initially applied to understand the direct relationships between individual attributes and mental health scores. This model highlighted specific predictors, such as sleep patterns, physical activity, and chronic medical conditions, that showed a strong linear correlation with mental health status.
- b. While effective in identifying straightforward relationships, linear regression is limited in handling non-linear interactions and complex patterns within the data. Thus, although it offered clarity on some primary factors, it lacked the capacity to capture deeper, multifaceted relationships.

2. Stacking Ensemble:

- a. To address these limitations, we used stacking as an ensemble learning approach to combine predictions from multiple base models. In this study, **Logistic Regression** and **K-Nearest Neighbours (KNN)** were used as base learners, and a **Random Forest** acted as the meta-learner.
- b. This ensemble approach provided a more nuanced prediction model by effectively combining the strengths of each base model. Logistic Regression contributed robustness to linear relationships, while KNN captured local similarities within the data. The Random Forest meta-learner further integrated these outputs, enhancing overall predictive performance.
- c. Stacking proved particularly effective in identifying subtle interactions, showing improved accuracy over Linear Regression alone. This result underscores the effectiveness of ensemble methods in capturing complex dependencies, especially in datasets with diverse attributes like socio-demographic and lifestyle factors.

INTERPRETATION OF KEY FEATURES

Across both models, certain attributes consistently emerged as influential predictors of mental health. **Sleep patterns** were identified as a primary indicator, with irregular or insufficient sleep strongly associated

with higher mental health risk. This finding aligns with a body of research that links sleep quality to emotional and cognitive well-being.

In addition, **dietary habits** and **physical activity** showed a significant correlation with mental health, suggesting that lifestyle factors are essential in mental health risk assessment. **Family history of mental illness** and **chronic medical conditions** further amplified the risk, supporting the relevance of genetic and physiological factors in mental health outcomes.

DISCUSSION

This study investigated the potential of machine learning techniques, specifically Linear Regression and Stacking, to predict mental health risks based on behavioural and socio-demographic attributes such as marital status, physical activity, substance use, sleep quality, and family history of mental illness. By analyzing a comprehensive dataset with over 10,000 entries, we aimed to uncover meaningful patterns that could aid in early detection and intervention for mental health challenges.

LIMITATIONS

While this study provides valuable insights, it also has certain limitations. One primary constraint was the **limited scope of behavioural attributes** within the dataset. Mental health is influenced by a complex array of factors, including psychological and social elements not captured here. Expanding the dataset to include real-time data such as social interactions or wearable device metrics could enhance predictive accuracy and give a more holistic view of mental health. Moreover, the **stacking ensemble**, while robust, increases computational complexity and the potential for overfitting, particularly with limited datasets. Further cross-validation and hyperparameter tuning can help mitigate this risk in future studies, improving the model's generalizability.

IMPLICATIONS OF FUTURE RESEARCH

This study highlights the potential of machine learning, particularly ensemble methods like stacking, in mental health prediction and risk assessment. By combining the strengths of various algorithms, stacking offers a promising approach to modeling complex data and can serve as a foundation for developing diagnostic tools. Future research could explore more **advanced ensemble methods** and **deep learning** techniques to assess unstructured data, such as sentiment from text or vocal tone analysis, to capture a more comprehensive view of mental health.

Additionally, incorporating physiological data, such as heart rate variability or activity from wearable devices, could improve real-time monitoring and offer more responsive intervention strategies.

CONCLUSION

This study demonstrates the potential of machine learning algorithms, specifically Linear Regression and Stacking, to predict mental health risks based on behavioural, socio-demographic, and lifestyle attributes. By analyzing a comprehensive dataset, we identified critical predictors of mental health, such as sleep quality, physical activity, family history, and chronic medical conditions. The linear regression model provided an initial understanding of the direct relationships between individual features and mental health outcomes, while the stacking ensemble method improved prediction accuracy by effectively capturing complex interactions between attributes.

The results indicate that machine learning models can be powerful tools in the early detection of mental health risks, potentially aiding in timely interventions and personalized support. However, the study also highlights the challenges and limitations inherent in predictive modeling for mental health. Real-world mental health diagnostics involve dynamic, multifaceted factors that are not entirely captured by static behavioural data. Incorporating real-time metrics and more detailed psychological and physiological data could enhance model accuracy and practical relevance. In conclusion, while machine learning models alone cannot provide a complete picture of an individual's mental health, this research underscores their value in complementing traditional diagnostic methods. The insights gained here encourage further exploration into advanced machine learning techniques, integrating more diverse data sources to refine and expand mental health prediction models. With continued research and data-driven innovation, these models hold promise for empowering healthcare providers with actionable insights, contributing to improved mental health care and well-being in society.

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