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A Review On Mental Health Analysis Using Artificial Intelligence

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Abstract: Stress, depression, and anxiety are the foremost matters in today's world because these not only affect individuals but also have an impact on healthcare and companies. A lot of people make use of the Internet for expressing their thoughts and beliefs, which in turn enables the Natural Language Processing research community to look at and analyze the media content and its effect on mental health. It is postulated that the social media platform is a social sensor ecosystem where every user of the social media platform is a cloud sensor. Cross-sectional and longitudinal studies on social media profiles highlight the importance of real-time, role- intelligent models for mental health analysis. Existing approaches in the literature provide an online detection of mental illness, but there is a need for early detection of stress. The developments in machine learning (ML) and deep learning (DL) enable AI modeling for early detection of mental health on social media.

This paper explores the existing study and possible research directions for processing information on social media platforms to learn about anxiety, depression, stress, and suicide. This paper is mainly focused on the model building by the use of advanced AI-based models for the classification and prediction of stress, anxiety, depression, and suicide in the initial stage by analyzing social media data.

Index Terms - Mental Health Analysis, Natural Language Processing, Sentiment Analysis, Machine Learning, Artificial Intelligence, Deep Learning.

I. INTRODUCTION

Mental illness, particularly anxiety, is increasingly recognized as a significant issue in our society today (Can et al., 2019). Stress has woven itself into the fabric of our daily lives, impacting individuals, families, healthcare systems, insurance companies, employers, coworkers, and society as a whole (Kassymova et al., 2019). The American Psychiatric Association defines mental illness as a serious condition that alters a person's thinking, mood, or behavior, often exacerbating their situation (Chen et al., 2022).

Mental health challenges encompass depression and difficulties in relationships, work, or family dynamics. The World Bank has highlighted that the world is grappling with a serious mental health crisis, noting that depression affects 350 million people and ranks as a leading cause of disability globally.

It is the third leading cause of death worldwide and is widespread across nearly every nation. Implementing comprehensive mental health assessments in the traditional healthcare system proves to be quite challenging (Batty et al., 2017). The economic and health repercussions of global stress are more significant than previously anticipated. A population study conducted in Europe identified stress as the second most prevalent health issue (EU-OSHA, 2013).

This study revealed that 51% of European employees experience workplace stress, and 40% of them feel that stress is not handled effectively (Euro found, 2012) Financially, workplace stress costs European companies approximately 25 billion Euros annually (Hassard et al., 2014). This issue is not confined to Europe; similar findings have emerged from various countries.

For instance, in the United States, 40% of employees report high levels of job-related stress, while 29% express a moderate level of job satisfaction. It is estimated that the U.S. spends around 300 billion dollars each year on stress- related health issues (Can et al., 2019). Recent reports from other nations, including China and Australia, underscore the global significance of the stress problem (Xiong et al., 2015). Given the profound effects of stress, its prevention and management have emerged as critical public health concerns (Greene et al., 2016).

In developed countries, only half of the population has access to medical care, and even prescribed medications may not be effective. This issue is exacerbated in nations facing overpopulation and a shortage of mental health professionals like psychiatrists and psychologists. Individuals suffering from severe depression and mental illnesses are at a greater risk of suicide and have an increased likelihood of experiencing heart attacks or strokes (Ji et al., 2021). Mental health issues are not confined to adults; reports indicate that the number of students with mental disabilities is rising, even among those in primary school (Zhu et al., 2017).

A significant challenge for governments and health organizations is that many individuals hesitate to discuss their mental health due to the fear of social stigma. Consequently, the actual number of people with mental illnesses is likely underestimated, complicating efforts to provide assistance. There is a shortage of institutions and mental health professionals available to support the vast number of individuals facing these challenges.

Traditional methods for managing and treating mental health issues typically involve doctor visits, individual psychological support, and medication, which can sometimes be costly and ineffective. To address these challenges, it is recommended to develop innovative solutions for the early detection of mental disorders by leveraging machine learning and deep learning algorithms on social media platforms. Millions of users around the globe engage with platforms like Facebook, Instagram, and Twitter daily to communicate and share information (Agarwal et al., 2017), (Greene et al., 2016),(Ji et al., 2021).

