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High School Emotional Well-Being: Identifying Factors And Creating A Working Model For Prediction

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ABSTRACT

In high schools across the world, a mental health crisis is happening. High school students' mental health has been decreasing at an alarming rate since the 2000s, and the negative impacts of this crisis such as suicide rates have been exacerbated. Two significant issues are causing the problem. The first is the lack of data concerning high school students' emotional well-being. There is no current data set that attempts to correlate and categorize the causes of these mental health issues with the emotional health of students. The second is the lack of available tools to help teachers and counselors identify those with mental health issues and help them get access to treatment. This study resolves these two problems with the creation of an accurate machine learning algorithm to model and predict students' mental health as well as the collection of a data set about high school students that contain potential causes. The model attempts to use potential stressors collected by a survey to predict students' mental health; the best possible model predicts mental health on the Subjective Happiness Scale with a mean squared error of 0.41 and an r2 of 0.52, which is satisfactory for a subjective study.

Introduction

According to the World Health Organization (WHO), mental health is defined as "a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well and contribute to their community." Mental health is one of the most important aspects of our daily lives, dictating a person's emotional, psychological, and social well-being and influencing our ability to make rational decisions, form relationships, and face challenges. Unfortunately, according to a longitudinal study by the Center for Disease Control (CDC), the emotional health of high school students has been slowly declining, and the overall percentage of students who experience persistent feelings of loneliness and sadness have been increasing steadily over 10 years, indifferent of race or ethnicity (CDC 22, pg. 64). In 2017, 13% of US students aged 12-17 reported at least one depressive episode in the past year, up from just 8% in 2007 (A.W. Geiger & Davis, 2019). Another survey in the fall of 2018 reported that 70% of students surveyed cited depression and anxiety as major problems for their age groups, while another 26% cited it as a minor problem (Horowitz & Graf, 2019). Additionally, about 1 in 5 children aged 3-17 years were diagnosed with a mental health disorder, with those in high school making up the majority of the group (Centers for Disease Control and Prevention, 2022). Poor mental health can have disastrous effects as well; as a result of the declining trend of mental well-being, there has been a steady rise in the rate of suicides, attempted suicides, and usage of products such as vaping and e-cigarettes (CDC 22, pg.68)(Wein 19).

Research has shown that early detection of mental health problems in students prevents serious mental health issues from developing (National Research Council (US) and Institute of Medicine (US), 2009) as well as "lessen long-term disability and prevent years of suffering"(Mental Health Screening | NAMI: National Alliance on Mental Illness, n.d.). Despite the benefits of detecting mental health conditions early on, the process leading up to diagnosis is sorely lacking; the average time elapsed between symptoms and diagnosis is approximately 11 years (Mental Health Screening | NAMI: National Alliance on Mental Illness, n.d.). In schools, there exists a framework for the detection of mental health issues that is based on interagency and interdisciplinary networks, but the prospect for early detection of mental health conditions has not improved (Forness et al., 1996). School counselors and teachers are in optimal positions to provide direct interventions to improve the mental health of their students (Collins, 2014).

Despite this, they are often unable to identify and help these struggling students. For example, in a study conducted by professors at Cambridge that measured the effectiveness of teachers, teachers miss over 30% of those who are battling depression and mental health issues and have a false-positive rate of 70% in diagnosing depression in students (Anderson et al., 2018). Another study finds that most teachers receive little or no training regarding student mental health, and if they do receive training, the training is often inadequate, as teachers regard the training to have little application in the classroom (Deaton et al., 2022).

Many research studies have been done to examine the link between factors such as self-esteem, hope, etc., on the mental health of students, such as Ciarrochi et al. (2007). But these studies are either too narrow or do not address the root of the causes of depression and other mood-related mental health issues. The root causes of depression and anxiety in high school are often too broad to be combined into a single factor such as positive emotions or social relationships, as a combination of multiple factors influences a student's day-to-day life. Currently, there are only 2 models (known to the author) that focus exclusively on predicting high school emotional health based on factors without specifying a specific period of time (e.g Covid), and zero models that combine factors in broad areas to predict high school mental health, which makes this research study unique in its scope and approach. Additionally, there is no available dataset on high school students' mental health which creates a barrier against further research in this area.

