Exploring Machine Learning Models to identify Mental Health Concerns among Students in Singapore in an Uncoerced Manner

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Abstract

In recent years, the World Health Organization has recognized mental health to be at the forefront of concern. Subjected to mental stress, people develop mental health conditions with severe consequences, including suicide. This report details a comprehensive machine learning model that is novel in detecting mental health conditions among university students in Singapore. With this, universities can utilize this model to identify students with mental health issues and provide apposite assistance to help them safeguard and ameliorate their mental well-being.

1 Introduction

Mental health was ranked the second most pressing health concern in Singapore in 2021, higher than cancer (Ipsos n.d.). According to the National Population Health Survey, the prevalence of poor mental health in Singapore increased by about 7.2% from 2017 to 2020 (Ministry of Health n.d.). Youths (aged 18-29) showed the most significant increase of 30%. Factors that contributed to this surge included the COVID-19 pandemic, the competitive environment Singapore youths face, and the influence of social media.

	NPHS	NPHS
	2017	2020
Total	12.5 (10.9, 14.0)	13.4 (12.4, 14.5)
ASR	12.6	13.8
18-29	16.5 (12.7, 20.3)	21.5 (18.4, 24.6)
30-39	12.8 (9.8, 15.7)	12.6 (10.5, 14.8)
40-49	10.9 (8.1, 13.6)	12.4 (10.2, 14.6)
50-59	10.6 (7.8, 13.5)	11.4 (9.2, 13.7)
60-74	11.4 (8.8, 13.9)	9.4 (7.8, 11.1)

Figure 1: Crude prevalence (%) of poor mental health among Singapore residents aged 18 to 74 years by age group, 2017 and 2020 (Ministry of Health n.d.)

The COVID-19 lockdown has dissociated people from their families and friends, resulting in physical isolation and loneliness. These make them more susceptible to certain mental illnesses such as depression and anxiety disorders (Singh et al. 2020).

Singapore has cultivated a competitive culture to remain economically relevant to the world (Asianlink). Inadvertently, this has created a competitive environment in education and work (Wong 2021). Experts share that students are highly pressured to excel in academics and later secure high-paying jobs, which increases their risk of developing stress-induced mental illnesses (Wong 2021).

Social media has served as a platform for people to actively engage with one another (Luttrell 2018). Singapore has approximately 4.96 million social media users, with a large proportion of them aged 16 to 24 (Tan 2021). While social media has its benefits, there has been a significant increase in youths reporting depression stemming from cyberbullying (Miller n.d).

Presently, many Singaporean youths are considered to be sheltered and provided for due to the better standard of living (Sameer 2021). As a result, these youths lead more privileged lifestyles and lack adequate coping mechanisms to deal with adversity (CNA 2019).

Early symptoms of mental illnesses include sleep deprivation, loss of appetite and an inactive lifestyle (Skyland Trail 2018). Without adequate sleep, diet, and exercise, the body starts developing health conditions, such as obesity and heart diseases (Shmerling 2016).

Subsequently, they can develop worse symptoms such as anhedonia – the inability to derive pleasure (Gabby et al. 2015). Common in patients with depression and anxiety, it causes them to have difficulty in concentrating and possibly lose interest in the activities they once enjoyed (Healthline 2021). These make patients more prone to self-isolation, further deteriorating their mental well-being.

If left untreated, the mental well-being of the patients would worsen and could lead to self-harm or suicide as a means to relieve themselves of their suffering (Goh, 2020). In 2019, the age group with the highest suicide rate in Singapore was those in their 20s.

Considering the serious effects of poor mental health, existing stigma in Asian societies like Singapore accentuates this issue (APA 2020). This stems from the negative connotations associated with mental illnesses, such as violent tendencies from patients admitted to mental institutions. Furthermore, in Singapore, it is deemed embarrassing to have a mental illness due to the pride-focused culture instilled in Singaporeans. (Cigna 2020). These inhibit those at risk from seeking treatment out of fear of prejudice and discrimination.

In light of this, we aim to design and develop a suitable machine learning (ML) model capable of identifying university students at risk of mental illness. We chose the target user of our ML model to be the university counseling department and the target audience to be the university student population. This model can be utilized by universities to safeguard their students' mental well-being. It provides a node to uncover and identify vulnerable student groups, particularly those who are apprehensive about seeking help due to the existing stigma or their negligence of mental health. Consequently, counseling teams are given the opportunity to enact programmes to outreach and assist them in coping with their mental health condition even if students do not seek help on their own accord.

