Evaluating Mental Well-being in Youth: Identification and Diagnostic Tools

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Abstract
The COVID-19 pandemic significantly affected global mental health, intensifying existing issues and introducing new challenges. Mental health is often overlooked due to stigma and cultural norms, and during the pandemic, much of the attention and resources were focused elsewhere. In response, a machine learning-based system was developed to specifically detect anxiety and depression. Various algorithms, such as random forest, logistic regression, KNN, Naïve Bayes, and SVM, were evaluated for their effectiveness in identifying these mental health conditions. The system utilizes a trained machine learning model alongside a questionnaire to identify early signs of mental health concerns. Being web-based, the tool has the potential to reach a global audience, offering a broader approach to addressing mental health. Early detection through this system allows for timely interventions and treatments, ultimately improving mental well-being.

Keywords: Data science, Machine learning, Anxiety, Depression, and Mental health detection

Introduction

Our mental well-being has a profound impact on our daily lives, influencing how we eat, sleep, communicate with others, and express our emotions. Despite its importance, many of us tend to overlook mental health due to fear of judgment and societal pressures. According to a report by the World Health Organization (WHO) in January 2020, depression is the leading cause of disability worldwide, affecting nearly 264 million people of all ages. Unfortunately, by the time many individuals are diagnosed with depression, they are often already in advanced stages of the disorder. This underscores the need for technology to aid in both early detection and effective treatment of mental illness. In today’s digital era, where access to information is readily available, identifying mental health conditions has become more manageable. To address this, we have developed a system that prompts students to fill out a questionnaire with basic personal details to assess whether they may be experiencing mental health issues. The results are then shared with the individual who completed the test. Our online platform serves as the central hub for managing these interactions, collecting data based on the responses provided. The purpose of the questionnaire is to offer an overall snapshot of the student's well-being, helping to determine if they may be struggling with mental health challenges. Mental health is deeply influenced by both internal and external factors, making it a true reflection of a person's mental state.

Machine learning has the potential to assess a person’s mental health by analyzing signals and data from the brain. Through artificial intelligence, the system can determine whether someone is functioning normally or facing mental health challenges based on the information it gathers and the questions it poses. This innovative approach has transformed the mental health care landscape by providing more personalized support, effective treatment plans, and various delivery methods for services. Timely mental health evaluations can lead to significant changes in a student's behavior, especially if they receive short-term interventions when needed. After obtaining predictions from the machine learning model, individuals can consult with mental health professionals, such as psychologists or psychiatrists, for further guidance. Early diagnosis enables prompt treatment, which can greatly improve an individual's mental well-being.

Literature Review

The innovative integrated mental health assessment approach, which is designed to help identify and treat anxiety and depression early on, combines traditional screening methods with state-of-the-art technologies. The method is designed to work with a wide range of age groups and includes age-specific screenings that use standardized questions to identify early indicators of sadness and anxiety [2]. Serious cases found during these checks are quickly referred for expert assistance. Simultaneously, a machine learning initiative employs predictive analysis through behavioral biomarkers to evaluate anxiety and depression in pupils, taking into account linked attributes including marital status, age, gender, state, and religion. Natural language processing techniques are used to analyze a variety of text formats, such as social media postings, interview transcripts, and clinical notes, in order to simultaneously detect anxiety and depression[5]. This supports early detection of anxiety and sadness in addition to enabling proactive mental health care.

With a customized approach, the AI-powered decision support system includes a sophisticated series of questions aimed at accurately diagnosing anxiety and depression. The paper explores the moral issues related to the application of AI in mental health care and offers recommendations for the moral incorporation of these cutting-edge instruments. Furthermore, a survey employing sentiment analysis and deep learning approaches investigates mental health detection in online social networks with a focus on anxiety and sadness. By skillfully merging conventional and cutting-edge techniques, this thorough integration of approaches seeks to revolutionize mental health care and promote a more nuanced understanding of anxiety and depression for better diagnosis and assistance.

Research into youth mental health assessment and diagnosis has gained considerable attention due to the increasing rates of mental health disorders among young people. According to Kessler et al. (2005), about half of all mental illnesses begin by mid-adolescence, underlining the critical need for early diagnosis. Similarly, Merikangas et al. (2010) conducted a thorough study that revealed high occurrences of anxiety, mood, and behavioral disorders among teenagers, pointing to the necessity of more effective diagnostic methods.