This research study proposes a tool for determining and diagnosing students with mood and mental health issues such as depression or anxiety by analyzing the effects of various factors including but not limited to difficult classes, social life, family life, etc. on student mental health. The study utilizes machine learning techniques to model these factors against a common measurement of happiness, which could help school counselors and teachers diagnose and identify those who may have mental health issues. As the author is a current high school student, the author believes that this research study will be more accurate, as the features were carefully selected by the author and his peers in order to best identify variables that affect the emotional well-being of high school students. Therefore, one objective of this research study is to identify a correlation between the factors and the subjects' happiness and develop the best possible model to accurately predict the emotional well-being of students. Another sub-objective of this study is to investigate and identify the most prominent factors affecting the mental health of high school students in preparation for additional studies in the future.

The other objective of this study is to create a comprehensive data set of high school student's emotional health and the corresponding factors that influence mental health. This study will provide the only dataset that can be used to study correlations between various factors and high school mental health. By making the dataset publicly available, researchers will have the tools to advance their research on. As there is no data set available yet about the proposed data set, this study will also be unique. This data set will be uploaded onto Kaggle for further studies of this subject.

Methods

Data Collection Preparations

To accomplish the goal of accurately determining the subject's emotional well-being, one must determine the wide range of factors that influence mental health and compile them with a measurable scale so it can be modeled. As mentioned, the factors that affect mental health range over a broad expanse of issues. To obtain the best and most encompassing possible features (factors), the author compiled a list of relevant factors, with the help of co-students (see acknowledgments), that might influence mental health by asking about possible stressors in a student's life at his school. Next, the author asked his classmates across different grades, ethnicities, and gender in order to determine the best-fit factors for the survey questionnaire for the study. After taking into consideration that different genders may be susceptible to depression and anxiety in different amounts, as proven by (Nolen-Hoeksema et al. 1994), as well as the personal experience and observation that grade level can have a significant impact on stress, such as juniors having significantly more stress than freshman (it is important to note that the research was conducted after college application season). The final list of factors is shown in table 1.

Table 1. List of factors that affect mental health

How many hard/rigorous classes are you taking
Hours of sleep per night
Hours of extracurriculars, as well as enjoyment of said extracurriculars
Hours of work per week
Social relationships
Hours of free time
Currently in a relationship?
Family life
personality type (introvert vs extrovert vs ambivert)
Grade level
Gender
Personal perception of loneliness and other negative emotions

Questions were written for all of the categories with answers being a positive whole number or a positive decimal number. For questions that require a direct number answer, such as the number of hours of sleep one gets (Table 1, row 2), the number can be entered directly by the survey respondent (see figure 1). But for questions that are qualitative, there is one extra step of creating a scale for the user to select a number that corresponds with their answer (see figure 2).