2 Methodology

Given our target user and audience, we propose a two-part solution 1) data collection method that allows students to feel more comfortable in truthfully indicating their conditions, and 2) an ML model that enables the school's counseling department to identify vulnerable groups of university students who require treatment but are hesitant to seek treatment.

2.1 Data Collection

We conducted a survey to gather information on university students. The following sections state the factors we inquired on and attributed to our ML model.

Considering our target demographic, age was a major factor in the ML model. Research has shown that youths transitioning from adolescence to adulthood are more susceptible to mental strain (Rosenberg 2019). This is because younger youths are more easily influenced by their surroundings, especially in Singapore, where they are entering a new competitive environment in university (InContact 2021).

Gender was another factor considered in the model. Females are found to be more prone to stress-induced mental illnesses, such as depression and anxiety (McLean Hospital 2020). In Singapore, studies have shown that females with higher education levels are at higher risk of mental illnesses due to the exposure to a more stressful environment and the expectations placed on them (Ng 2017).

Additionally, family history was another important consideration. Studies show that mental illnesses can be hereditary, where genes responsible for the serotonin function are implicated (Su 2009). On a genetic level, offspring of these patients are more susceptible to stress, and thus more prone to develop stress-induced mental illnesses.

Lastly, we asked our respondents how their concentration at work would be impacted if they had a mental health condition. Due to the perturbed serotonin hormone's activity in their bodies, patients with mental health conditions are inclined to face difficulty in concentrating at work as they experience loss of interests and mood swings (Healthline 2021). Hence, we decided to consider it in our model.

In addition to this, it is important to note that we deliberately asked the participants if they had sought treatment instead of directly asking if they have a mental illness. This is because mental illness is a sensitive issue and by rewording, we hope that participants feel more comfortable to answer truthfully.

Have you sought treatment?	If you have a mental health condition, does it interfere in your work?	ML Treatment prediction **(relabeled)**
1	1	1
1	0	1
0	1	1
0	0	0

Figure 2: Hypothesis 2 - Relabelling Methodology

The treatment question is used for the labeling of our data, where having sought treatment would mean they have a mental health condition. Hence, we are able to train our model by using the treatment labels. However, our survey responses reveal cases where respondents indicated that they did not seek treatment but responded that their mental health condition had interfered with their work (see Fig. 2). The latter responses were derived from the following question: "If you have a mental health condition, do you feel that it interferes with your work?" - which was one of the 4 factors we inquired in our model. Responding "Never", "Rarely", "Sometimes", "Often" and "Always" implies that they are subconsciously aware of an underlying mental illness (labeled 1). Indicating "NA" would mean that the person does not feel that he or she has an underlying mental health condition (labeled 0).

Apart from testing with our original treatment label (hypothesis 1), we derived a second hypothesis that the survey responses could be relabeled by factoring in the `work_interference` responses to better represent the true value of whether the person needs to seek treatment (see Fig. 2). This is useful as we can assess if our ML model would be able to identify cases where students may be aware of their mental health illness but avoid seeking help due to stigma or other reasons, and hence cater to our target audience. Although the model is trained using the treatment labels, we would like to further evaluate it against the relabeled treatment labels to see if our model is able to account for respondents who are in the case of 0-1-1, highlighted in gray.

2.2 Machine Learning Usage

Based on our app's purpose, we have chosen a few models to help the school's counseling department to uncover students who are in denial of their mental health due to stigma or personal reasons. Among the many ML models tried, we identified 3 models that can best suit our issue and produce high accuracy.

To identify significant factors that contribute to poor mental health, we have naturally chosen Decision Trees (DT). Playing on DT's strengths of being a white-box model and having expressive hypotheses, we can divulge information on the attributes that contribute more to a student's poor mental health based on information gain. Such knowledge is exceptionally useful for assessing if a student has a mental health condition and should seek treatment. Furthermore, it can help to identify if a certain demographic of students are at higher risk. As mental health factors come in variety, DT's ability to accept continuous, discrete and non-numeric attribute values provides flexibility to add new factors without much data pre-processing. However, DT also has its weaknesses. By Occam's Razor, shorter trees are preferred to avoid overfitting, but this may mean that not all factors are used for classification. While this may be favorable to deduce key factors that affect mental health, it limits our model from correctly classifying cases that are distinguished by other less significant factors.

Understanding that mental illness is a black-box issue, where one's true feelings are often unknown, our next intuitive choice is to select neural networks (NN). As respondents may not disclose the full truth, some observations are bound to be inconsistent, affecting the final label. NN's robustness to noise helps address this issue. Considering that mental illness stems from an amalgamation of factors, a more accurate diagnosis of the person's mental condition could be obtained using NN which assigns a weight to every input factor.