According to the Digital in 2017 Global Overview on digital media usage, as of January 2017, there were 2.8 billion social media users worldwide, with platform adoption increasing by 21%. Social media can serve as a low-cost, non-invasive means to influence behavior. These platforms can be viewed as a social sensor ecosystem, where each user acts as part of a "social sensor cloud", and the messages they share can be likened to a “social-sensor cloud services” (Sakaki et al., 2010).

People utilize these platforms to express their thoughts and opinions on a wide range of topics, including news, science and technology, sports, politics, and health issues. Each social media service provides insights into the user's current well-being. Research into these platforms can help governments and health organizations gauge the overall health status of specific populations in various regions and identify potential health concerns. Early identification of suicide risk can lead to the implementation of preventive measures through targeted outreach. Approximately 8 million individuals are unable to access specialist care because their conditions are not deemed serious enough. This highlights the importance of automation in mental health research via social media, where individuals can freely share their feelings, thoughts, and beliefs.

Psychology has long aimed to develop theoretical methods for identifying signs of suicide, often relying on lengthy face-to-face interviews. However, around 80% of individuals in high-risk categories are hesitant to share their levels of stress and anxiety (McHugh et al., 2019). Additionally, heightened stress and anxiety can contribute to suicidal thoughts. Research studies on suicide prevention (Stone, 2021) has enriched the research community with dataset, resources and provides motivation for new-frontiers. The literature includes cross-sectional studies that utilize AI models for classifying and categorizing mental disorders based on self-reports. These advancements help lower the costs associated with identifying high-risk groups by minimizing the need for in-person consultations with healthcare professionals. Previous studies indicate a strong connection between social media platforms and user comments, with approximately 80% of individuals reporting suicidal thoughts online (Chancellor & De Choudhury, 2020; Guntuku et al., 2017;

Luxton et al., 2012), (Golden et al., 2009). The emergence of the Papageno effect suggests that the prediction of mental illness through social relationships can elevate suicide risk, while user opinions that prolong media narratives can aid in the early detection of suicidal tendencies (De Choudhury, 2013), (Shing et al., 2020), (Sawhney et al., 2021), (Niederkrotenthaler, 2017). This notable progress enhances confidence in developing learning-based systems to tackle the challenges of mental health.

II. RELATED WORKS

S. Ray, V. Goswami, and C. M. Kumar (Ray et al., 2024) examined how the COVID-19 pandemic and subsequent lockdown affected the mental health of children and adolescents. They utilized the Short Self-Report Questionnaire (SSRQ) to evaluate anxiety levels in individuals aged 9 to 18 years. The study employed observational and descriptive cross-sectional methods, conducting an online survey with 369 students. Depression levels were categorized as low, moderate, or severe based on pre-test and post-test scores.

G. Anuradha and D.N. Jamal (Anuradha & Jamal, 2021) employed electroencephalography for diagnosing dementia and applied machine learning algorithms to forecast treatment outcomes. Their neural network model achieved a classification accuracy of 94.4% for dementia with Lewy bodies, while an event prediction model analyzed 476 reported cases and demonstrated an accuracy of 93% in a cross-validation (Koklonis et al., 2021).

Other studies focused on detecting, preventing, and treating COVID-19 through machine learning and deep learning techniques (Biabani & Tayyib, 2022).

The authors (Anuradha et al., 2017) sought to identify dementia in patients with mild cognitive impairment by examining EEG abnormalities. In (Kim et al., 2020), a deep learning model was developed to evaluate the psychological status of social media users based on their posts, utilizing CNN to accurately detect symptoms of depression, anxiety, bipolar disorder, and personality disorders. In experiments (Lawrence et al., 2022) and (Sundarasen et al., 2020), a system was proposed for identifying depression through speech analysis, employing random sampling to enhance the data quality.