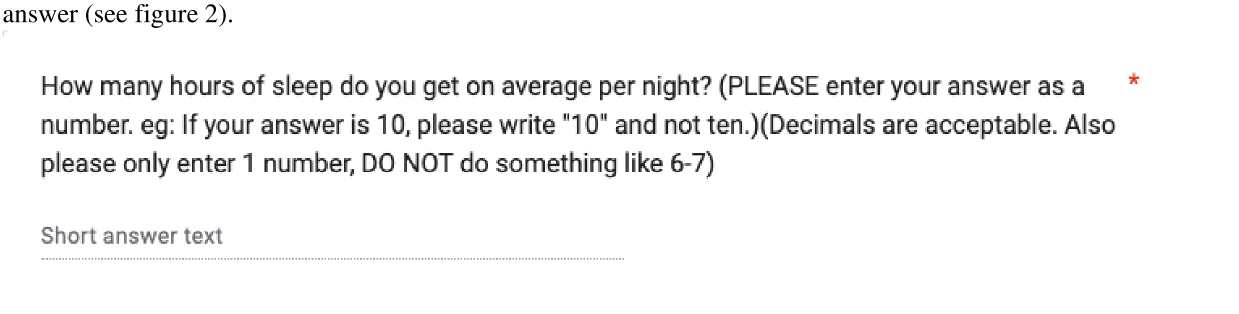

Figure 1. Direct Numerical Problem

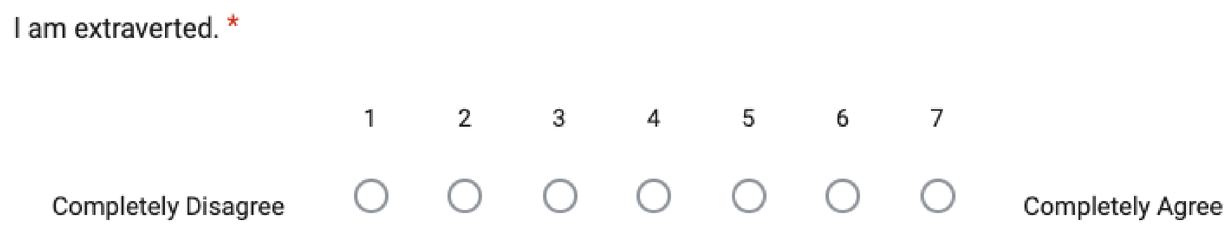

Figure 2. Scale Problem

To utilize machine learning models, a label (value the model predicts based on the features) must be used. This study uses the Subjective Happiness Scale as the scale of choice for measuring mental well-being. The Subjective Happiness Scale is a proven psychological scale for measuring happiness on a scale from 1-7, with 1 being the least happy and 7 being the happiest; it has a dependable stable reliability of 0.72, and confirmed correlations with other happiness measures (Lyubomirsky & Lepper, 1999). Additionally, as another safeguard to ensure the validity and accuracy of the Subjective Happiness Scale, survey respondents were also asked to estimate their own emotional health on a scale. The user's self-reported number is compared to the Subjective Happiness Scale reading, and if the two numbers differ by too much without a valid reason, that specific data point will be disabled.

Data Collection

The data collection was done using online Google Forms. The survey consisted of five parts as follows:

1. Consent Form: As the survey was targeted towards minors, a consent form needed to be consented to by both the minor in question and the parent. The consent forms clarified the purpose of the research study, the rights of the participants, the anonymity of the survey, the risks and benefits of participation, and the voluntary nature of the survey.
2. Basic Information: The basic information portion included required information about biological gender and current grade level.
3. Numerical Questions: Questions that can be answered through a number, such as the average number of hours of sleep per night. This section included information about academics and objective data such as hours of work.
4. Scale Questions: Questions that allow the responder to answer on a scale. For example, on a scale of 1-7, how extroverted are you? This contains subjective questions such as degrees of enjoyment of a particular activity.
5. Subjective Happiness Scale: This is the label of the model; it surveys the user about their current mental health.

The survey was released to the author's high school in Georgia, United States, and was distributed by teachers the author handpicked to ensure an approximately equal number of each grade (9th, 10th, 11th, 12th) answered the survey. The survey was also posted online on social media to other high school students on Instagram and Reddit (r/APStudents, r/teenagers) for diversification of data (See the acknowledgment section for people who helped with the distribution process). In total, 513 responses were received by the author, with 402 from the author's high school and another 111 received from the internet. After cleaning the data of unusable data points, there are a total of 41 responses dropped resulting in a grand total of 472 responses to the survey; the spread of the data with respect to grade and gender is as below (see Figures 3 and 4).