With larger datasets, the ML could be easily implemented into a Deep Neural Network, but NN is chosen for now as our datasets are relatively smaller. Since NN is a black-box model, it limits us from identifying factors that contribute more to poor mental health. This further hinders the counseling department from determining the demographic of students who require more attention and help.

Finally, as our output is a binary classification of whether the person should seek treatment or not, Logistic Regression (LR) was chosen. The easily interpretable coefficients of LR are beneficial in determining the important factors and their correlation with the outcome. Furthermore, the model easily updates itself when new data is added via stochastic gradient descent. With a low dimensional dataset, LR is less prone to overfitting. However, LR requires average or no multicollinearity between independent variables. While the existing variables satisfy this condition, additional factors may introduce multicollinearity.

Hence, as we try to balance between the ability to identify major contributing factors and the usage of all factors in classification, we have decided to implement the stacking of the 3 models above. Stacking could be implemented with NN and LR as the base models and DT as the meta classifier since these models are of different categories.

2.3 Training and Testing of Model

A mixture of *tensorflow*, *sklearn* and *keras* in Python as well as *rpart* and *e1071* packages in R was used to implement our models. An open-source dataset that collected responses on a mental health survey from around the world was used to train our models (Kaggle 2018). Since mental health is a global issue with symptoms being similar across regions, it is valid to use this data to train and predict the outcomes of Singapore observations (Lilienfeld 2009). The 4 variables used in our survey were also selected from our global dataset. The data was filtered to select training examples within our target age group. Our models were validated against our survey data on Singapore university students, testing the accuracy on both treatment (hypothesis 1) and our relabeled treatment values (hypothesis 2).

3 Results

When testing our models on treatment values (hypothesis 1), we found our best performing models gave a relatively low accuracy of 79.6% (figure 3). Based on the confusion matrices, many observations were classified as false positives, meaning that more observations were predicted as 1 (the need to seek treatment) when their treatment label was 0 (figure 4). This was riveting as it suggests that our ML models were factoring in certain attributes to predict that the respondent should seek treatment despite not doing so. Thus, we decided to test our model on hypothesis 2 (relabeled treatment) values to verify such a case.

ML Algorithm	Accuracy (treatment - hypo. 1)	Accuracy (relabeled treatment - hypo. 2)
Decision Tree	79.57%	98.92%
SVM	82.80%	95.70%
Naive Bayes	80.65%	97.85%
Logistic Regress	79.57%	98.92%
Random Forest	80.65%	97.85%
KNN	79.57%	98.92%
Bagging (DT, ensemble learning)	79.57%	98.92%
Boosting (DT, adaboost)	80.65%	97.85%
Stacking (NN, logistic, DT)	79.57%	98.92%
NN	79.57%	98.92%

Figure 3: Accuracy table of our models

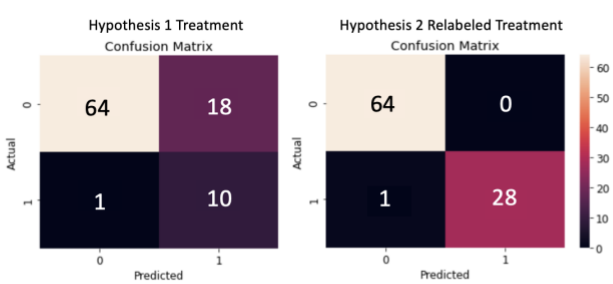

Figure 4: Confusion matrix; testing with hypothesis 1 (left) & testing with hypothesis 2 (right)

Upon testing hypothesis 2 on our models, the accuracy of our models increased greatly to 98.9% (figure 3). In addition, all observations labeled false positives turned into true positives (figure 4). On further analysis, it was refreshing to find that our model picked up on cases that corresponded to our main target group - those in denial. Specifically, it identified respondents who did not seek treatment but indicated they experienced work interference.

As predicted, stacking performed best and produced the highest accuracies. We also interchanged the models for the meta classifier and the base models. It revealed that DT as the meta classifier achieved the highest accuracy. Interestingly, the DT, NN, LR models individually produced the same highest accuracy.

4 Evaluation

While other models produced the same accuracy as stacking, it is still our preferred model as it is the most comprehensive. It utilizes NN's ability to take into account all factors, LR's benefits of predicting binary outputs and DT's prowess in showcasing the main important factors that contribute to the prediction. As such, stacking satisfies our main objective since schools will not only be able to accurately predict which student groups are vulnerable, but also identify the main factors that contribute to poorer mental health. Furthermore, the models are able to detect our main target group of those that are subconsciously aware of their mental illness but have not sought treatment.