Hana Alharthi (Alharthi, 2020) applied the ML model AdaBoost and a neural network to assess the risk of anxiety among students, finding that gender, support, and family income were significant factors influencing stress levels. Various machine learning models have investigated the impact of COVID-19 on student health in China and India. While the findings of (Ren et al., 2021) highlighted isolation and family income as key predictors of stress and depression, the results of (Khattar et al., 2020) indicated that online education was failed to facilitate effective knowledge transfer.

Donna Wang (Wang et al., 2021) used hierarchical multiple regression analysis and found that age, friends and family support, support from school, drug use, government measures, exposure to COVID-19 news and social unrest were identified as contributors to health deterioration of the student.

Zhao et al. (Zhao et al., 2022) investigated mental health symptoms and quality of life among frontline physicians who treated COVID-19 patients compared to those who did not. They employed the Patient Health Questionnaire-9

(PHQ-9), Generalized Anxiety Disorder Scale-7 (GAD-7), Insomnia Severity Index (ISI), and the World Health Organization Quality of Life Questionnaire-brief version (WHOQOL-BREF) to assess anxiety, insomnia, and overall quality of life (QoL). This cross-sectional study used convenience sampling and was conducted from October 13 to 22, 2020, five months after the COVID-19 outbreak began in China. Propensity Score Matching (PSM) was applied for group comparisons, and generalized linear models (GLM) were utilized to analyze differences. Additionally, researchers have incorporated natural language processing (NLP) in their mental health research. DL has received more attention and is better than ML. Researcher also used NLP in mental illness detection in the NLP research (Zhang et al., 2022).

A. Chaudhary, N.S. Sonar, J. Tr, M. Banerjee, and S. Yadav (Chaudhary et al., 2021) investigated symptoms of fear, depression, and anxiety among 324 college students in India during the pandemic. This web-based survey, conducted via Google Forms, included questions regarding health and psychosocial indicators. The findings revealed that 68.8% of students expressed fear of COVID-19, 28.7% experienced mild to severe depression, and 51.5% reported mild to severe anxiety. Moreover, the fear index related to COVID- 19 was found to be associated with anxiety and depression.

Chaturvedi, D. K. Vishwakarma, and N. Singh (Chaturvedi et al., 2021) explored how COVID-19 affected students, particularly in terms of online learning, changes in sleep patterns, health issues, weight, lifestyle, and mental well- being. Their findings emphasize the necessity for public authorities to tackle the adverse effects of COVID-19 on education.

Mahapatra and P. Sharma (Mahapatra & Sharma, 2021) investigated psychological challenges by focusing on depression in children and adolescents and its implications for both short- and long-term mental health. An online survey was conducted with 4,342 primary and secondary school students in Shanghai from March 13 to 23, 2020, to assess their mental health, life satisfaction, and feelings of loneliness. The survey revealed that anxiety (24.9%), depression (19.7%), and another form of depression (15.2%) were prevalent. Children faced stress, missed growth opportunities, and food shortages at school (Tang et al., 2021). A study in eastern India

assessed the effects of the COVID-19 lockdown on the mental and behavioral health of children undergoing psychiatric treatment. This study utilized telephone interviews with 225 participants between June 1 and July 8, 2020 (Patra et al., 2020).

A. Lawrence, J. Garcia, C. Stewart, and C. Rodriguez (Lawrence et al., 2022) examined how stay-at-home orders influenced mental health, physical activity, screen time, and alcohol consumption among community service students. The findings indicated an increase in stress, depression, and screen time during the pandemic, highlighting the need for enhanced support for students and its effects on community service-learning engagement.

The authors investigated the impact of COVID-19 on Malaysian university students, concentrating on stress levels and associated factors. A cross-sectional study involving 983 participants using the Zung Self-Assessment Questionnaire showed varying degrees of anxiety, with financial difficulties, distance learning, educational challenges, and job uncertainty identified as primary stressors (Sundarasen et al., 2020). A study involving 162 college students in northern New Jersey utilized multiple regression analysis to explore factors linked to mental health during the pandemic (Kecojevic et al., 2020). In addition, another study with 233 students enrolled in a health course evaluated changes in lifestyle, mental health, and learning outcomes (Gadi et al., 2022).