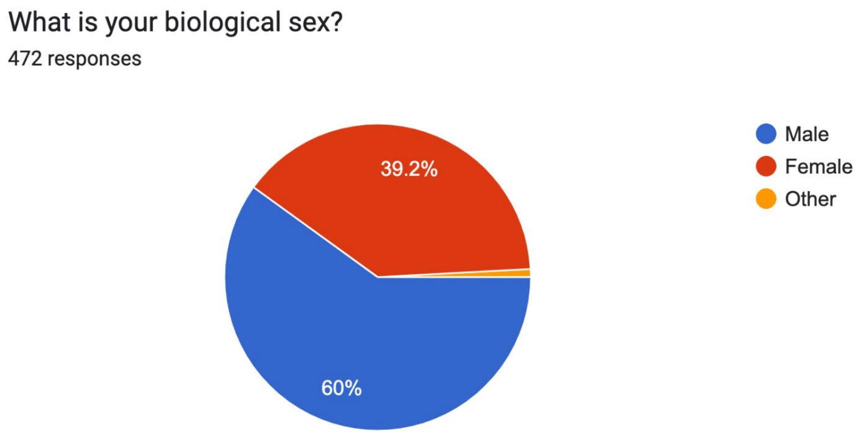

Figure 3. Sex distribution of respondents

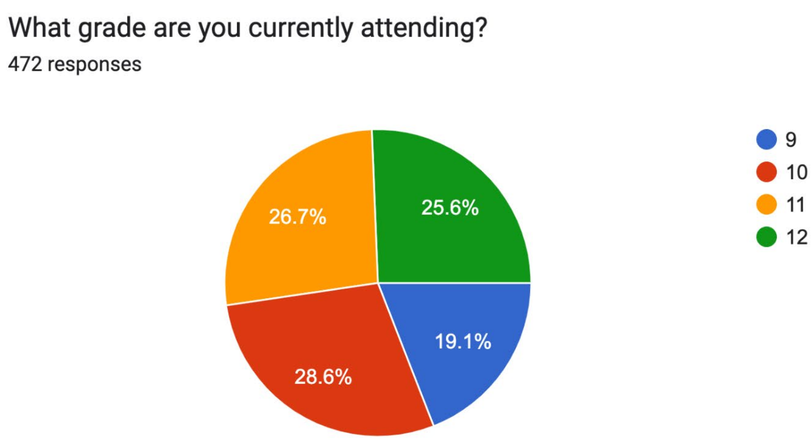

Figure 4: Grade Level Distribution of the Respondents

Data Cleaning/Preparation

Using Google Form's feature to transfer responses, all of the data from the survey was stored and displayed in a Google Sheets. The data preparation process was done through x steps with the purpose of preparing the data set for modeling.

1. Correction of Respondee errors
2. Dropping of unsatisfactory responses
3. Deleting Unnecessary Information and Hot Encoding
4. Scaling Feature/Labels and Final Preparation

Libraries and Environment Used

All of the data preparation was done in the Google Colab coding environment using the Python programming language. Table 2 shows a table of libraries used and their function.

Table 2. Libraries Used and Their Function

Library Used	Function
Matplotlib	Visualizing data through graphs
Numpy	Creating and managing arrays
Pandas	Managing and manipulating data
Sklearn	Tool for predictive data analysis
Tensorflow	Training and configuring of neural networks
google.colab	Google-related functions such as connecting to an external Google sheets
Numpy	Creating and managing arrays

Correction of Respondee Errors

During the data collection process, many respondees did not read the requirements for entering in answers correctly, resulting in responses such as “ten” or “5-7” for answers that require a numerical digit response. The problem was addressed through a pandas command that looped through the entire data set, looking for characters that are not numbers and highlighting them to the programmer. The faulty data will then be fixed, and if the original user intent is indecipherable, it is dropped. For example, the error “ten” will be corrected to “10”, but the error “...” will cause that response to be dropped.

Dropping of Unsatisfactory Responses

After the initial cleaning of human errors, the next step is to discard the responses that are unsatisfactory. Unsatisfactory here is defined as the difference between self-reported happiness and the measurement by the Subjective Happiness Scale differ by more than 2.

A response will be dropped if $|SHS\ Rating\ -\ Self\ Reported\ Happiness| > 2$

This means a discrepancy between measured and self-reported happiness, which could mean faulty data. So as a precaution, the response is dropped.

