HIGH SCHOOL EDITION
Journal of Student Research
Volume 13 Issue 1 (2024)

Novel Neural Network Models for Predicting Mental Health Outcomes in the U.S. Youth Population

Avi Verma[1] and Kaustubh Supekar[#]

[1]Palo Alto High School, Palo Alto, CA, USA
[#]Advisor

ABSTRACT

Anxiety and depression are two of the most pressing mental health issues, particularly among young adults. Given the success of neural networks for predictive modeling, we developed novel neural network models for classifying anxiety and depression using Substance Abuse and Mental Health Services Administration's Mental Health Client- Level Data (SAMHSA MH-CLD) on 382,174 young adults (15 to 24 years old). The SAMHSA MH-CLD included mental health and general background data collected in 2020 for individuals reporting to state-accredited hospital service centers across the United States. The neural networks were trained on 10% randomized k-folds of the dataset and tested on the remaining 90% for each fold. We found that neural network models predicted anxiety and depression with high accuracy (91.5% to 94.2% accuracy, 8.4% to 3.1% loss), outperforming conventional statistical models. Additionally, for all tested variable sets, our neural network model outperformed expectations for the average therapist consultation (46% to 50% accuracy), as reported previously. For the optimal neural network model with the highest accuracy, the variables most correlated with anxiety and depression were age, education, gender, race, employment, marital status, and stressor events, not accounting for redundant and minimally correlated variables. The effectiveness of our neural network model indicates that it can be implemented alongside therapists in clinical environments to improve psychiatric diagnosis among young adults.

Introduction

Despite the proliferation of efforts targeted at improving individuals' well-being, mental health has become an increasingly challenging issue in the United States, particularly among teenagers and young adults. In 2019, more than a third of high school students experienced persistent feelings of sadness or hopelessness (Centers for Disease Control and Prevention [CDC], 2021). Furthermore, these numbers increased significantly during the COVID-19 pandemic, as 37% of high school students reported having poor mental health, and 44% reported that they dealt with feelings of sadness or hopelessness nearly every day for at least two consecutive weeks (Schaeffer, 2022). These concerning figures coupled with the stigma surrounding the utilization of mental health services among young adults makes it difficult to provide them with timely intervention for psychiatric disorders (Vernooij-Dassen et al., 2005). To address this issue, a variety of methods have been proposed to proactively identify mental health cases. The traditional approach for diagnosing psychiatric disorders is telemedicine, often leading to sessions with skilled psychologists. While useful, these sessions tend to be limited by their in-person nature and obstructed by financial barriers (Rowan et al., 2014). Moreover, even psychologists are only able to accurately diagnose 46% of anxiety and 50% of depressive disorders (Al-Huthail, 2008). On the other hand, novel advances in statistical regression and machine learning models, particularly neural networks, can be used to quickly discern anxiety and depression, two of the most common mental health illnesses in the youth population. Neural network approaches have been successfully implemented for predictive modeling tasks in healthcare (Davenport & Kalakota, 2019). In this study, we developed neural network models implemented on a large dataset to predict anxiety and depression outcomes in the U.S. young adult population. We also compared the results of our neural network model against baseline logistic regression models for cross-testing accuracy and loss.

Literature Review

Overall, poor mental health among youth has increased by 40% since nation-wide tracking was launched in 2009 (CDC, 2021). Subpar mental well-being is associated with lifestyle disruptions, as disorders like anxiety and depression can prevent the continuation of day-to-day activities (Schaeffer, 2022). Additionally, the CDC determined that approximately 1 in 6 youth reported to plan suicide, a significant increase from previous figures, further representative of the worsening of mental health in the last decade (CDC, 2021).

However, even with the rising prevalence of mental health disorders, the majority of online interventions are based on telemedicine, which is often too generalized for effective implementation (Wu et al., 2021). In addition, telemedicine frequently leads to sessions with psychologists. These therapy sessions can be hindered by the stigma surrounding in-person discussion about mental health as well as financial cost, as the price for one session can exceed 200 dollars (Barron, 2023; Sava et al., 2009).

As a result, many individuals displaying single risk factors for anxiety and depression remain undiagnosed (Ebert, 2017). To improve proactive diagnosis for psychiatric disorders, predictive algorithms, powered by statistics and machine learning tools, can be implemented for early identification of mental health flags. Such approaches have been used successfully for predictive modeling and diagnosis tasks in other areas of healthcare, including early diagnosis of Alzheimer's disease, classification of congestive heart failure, and skin cancer prediction (Miotto et al., 2017).