It is worth noting that our model, when tested on both hypotheses, consistently had one respondent in the false negatives. This observation represents someone who has sought treatment but responded "NA" to work interference. A possible explanation could be that the respondent had sought treatment but currently felt that he or she did not have any underlying mental health condition. However, this is a gray area as we may never know the respondent's true mental health status without a professional assessment. As our data is limited with only one such observation, we are unable to verify if the model is accurate for such classification. This could be improved in the future with more of such observations.

5 Discussion

Although our models are of high accuracy, they could have been oversensitive. This is because based on the analysis of our models, the work interference factor has more weight in the prediction of the classification. Hence the addition of more questions will garner more factors for our ML model to evaluate, which could increase our accuracy. For instance, more questions could be added from the PQH9 Questionnaire, commonly used in healthcare settings to assess mental health (Negeri 2021).

Nonetheless, since our model sufficiently captures students who need treatment for their mental health, it achieves the model's main aim to allow schools to identify vulnerable groups of students and take actions to help them cope. Furthermore, as mental health is a serious but often neglected issue, any small indication of mental illness should be addressed and treated expeditiously. Hence, for now, our current model is adequately effective and sensitive to ensure that more students keep their mental well-being in check.

Additionally, mental illness is difficult to detect as the true treatment label of a person may never be known without a professional diagnosis. However, our models are still effective to identify university students in denial, who would be hesitant to seek treatment on their own accord due to stigma or personal reasons. Through the implementation of our model, we hope it would go a long way to alleviate some students' struggles and provide them with a lifeline for help.

Our model could also be improved in a few ways. First, by providing an ordinal output instead of a binary output, our model can better assess which groups of students' mental health conditions are more severe. This would allow the schools to efficiently allocate appropriate resources and programmes to help these groups based on their needs. However, in order to do so, having more training examples would allow the model to identify the decision boundaries better. Furthermore, as our current dataset is small, there is a possibility that our ML model is overfitted. Having a larger dataset would reduce any potential overfitting but could introduce noisy data, which would need to be further addressed through analytical models.

Looking forward, we could explore the use of our ML model in Singapore's healthcare and education sector such as NUS staff, and groups that are deeply affected by the COVID-19 pandemic. We could further explore the use of MLs in detecting distress in SOS calls which could help professionals with early and better diagnosis.

6 Reflection

Our manpower was efficiently allocated by drawing on the strengths of the team members. Those who are proficient at research (Yu Yean and Raphael) were in charge of establishing the background of the issue and the structure of the report while those who are adept at coding (Matthias, Sneha and Yu Him) focused on the technical aspects which included the development of the ML models. However, to embrace the joy of learning, we ensured that everyone had an opportunity to have a taste of each other's roles, effectively allowing each of us to grow and build upon one another's knowledge. As mental health is a difficult topic to grasp, frequent group meetings were held where we comprehensively discussed our progress and crafted the direction of our project to ensure that everyone remained on the same page.

Additionally, since mental illness is a sensitive topic that is difficult to measure, we had to ensure that our survey questions were crafted in a manner that encouraged respondents to be truthful. Despite this, we had to face the hard truth that treatment labels are limited and do not give the full picture of the respondent's mental status. This gave rise to the exploration of relabeling our data to get a clearer idea of our actual treatment values, thus proposing a new hypothesis 2 for evaluating the effectiveness of our model. Hence, it was satisfying that our model was able to validate the new hypothesis 2.

Through this project, we gained a deeper understanding of the ML models, discovered new models and saw the application of ML in real life. Moreover, it was invigorating to have the liberty to experiment with the different parameters to finetune our models. This included the learning rate, booster algorithms, epoch and complexity parameters. Furthermore, this project allowed us to explore the various methods of model evaluation.

7 Conclusion

Mental health is indispensable yet often neglected, especially amongst youths in Singapore. Stigma and negligence play an important role in deterring students from seeking treatment. Therefore, we developed an efficacious ML approach to discern the mental health of university students in Singapore and respond to the silent cries for help of those in need in an uncoerced manner. Utilizing the strengths of NN, LR and DT, the stacking model successfully identifies the key factors that affect students' mental well-being, and the vulnerable groups. With this model, universities can detect mental health issues among students and address them promptly. The advantages of our model cannot be measured by tangible means but rather in terms of the countless lives that schools can save. It is gratifying to contribute towards providing students with a nurturing school environment, and making positive repercussions in their lives. Looking ahead, further improvements could be made to the model with the addition of more factors, larger datasets, and ordinal outputs to better identify at-risk students and allow a more efficient and effective allocation of help resources.

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