Deleting Unnecessary Information and Hot Encoding

After cleaning the data, the next step is to prepare the data for modeling, which is done by eliminating unnecessary columns and hot encoding non-numerical answers. From the original survey responses, the column “consent to the consent forms” information in there is irrelevant to the data. The columns that contain the questions that the Subjective

Happiness Scale was also dropped from the pandas data frame because their only contribution is to calculate the Subjective Happiness Rating; in addition, the self-reported happiness score is also dropped as its function is to verify the Subjective Happiness Rating. Because machine learning can only model numerical data, it is necessary to convert non-numerical data to numerical data in order to create a model. The only non-numerical data in the survey is the sex of the respondees, so the process is done by one hot encoding code by converting “male” to “0” and female to “1”.

Scaling Features/Labels and Final Preparation

Now the features, which is all the questions and data regarding the respondee, and the label, which is the Subjective Happiness Scale rating are separated, and each is reshaped into its own array. Then the features and the labels are scaled by Sklearn’s Standardscaler. Scaling is important in the development of a model because it allows the features in the data set to contain numerical values of a similar scale, to improve optimization and speed up the algorithm for creating a model. Note that the label is scaled in this study, which is not completely necessary, but it does generalize the process. Finally, the data is split into a training and validation set with a 75%/25% split of training versus validation.

Model

The model is a neural network with hidden layers with the final layer having one node, or output. The final loss compiled will be according to the mean squared error because this is a numerical model problem. The model will then be used in the validation set to compare the predicted validation label with the actual validation label values, with the mean squared error and the r^2 value returned. The neural model will then be compared to a baseline linear regression model to determine the superior model based on accuracy.

Results

First, the test use of different activation functions determines “relu”, or rectangular linearized activation unit: the most common activation function, to be the best in this study partly due to the linear nature of the relationship between the feature and the label. Shown in figure 5 is the graph of how increasing hidden layers affect the mean squared error. Shown in figure 6 is the graph of how increasing hidden layers affect the r^2 value.