A key step that is necessary for ensuring the reliability of predictive models for mental health diagnosis is the analysis of the effect of varied factors on model output. There are a number of known factors that impact mental health, such as acculturation, race, gender, age, socioeconomic standing, and past stressor events.

There are a substantial number of individuals each year who change living and, accordingly, community situations, tending to lead to poor mental health outcomes (Koneru et al., 2007). Beyond the impact of acculturation, race plays a large role in determining mental health. For example, it is known that African American students more commonly deal with deteriorated mental health than other races (CDC, 2021).

For gender, previous research has shown that women, particularly those in worse socioeconomic standing, experience a greater frequency of events negatively impacting mental health (Afifi, 2007). Looking at socioeconomic status in isolation, decreased income and poor housing have a statistically significant effect on individual and community mental health (Evans et al., 2003). Education has also been shown to be associated with mental health, as those with higher levels of education tend to experience less stressor episodes and better mental health (Araya, 2003).

Pairing demographic background with socioeconomic status, past studies demonstrate that poor, minority individuals experience a significantly higher number of stressful life events (Businelle et al., 2013). As determined by Businelle *et al.*, the number of life stressors was the principal mediator of the relationship between mental health and demographic data. Furthermore, demographics have been found to account for 24% of the variance in participants' psychological help seeking attitudes, exacerbating the relatively low psychological help-seeking openness scores of unmarried Americans, many being young adults (Mackenzie et al., 2006).

Therefore, in this study, we implemented neural network and logistic regression models that accounted for various demographic and socioeconomic factors, in addition to mental health stressor events for predicting anxiety and depression among young adults.

HIGH SCHOOL EDITION
Journal of Student Research

Volume 13 Issue 1 (2024)

Methodology

Data Collection and Variable Summarization

The original data was anonymized survey responses of 6.9 million participants in state hospital service centers and was collected in 2020 as part of the Substance Abuse and Mental Health Services Administration's Mental Health Client-Level Data (SAMHSA MH-CLD). The data was cleaned and summarized in the Jupyter Notebooks environment using the pandas library. The cleaned data analyzed in this study included 382,174 young adults, aged 15 to 24, of which 26.5% had anxiety and 35.7% had depression. Table 1 shows the categorical distribution of the variables most correlated with anxiety and depression outcomes in the dataset.

Table 1. Categorical Distributions for Most Correlated Input Variables in Cleaned Data

Category/ Variable	**Category 1**	**Category 2**	**Category 3**	**Category 4**	**Category 5**	**Category 6**	**Category 7**	**Category 8**	**Category 9**	**Category 10**
Age	15-17 Years (45.85%)	18-20 Years (29.06%)	21-24 Years (25.09%)							
Education	6th to 8th Grade (19.97%)	9th to 11th Grade (44.30%)	12th Grade or General Education (29.56%)	College or Above (5.65%)	Special Education (0.52%)					
Race	American Indian/ Alaska Native (3.90%)	Asian (2.35%)	Black or African American (16.45%)	Native Hawaiian or Pacific Islander (0.30%)	White (46.34%)	Other Race or Missing (30.66%)				
Gender	Male (47.73%)	Female (52.27%)								
Mental Health Diagnosis 1	Trauma and Stressor Related Disorder (17.90%)	Delirium or Dementia (9.97%)	Conduct Disorder (2.20%)	Bipolar Disorder (6.78%)	Oppositional Defiant Disorder (2.20%)	Pervasive Developmental Disorder (2.85%)	Personality Disorders (0.35%)	Schizophrenia or Other Psychotic Disorder (7.86%)	Alcohol or Substance Use Disorder (10.62%)	None (39.53%)
Mental Health Diagnosis 2	Trauma and Stressor Related Disorder (2.57%)	Delirium or Dementia (3.35%)	Conduct Disorder (0.88%)	Bipolar Disorder (0.94%)	Oppositional Defiant Disorder (1.02%)	Pervasive Developmental Disorder (0.79%)	Personality Disorders (0.32%)	Schizophrenia or Other Psychotic Disorder (0.90%)	Alcohol or Substance Use Disorder (0.24%)	None (89.02%)