III. PROPOSED METHODOLOGY

AI-based models' objective is to identify the underlying causes of a patient's mental illness as early as possible. In the literature, most mental health systems utilize natural language processing (NLP) technology to gather insights from social media. For instance, current technologies collect user comments from social media platforms like posts from Reddit, Instagram, and Facebook, and tweets from Twitter, and search a database for content that matches medical and health-related terms to determine if the user may be experiencing issues.

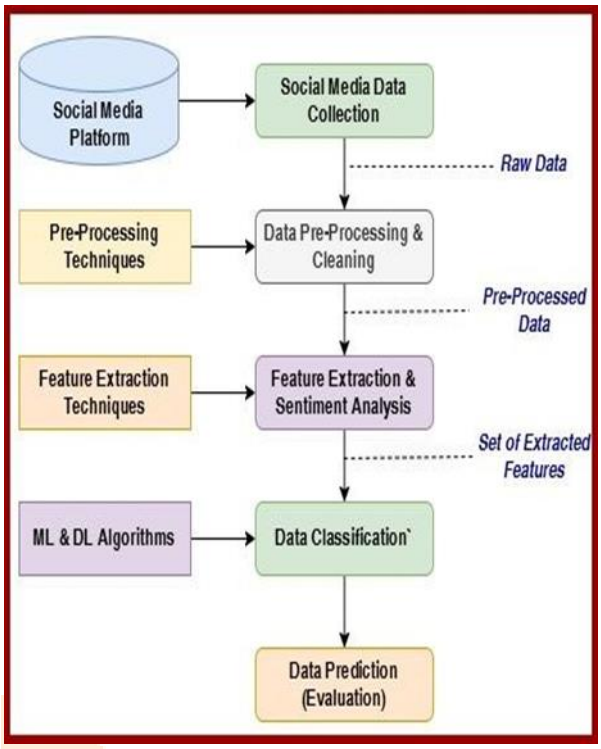
The disadvantage of this approach is that it does not facilitate early diagnosis. Our past behaviours and thoughts can significantly influence our current mental health. Thus, it is necessary to analyze historical data alongside machine learning and deep learning, which could pave the way for early detection.

We propose a framework to identify patients with mental disorders who are active on social media. Each section of this framework will include specific questions.

As illustrated in Figure 1, the entire process can be broken down into several tasks, including raw data collection from social media platforms, data storage and maintenance, data preprocessing to remove unwanted text and bring it to the required format, feature extraction and sentiment analysis, and employing machine learning and deep learning techniques to classify users as either mentally ill or not, which is essential for monitoring classification algorithms.

The software tools that will be used to implement this framework include Google Collaboratory with the Python language with Text Blob, Keras, TensorFlow, and the Sci-kit library and Graphics Processing Unit (GPU) for building and testing AI-based models for mental health analysis; NoSQL database systems like MongoDB; and Twitter API will be used to fetch tweets from the Twitter platform.

We chose Python as our primary programming language due to its growing popularity in the data science community, its presence in the latest deep learning courses, and its user- friendly nature. MongoDB serves as our repository for storing all social media data, as it organizes information in JSON format, which is also the format returned by Twitter API. Additionally, being a NoSQL database, MongoDB is horizontally scalable and capable of managing large volumes of data. Text Blob will be used for sentiment analysis due to its robustness and ability to handle extensive text files while performing various NLP tasks. Sci-kit, Keras, and TensorFlow libraries will be used to apply machine learning and deep learning algorithms for classification.



IV. CONCLUSION

Our aim is to early and effectively predict suicide risk, depression, anxiety, and stress using data from social media with high accuracy. Advancement in AI can help to build a framework that can predict mental health with high accuracy. Mental health professionals, such as psychiatrists and psychologists, can utilize this framework to gain deeper insights into their patients' mental states. Additionally, governments and health organizations can leverage this information to identify regions where individuals are struggling with mental health issues and to offer suitable support services. This approach can also be applied to assess other social behaviors, including cyberbullying and monitoring employee well-being in the workplace.

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