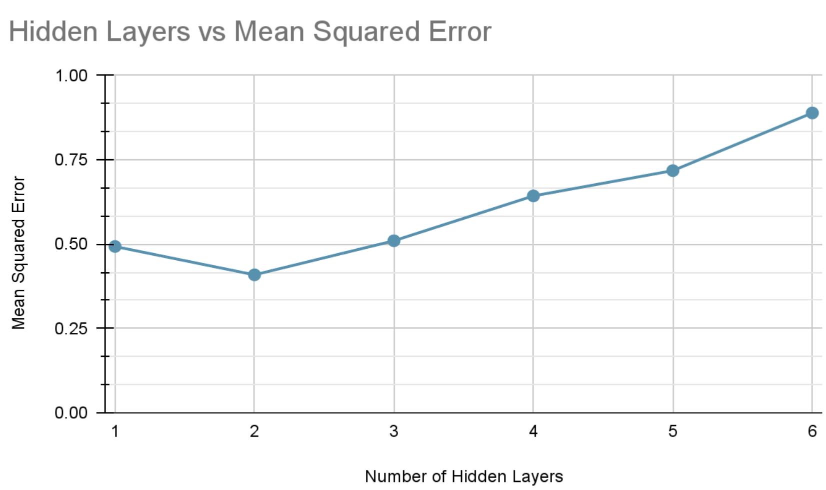

Figure 5: Effect of Hidden Layers on Mean Squared Error

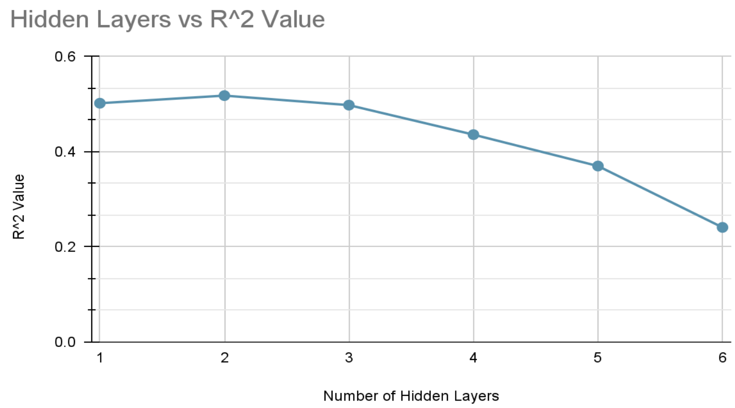

Figure 6: Effect of Hidden Layers on r^2 Value

According to the graphs, fine-tuning of the hyperparameters of the neural network as well as the manipulation of the number of hidden layers shows that a total of two hidden layers with 1 node and activation function "relu" yields the best mean squared error of 0.4088 and the best r^2 value of 0.5176. In contrast, the mean squared error of linear regression is 0.4090 and the r^2 value is 0.5174 on the scaled data. The regression coefficients are better determined by the unscaled regression, and the coefficients based on the unscaled regression are shown in table 3.

Table 3. Chart of Regression Coefficient of Features

Column Title (Feature)	Regression Coefficient
Sex (0 = Male) (1 = Female)	-0.1318
Number of Rigorous Classes	-0.049
Hours Spent on Homework Each Day	-0.043
Strictness of Parents	-0.032
Hours of Freetime per Day	-0.017
Social Life at School (Friends)	-0.016
Hours of Work per Week	-0.003
Healthy Romantic Relationship	0.003
Hours Spent on Extracurriculars per Week	0.020
Enjoyment of Extracurriculars	0.070
Enjoyment of One's Family Environment	0.105
Hours of Sleep per Night	0.1086
Grade Level	0.1103
Level of Extraversion	0.225
Self-Reported Loneliness	0.299

Discussion

In summary of the results of the study, both the neural network and the baseline linear regression have comparable mean squared errors and r^2 values, thus advancing the claim that they are almost equally effective at predicting the label based on the given features. This section will focus primarily on the results of linear regression of the data.

The r^2 value, or the coefficient of determination, measures the amount or proportion of the dependent variable that is actively influenced by the dependent variable. In the field of psychology and social sciences, which is what the study of mental health belongs to, a coefficient of determination of above 0.10 without independent variable collinearity and the existence of statistical significance of the independent variable is generally accepted (Ozili, 2022). In the case of this study, the r^2 score is about 0.52, which is beyond satisfactory and is considered highly correlational in the context of a subjective study and a self-reported survey in social science.

In this case, the statistically significant factors that affect can also be identified through the regression coefficients of each of the features. Additionally, this study also achieved the goal of creating a tool that relatively accurately predicts the mental health of students. The mean squared error for the model is 0.41, which means the mean error of the label is $\sqrt{0.41} = 0.6403$, which brings the range of the prediction to be ±0.6403 of the actual label. A range of 0.6403 is exceptionally remarkable and useful for predicting emotional well-being issues because of emotional health issues. Additionally, well-being issues are identified by a range of Subjective Happiness Ratings, such as a range 1-3; this makes the uncertainty of the label even more insignificant because the purpose is not a precise value of the scale.

According to table 3, statistically significant values of the regression coefficients of the features can be determined through comparison. This allows further isolation of key independent variables for further study. The relatively significant features were: sex, grade level, hours of sleep per night, level of extraversion, enjoyment of one's family environment, and loneliness according to a comparison of the magnitude of the correlation coefficients. All the features mentioned previously had a positive correlation with the Subjective Happiness Scale except sex, meaning that an increase in all of the above features except sex will result in a higher Subjective Happiness Scale rating, while being female decreases the Subjective Happiness Scale rating by 0.1318, which supports findings of other studies that identify females are more likely to experience depression (Gao et al., 2020).

Therefore, the study also identified areas where students' mental health is most influenced by. It is surprising that contrary to popular belief, the amount of rigorous classes does not influence mental well-being in a significant amount: the increase of 1 rigorous class only decreases the happiness rating by 0.049. This could be attributed to potential student enjoyment of the rigorous course. Future studies are encouraged to look into this area of student life deeper, possibly uncovering whether enjoyment of a class will lower stress instead of creating stress. Another surprising fact is the impact of personality factors such as extraversion and loneliness on the label. Loneliness is, according to this study, the largest cause of mental health issues, which is consistent with previous studies citing a strong correlation between loneliness and depressive disorders (Dziedzic et al., 2021).