Mental Health Diagnosis 3	Trauma and Stressor Related Disorder (0.40%)	Delirium or Dementia (0.49%)	Conduct Disorder (0.20%)	Bipolar Disorder (0.16%)	Oppositional Defiant Disorder (0.30%)	Pervasive Developmental Disorder (0.19%)	Personality Disorders (0.15%)	Schizophrenia or Other Psychotic Disorder (0.036%)	Alcohol or Substance Use Disorder (0.24%)	None (97.91%)
Marital Status	Never Married (98.91%)	Now Married (0.79%)	Separated (0.15%)	Divorced (0.15%)						
Employment	Full-Time (8.54%)	Part-Time (7.40%)	Undifferentiated Employment (1.44%)	Unemployed (18.34%)	Not in Labor Force (64.27%)					

Model Creation and Evaluation

The logistic regression model was set up in Jupyter Notebooks, and neural networks in Google Colab with Adam optimizers, 10 ReLU activators and a final sigmoid layer. The logistic regression models were trained on a randomized three k-fold subset of the dataset, while neural networks were trained on 10% k-folds of the data and evaluated against the remaining 90%, with the tests averaged to obtain the final accuracy and loss results. For both neural network and logistic regression models, the first variable set, V1, included 38 of 40 available variables in SAMHSA MH-CLD. As we aimed to determine the model with the highest cross-testing accuracy, we stepwise- removed variables with the least predictive correlation in sets V2 to V5. Overall, all sets from V1 to V5 included the minimum of the following variables, as suggested by previous literature: race, gender, education, demographics, and stressor events (Afifi, 2007; Businelle et al., 2013; CDC, 2021; Koneru et al., 2007). A visual representation of our stepwise-removed variable sets is shown in Figure 1.

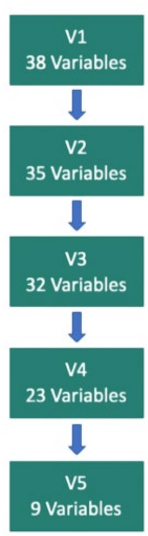

Figure 1. Stepwise-removed Variable Sets, V1 to V5

Results

We found that neural network models (91.5% to 94.2% accuracy, 8.4% to 3.1% loss) are more accurate in predicting anxiety and depression than logistic regression models (65.5% to 92.5% accuracy, 50.4% to 7.2% loss). The graphs representing the cross-testing accuracies for anxiety and depression diagnoses across each variable set, V1 to V5, are shown in Figures 2 and 3, respectively. Additionally, for all variable sets, both models outperformed expectations for the average therapist consultation (46% to 50% accuracy), as reported in previous literature (Al-Huthail, 2008). Although our neural network model performance was optimized with variable set V3 of 32 variables, the baseline for machine leaning performance exceeded 91%, even with variable set V5 of only 9 variables, which included race, gender, education, employment, marital status, and stressor events. In contrast, the accuracy for our logistic regression models worsened significantly, with accuracies as low as 79.8% for anxiety and 65.5% for depression prediction when overfitting or underfitting with variable set V1 or V5, respectively.

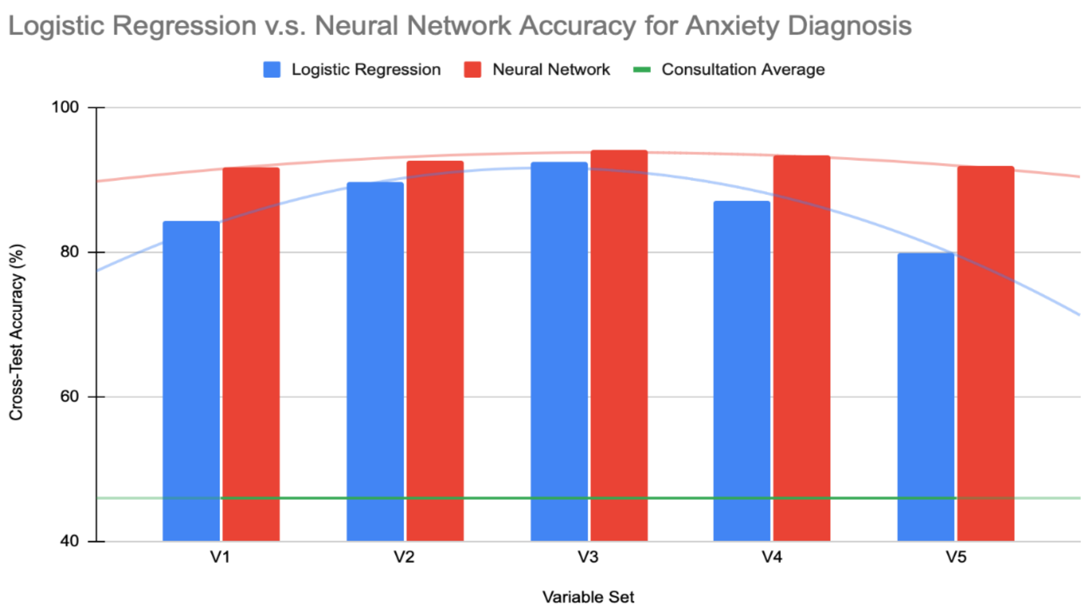

Figure 2. Logistic Regression vs. Neural Network Accuracy for Anxiety Diagnosis Across Variable Set V1 to V5