In recent years, efforts have focused on enhancing screening methods by incorporating standardized tools like the Patient Health Questionnaire for Adolescents (PHQ-A) and the Strengths and Difficulties Questionnaire (SDQ). These tools have been validated across different populations and provide an efficient way to identify mental health concerns in both clinical and school environments (Richards et al., 2015). However, as Loades and Myles (2020) suggest, these tools also face challenges, such as adapting to cultural differences and accounting for the developmental changes that occur during adolescence.

Technological advancements have played an increasing role in the recognition and diagnosis of youth mental health disorders. For instance, Ben-Zeev et al. (2015) explored the use of mobile health apps and real-time tracking, showing how smartphones and wearable devices can monitor mental health symptoms in young people. Similarly, Dwyer et al. (2018) reviewed how artificial intelligence (AI) and machine learning techniques are being used to predict mental health issues and provide early intervention through data from sources like social media and electronic health records.

Schools have also become key locations for mental health assessments. Studies like those by Fazel et al. (2014) highlight the importance of school-based programs and screenings as they often serve as the first point of contact for mental health services, especially for students who might not have access to traditional healthcare.

Despite these advances, challenges persist. Patel et al. (2007) identified significant disparities in access to mental health care for underserved youth, where resources are limited, and awareness of available services is often lacking. Additionally, the stigma surrounding mental health continues to be a major barrier, preventing many young people from seeking the help they need, as noted by Gulliver et al. (2010). Overcoming these barriers is essential to improving the early identification and diagnosis of mental health disorders in young populations.

Proposed System

Using a variety of machine learning methods, the system under discussion is intended to determine an individual's level of anxiety and sadness. Several phases are involved in the machine learning (ML) process of forecasting anxiety and depression. First, pertinent information is gathered, such as lifestyle variables and answers to questionnaires about mental health. Subsequently, pre-processing procedures tackle absent values and anomalies, and feature manipulation might entail generating novel variables that represent mental health. The target outcomes for anxiety and depression are then defined by labeling the data. The type of problem is taken into consideration while choosing machine learning algorithms, such as random forests, decision trees, and logistic regression.

Methodology

Using the Depression Anxiety Stress Scale (DASS21), the research centered on identifying symptoms of anxiety and depression. The Google Form was used to gather the data, and anyone in the 16–25 age range was welcome to participate. The DASS-21 has 21 questions total, with 7 questions assigned to each scale.
Each question has potential responses that can be provided in text or as numbers, and they are as follows:

0 wasn't relevant to me.
1 was somewhat true or occasionally true for me.
2 applicable to me a good portion of the time or to a significant extent.
3 was true for me either most of the time or very often.

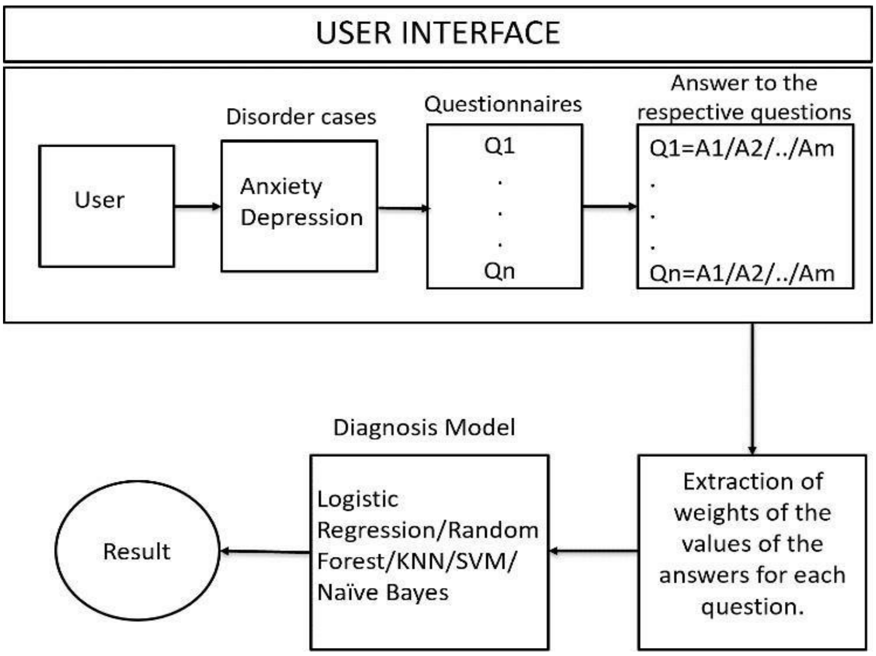

Figure 1. System Architecture

After the data was gathered, the participant's answers were coded using numbers ranging from 0 to 3. The scores were then determined by summing the values related to each question and use the method below:

$$\text{Score} = \text{sum of rating points of each class} * 2 \qquad (1)$$

After the final ratings were determined, they were classified as normal, mild, moderate, severe, and extremely severe. Streamlit was utilized to create interactive online apps with ease, incorporating data visualization tools and machine learning models into the user experience. Rapid prototyping and deployment were made possible by its user-friendly framework, which improved user experience and productivity. Streamlit's broad component ecosystem and simple syntax were leveraged to construct dynamic and responsive dashboards. Because of Streamlit's adaptability and scalability, research results and insights were effectively presented, enabling users to make well-informed decisions.

Results

Following the use of various machine learning methods, such as Support Vector Classifier, KNN, Naïve Bayes, Random Forest, and logistic regression, the following accuracy results were noted.

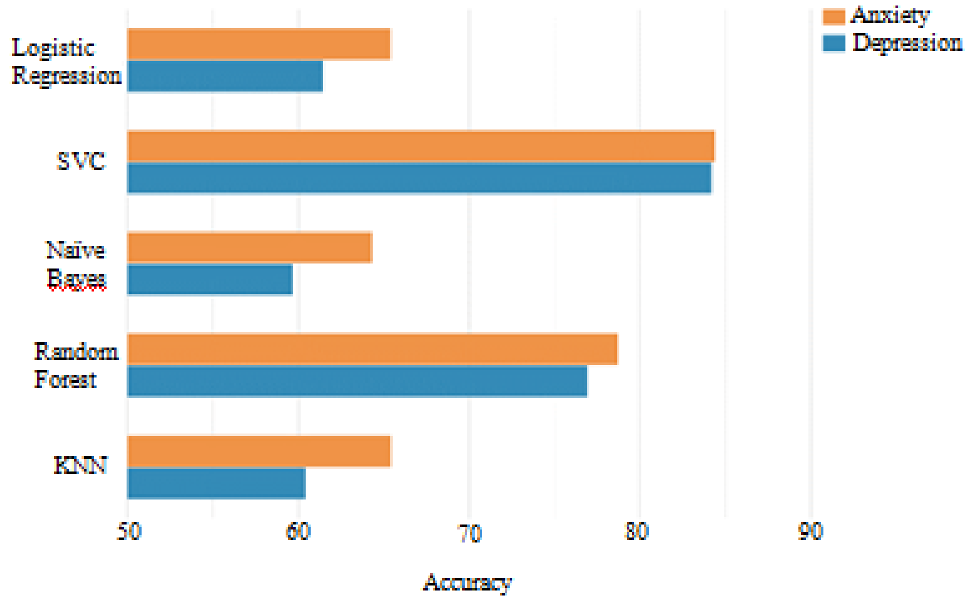

Figure 2. Comparison between ML models

Upon model deployment, the models that yielded the highest accuracy were the Support Vector Classifier, Random Forest, and Logistic Regression, in that specific order.

Personalized recommendations based on each person's performance are given when their score is predicted. By pointing out areas for growth or highlighting their merits, these recommendations seek to maximize their results. In order to pinpoint specific areas where the person might need more practice, explanation, or assistance, the system examines the performance data. Users are guaranteed to receive recommendations that are specifically customized to their needs, enabling them to make meaningful progress in their learning process.

Conclusion

An innovative method of early intervention is to use this application in conjunction with a trained machine learning model to identify mental health concerns in pupils. When users provide data, the model's predictive powers come into play, helping to quickly identify any mental health issues. This facilitates expert consultation and treatment in a timely manner, which in turn improves general wellbeing. This creative solution emphasizes the significance of preventative measures and technology breakthroughs in the sector while addressing the pressing and pervasive issue of mental health in today's culture. The technology makes a user-friendly and accessible platform for students that need help by integrating machine learning algorithms and human input in a smooth manner.

The predictive accuracy of the model increases the accuracy with which mental health conditions may be identified, highlighting the need of addressing these issues as soon as possible in order to improve overall well-being. This talks about a serious and common problem in modern culture.

Future Work

The work might be enhanced to incorporate a system for user profiles that would let people make and manage their own profiles. With this functionality, users could create unique profiles on the platform and safely keep track of their performance records and score histories. This feature makes it simple for users to access and evaluate previous evaluations, monitor their development over time, and pinpoint areas in which they still need to improve.

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