This model contains two important implications. First, as the pioneer of a new discussion and field of utilizing broad factors of high school life to predict students' emotional well-being, this model can be used by school counselors and teachers to diagnose possible problems in high school emotional health. As the budget of many schools is limited as teachers do not get enough training, a model that is simple to operate and free of cost such as this is substantially more cost-efficient than conducting full school screenings for mental health. Second, this study also creates a revolutionary data set that takes into account vast sectors of student life in an attempt to correlate it to student mental health. This could be used for further research and study in an attempt to develop a better model for predicting student mental health.

There are potentially some confounding factors in the papers. One, the first confounding factor of the study is the use of only neural networks and linear regression in an attempt to model the features against the label. This does not consider other models such as decision trees, random forest, XGBoost…etc. Therefore, there is a possibility that the results of this study do not yield the lowest possible error and the highest possible r^2 score as another model that the author did not test could have better results. Therefore, it is not certain to say that this model is the statistically best model, but the accuracy of linear regression of the data is satisfactory for psychology. The second confounding factor is the size of the data set. Because of the lack of reach and resources the author, the survey could only obtain 472 legitimate responses, which is far below the number of high schoolers in the World. Additionally, the data set is heavily skewed toward high school students currently living in the United States as that is where the author conducted his research. Consequently, it can then be argued that the data set is not a good representation of the population of high school students due to the about 60/40 ration of male to female respondee ratio, possible selection bias in the 100 responses posted in online communities (although the author attempted to alleviate this by posting the survey on the most diversified communities), and the fact that the author only conducted the survey in one school district, which is only a snapshot of high schools in the US.

Therefore, in future research endeavors regarding this topic, it is recommended that if the researchers have the capacity and the ability to do so, create a more thorough representation of high schoolers if they wish to pursue broad-scale research on high school mental health. Another possible research idea is to examine the areas of student life that showed the greatest correlation coefficients, namely sex, grade level, hours of sleep per night, level of extra-version, enjoyment of one's family environment, and loneliness, more closely to further examine the impact of one specific area on student life and to propose plans to help students that are struggling in that area.

Conclusion

As high school mental health problems continue to grow in the future, it is increasingly important that we as a society take steps to address that issue by diagnosing those with emotional well-being issues and treating the problem early, and the first step is to determine the causes of high school mental health issues as well as detect vulnerable students. This study has proposed a solution and created a great starting point for future research by identifying factors that cause high school depression, creating a working neural model as well as a linear regression model that predicts and diagnoses mental health issues, and creating a new dataset to advance further research in this field. The main findings and results of this study are a linear regression and neural model with satisfactory uncertainty ranges and r^2 values and the identification of major factors of mental health problems such as sex, grade level, hours of sleep per night, level of extraversion, enjoyment of one's family environment, and loneliness. Hopefully, with increasing awareness of high schoolers' mental health, an effort to understand their emotional health, and a desire to solve these health issues, there will one day be a systematic method in place to detect and solve emotional well-being issues in high schools around the world.

References

A.W. Geiger, & Davis, L. (2019, July 12). A growing number of American teenagers – particularly girls – are facing depression. Pew Research Center; Pew Research Center. https://www.pewresearch.org/fact-tank/2019/07/12/a-growing-number-of-american-teenagers-particularly-girls-are-facing-depression/

Anderson, J. K., Ford, T., Soneson, E., Coon, J. T., Humphrey, A., Rogers, M., Moore, D., Jones, P. B., Clarke, E., & Howarth, E. (2018). A systematic review of effectiveness and cost-effectiveness of school-based identification of children and young people at risk of, or currently experiencing mental health difficulties. Psychological Medicine, 49(1), 9–19. https://doi.org/10.1017/s0033291718002490

CDC. (2011). Youth Risk Behavior Survey. https://www.cdc.gov/healthyyouth/data/yrbs/pdf/YRBS_Data-Summary-Trends_Report2023_508.pdf