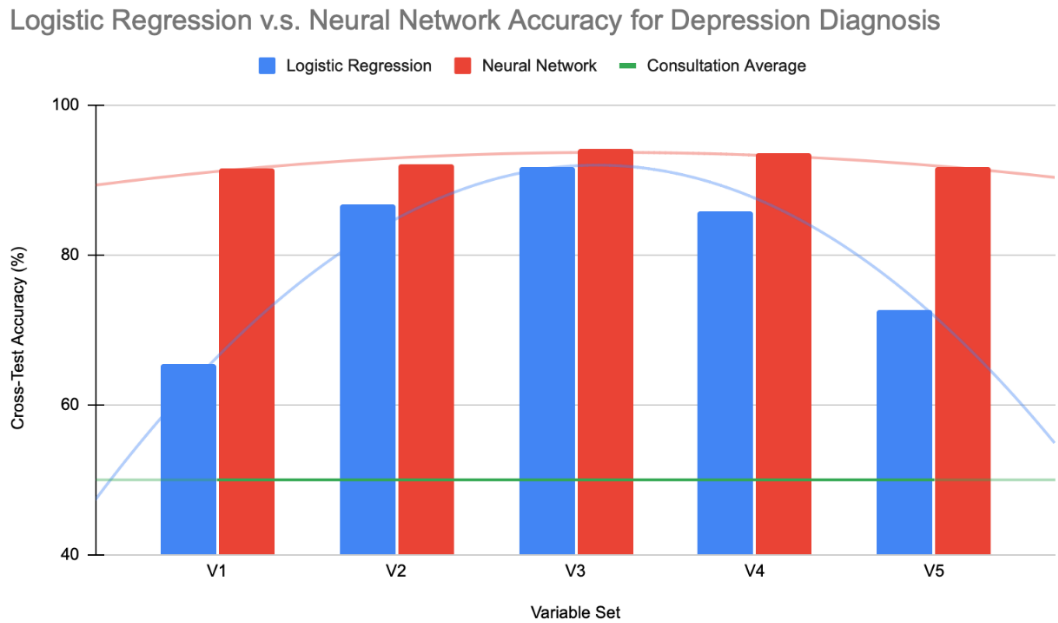

Figure 3. Logistic Regression vs. Neural Network Accuracy for Depression Diagnosis Across Variable Set V1 to V5

Conclusion

We found that neural networks were significantly more precise than logistic regression in all tested cases, confirming previous research which found that, unlike logistic regression, the weighting systems of neural networks can address the negative effects of redundant variables while also avoiding the effects of overfitting (McCaffrey, 2018). For anxiety and depression diagnoses, the evaluation of stepwise-removed variable sets enabled us to find that our neural network accuracy was optimized with set V3 of a total 32 variables. The effectiveness of V3 in predicting anxiety and depression indicates that a predictive model must retain specificity for variables that are highly correlated with mental health outcomes (e.g. demographics, living situation) but should not fit for inter- correlated (e.g. race, ethnicity) and insignificant (e.g. state of collection) variables. Overall, our optimal neural network model, with high cross-testing accuracy and minimal loss, can be used by therapists in clinical settings to identify previously misdiagnosed patients and improve overall diagnosis of anxiety and depression.

Future Research

Even with the high cross-testing accuracies of our novel neural network models, additional research is still needed to analyze the impact of other specialized variables that were not tracked in SAMHSA MH-CLD (e.g. neighborhood and school location, exact number and temporal variation in stressor event frequency). Also, moving forward, an important step is the testing of an in-field implementation of the proposed machine learning approach in clinical environments, which would help us understand the adjustments needed to be made to the model architecture for more effective use alongside psychologists.

Acknowledgments

I would also like to thank my school research teacher, Ms. Angell, for providing weekly guidance throughout the school year and my fellow classmates for bringing insightful discussion about a variety of exciting interdisciplinary topics to class.