Centers for Disease Control and Prevention. (2022, June 3). Data and Statistics on Children's Mental Health. Centers for Disease Control and Prevention; CDC. https://www.cdc.gov/childrensmentalhealth/data.html

Ciarrochi, J., Heaven, P. C. L., & Davies, F. (2007). The impact of hope, self-esteem, and attributional style on adolescents' school grades and emotional well-being: A longitudinal study. Journal of Research in Personality, 41(6), 1161–1178. https://doi.org/10.1016/j.jrp.2007.02.001

Collins, T. P. (2014). Addressing Mental Health Needs in Our Schools: Supporting the Role of School Counselors. Professional Counselor, 4(5), 413–416. https://eric.ed.gov/?id=EJ1063214

Deaton, J. D., Ohrt, J. H., Linich, K., Wymer, B., Toomey, M., Lewis, O., Guest, J. D., & Newton, T. (2022). Teachers' experiences with K-12 students' mental health. Psychology in the Schools, 59(5), 932–949. https://doi.org/10.1002/pits.22658

Dziedzic, B., Sarwa, P., Kobos, E., Sienkiewicz, Z., Idzik, A., Wysokiński, M., & Fidecki, W. (2021). Loneliness and Depression among Polish High-School Students. International Journal of Environmental Research and Public Health, 18(4), 1706. https://doi.org/10.3390/ijerph18041706

Forness, S. R., Kavale, K. A., Macmillan, D. L., Asarnow, J. R., & Duncan, B. B. (1996). Early Detection and Prevention of Emotional or Behavioral Disorders: Developmental Aspects of Systems of Care. Behavioral Disorders, 21(3), 226–240. https://doi.org/10.1177/019874299602100303

Gao, W., Ping, S., & Liu, X. (2020). Gender differences in depression, anxiety, and stress among college students: A longitudinal study from China. Journal of Affective Disorders, 263(1), 292–300. https://doi.org/10.1016/j.jad.2019.11.121

Horowitz, J. M., & Graf, N. (2019, February 20). Most U.S. Teens See Anxiety, Depression as Major Problems. Pew Research Center's Social & Demographic Trends Project.

https://www.nami.org/Advocacy/Policy-Priorities/Improving-Health/Mental-Health-Screening#:~:text=Mental%20health%20screenings%20are%20a

https://www.pewresearch.org/social-trends/2019/02/20/most-u-s-teens-see-anxiety-and-depression-as-a-major-problem-among-their-peers/

Lyubomirsky, S., & Lepper, H. S. (1999). A Measure of Subjective Happiness: Preliminary Reliability and Construct Validation. Social Indicators Research, 46(2), 137–155. https://doi.org/10.1023/a:1006824100041

Mental Health Screening | NAMI: National Alliance on Mental Illness. (n.d.). Www.nami.org. Retrieved March 13, 2023, from

National Research Council (US) and Institute of Medicine (US) Committee on the Prevention of Mental Disorders and Substance Abuse Among Children, Youth, and Young Adults: Research Advances and Promising Interventions. (2009). Preventing Mental, Emotional, and Behavioral Disorders Among Young People: Progress and Possibilities. In M. E. O'Connell, T. Boat, & K. E. Warner (Eds.), PubMed. National Academies Press (US). https://doi.org/10.17226/12480

Nolen-Hoeksema, S., & Girgus, J. S. (1994). The emergence of gender differences in depression during adolescence. Psychological Bulletin, 115(3), 424–443. https://doi.org/10.1037/0033-2909.115.3.424

Ozili, Peterson K, The Acceptable R-Square in Empirical Modelling for Social Science Research (June 5, 2022). Social Research Methodology and Publishing Results, http://dx.doi.org/10.2139/ssrn.4128165

Wein, H. (2019, March 8). Vaping Rises among Teens. NIH News in Health. https://newsinhealth.nih.gov/2019/02/vaping-rises-among-teens

World Health Organization. (2022, June 17). Mental health: Strengthening Our Response. World Health Organization; World Health Organization. https://www.who.int/news-room/fact-sheets/detail/mental-health-strengthening-our-response