References

Afifi, M. (2007). Gender differences in mental health. Singapore Medical Journal, 48(5), 385-391. https://pubmed.ncbi.nlm.nih.gov/17453094/

Al-Huthail, Y. R. (2008). Accuracy of referring psychiatric diagnosis. International Journal of Health Science, 2(1), 35-38. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3068718/

Araya, R. A. (2003). Education and income: Which is more important for mental health? Journal of Epidemiology & Community Health, 57(7), 501-505. https://doi.org/10.1136/jech.57.7.501

Barron, J. (2023, January 22). *Therapy session rates by CPT code*. SimplePractice. Retrieved August 20, 2023, from https://www.simplepractice.com/blog/top-billed-cpt-codes/

Businelle, M. S., Mills, B. A., Chartier, K. G., Kendzor, D. E., Reingle, J. M., & Shuval, K. (2013). Do stressful events account for the link between socioeconomic status and mental health? Journal of Public Health, 36(2), 205-212. https://doi.org/10.1093/pubmed/fdt060

Centers for Disease Control and Prevention. (2021, May 12). Mental Health. Centers for Disease Control and Prevention. Retrieved September 5, 2022, from https://www.cdc.gov/healthyyouth/mental-health/index.htm

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94-98. https://doi.org/10.7861%2Ffuturehosp.6-2-94

Ebert, D. D. (2017). Prevention of mental health disorders using internet-and mobile-based interventions: A narrative review and recommendations for future research. Frontiers. https://www.frontiersin.org/articles/10.3389/fpsyt.2017.00116/full

Evans, G. W., Wells, N. M., & Moch, A. (2003). Housing and mental health: A review of the evidence and a methodological and conceptual critique. Journal of Social Issues, 59(3), 475-500. https://doi.org/10.1111/1540-4560.00074

Koneru, V. K., Weisman de Mamani, A. G., Flynn, P. M., & Betancourt, H. (2007). Acculturation and mental health: Current findings and recommendations for future research. Applied and Preventive Psychology, 12(2), 76-96. https://doi.org/10.1016/j.appsy.2007.07.016

Mackenzie, C. S., Gekoski, W. L., & Knox, V. J. (2006). Age, gender, and the underutilization of mental health services: The influence of help-seeking attitudes. Aging & Mental Health, 10(6), 574-582. https://doi.org/10.1080/13607860600641200

McCaffrey, J. D. (2018). Why a neural network is always better than logistic regression. Retrieved April 7, 2023, from https://jamesmccaffrey.wordpress.com/2018/07/07/why-a-neural-network-is-always-better-than-logistic-regression/

Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2017). Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics*, *19*(6), 1236-1246. https://doi.org/10.1093/bib/bbx044

Rowan, K., Mcalpine, D. D., & Blewett, L. A. (2013). Access and cost barriers to mental health care, by insurance status, 1999–2010. Health Affairs, 32(10), 1723-1730. https://doi.org/10.1377%2Fhlthaff.2013.0133

Sava, F. A., Yates, B. T., Lupu, V., Szentagotai, A., & David, D. (2009). Cost-effectiveness and cost-utility of cognitive therapy, rational emotive behavioral therapy, and fluoxetine (prozac) in treating depression: A randomized clinical trial. Journal of Clinical Psychology, 65(1), 36-52. https://doi.org/10.1002/jclp.20550

Schaeffer, K. (2022, April 25). In CDC survey, 37% of U.S. high school students report regular mental health struggles during COVID-19. Pew Research Center. Retrieved September 26, 2022, from https://www.pewresearch.org/fact-tank/2022/04/25/in-cdc-survey-37-of-u-s-high-school-students-report-regular mental-health-struggles-during-covid-19/

Vernooij-Dassen, M. J. F. J., Moniz-Cook, E. D., Woods, R. T., Lepeleire, J. De, Leuschner, A., Zanetti, O., Rotrou, J. De, Kenny, G., Franco, M., Peters, V., & Iliffe, S. (2005). Factors affecting timely recognition and diagnosis of dementia across europe: From awareness to stigma. International Journal of Geriatric Psychiatry, 20(4), 377-386. https://doi.org/10.1002/gps.1302

Wu, D. T. Y., Xu, C., Kim, A., Bindhu, S., Mah, K. E., & Eckman, M. H. (2021). A scoping review of health information technology in clinician burnout. Applied Clinical Informatics, 12(03), 597-620. https://doi.org/10.1055/ s-0041-1731399