Lowering Depression and Anxiety: A Quantitative Research on the Effects of Six Common Behaviors on Human's Mental Health

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I. INTRODUCTION AND PROBLEM STATEMENT

Depression and anxiety are two widespread types of disorders that cause a tremendous consequence on human life. The World Health Organization (WHO) has ranked depression as the fourth leading cause of human disability. By 2020, it is expected to be the second leading cause [19]. Many researches touch the symptoms of anxiety and depression. As an example, depression causes health complications [32], cardiovascular diseases [14], in some cases increases the risk of cardiovascular diseases by 80% [25]. In case of anxiety, on average, up to 33.7% of the human populations experience it in their life time [12]. Anxiety not only affects the human body physically but also affects learning and reasoning capabilities [27][15]. Undeniably, these are two major risks for human life. This research analyzes data from the Behavioral Risk Factor Surveillance System (BRFSS)[4] for eleven years. It shows how these six behavior factors (physical activity, eating disorder, smoking, drinking alcohol, social media, and education/technology) are correlated to mental health (mainly depression and anxiety). It shows this relationship in an interactive visualization. It also analyzes the data and creates statistical models for predicting the possibility of having a mental health based on input on six factors. The research provides more enhanced models by tuning and add/remove features using advanced techniques such as PCA and feature importance score.

II. LITERATURE REVIEW

○ *The effects of physical activity?*
We have studied three research papers. The [30] paper provided a survey on the association between physical and therapeutic activity on depression and anxiety. The [21] paper analyzes multiple databases to identify factors causing depression as well as examine whether physical activity prevents depression. Both show that physical activity reduces and, in some cases, prevents depression and anxiety. The criticism on these papers are that they do not pay adequate attention to symptoms and approaches to deal with depression and anxiety as well as benefits of exercise training. Interestingly, the [31] found that there is no relation between vigorous physical activity and mental health or well-being. We believe the reason of this results is the vigorous nature of physical activity.

○ *The effects of alcohol abuse and smoking?*
We picked four papers [18][29][11][24] , all corroborated our hypothesis that abusing alcohol and smoking leads to anxiety and depression. Two of the researches used the BRFSS data set. These are valuable research to us. Almost all of them did show a shortcoming that the effects on mental health goes beyond one to two variables. Interestingly, research [24] from 96 advised school to look into using smoke to help teenagers cope with depression. We are not going to use this paper. Smoking may temporarily alleviate depression but it leads to more mental and health symptoms.

○ *The effects of social media?*
We have studied three research papers in this topic. They show a strong correlation between social media and depression and anxiety. The paper [20] emphasizes on the correlation between social media and depression while considering other environmental and factors such as family and financial. The second paper [17] analyzes social networking sites and the relation to depression in older adolescents. The participants used have small age difference which lowers the risk of many environmental factors skewing the results. The third paper [33] analyzes the use of social media and how it relates to depression, anxiety, sleep quality and self-esteem in adolescents.

○ *The effects of technology/education?*
We have studied three papers [16][13][23]. All show positive correlation between factors such as high usage of smartphone, low education level and type 2 diabetes, and depression and anxiety. They have confirmed our hypothesis that smartphone/education/diabetes are among leading factors of depression disorder and anxiety. All three papers touch particular aspects of technology and we think we should follow the same trend. We may focus on a particular technology, such as cellphone, instead of "technology" in general.

○ *The effects of eating disorder?*
The first of the three papers [26] shows that eating disorder leads to stress and anxiety in high school girls. The second paper [22] shows that women with eating disorder get highly stressed and the stress led to anxiety behaviors. They also concluded that traditional female role causes these symptoms. The third paper [28] shows genetically some patients are showing symptoms of eating disorder. This genetic issue leads to other issues such as depression and anxiety. The criticism we have on these papers that they only pick female population. For our research we will use these papers nevertheless, we will make sure to use data for both

male and female.

III. HYPOTHESIS AND PROPOSED METHOD

In the survey of this research, we noticed that almost all researches on mental health, covers one to very few number of factors. This research picked the most dominant human behaviors (smoking, drinking, eating, physical activity, education/knowledge, and social media/internet) at the current day and age and finds a relationship between them and mental health (depression and anxiety). The novelty of this work is that it not only picked more behavioral factors but it also used the state of art machine learning (ML) and deep learning (DL) algorithm to provide statistical models for predicting the possibility of having or getting mental disease. The results are not only shown in a traditional statistical figures and charts but also in a delicate graphic visualization that is interactive. The interactive visualization summarizes the results of the analysis in a very friendly, easy to use graphical model.

Our research hypothesis is that smoking, drinking, eating unhealthy, physical activity, education/knowledge, and social media/internet factors has direct effect on the mental health. They could deteriorate or enhance the mental health.

○ *The conducted research and the analytics*
We used data from The Behavioral Risk Factor Surveillance System (BRFSS) [4]. BRFSS is "the nation's premier system of health-related telephone surveys that collect state data about U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services"[4].

We have used 11 years of BRFSS data (3GB from 2007 to 2017). We obtain the data in SAS [10] XPT format and we converted it to SQLite [9] tables.This tremendously was helpful in extracting the factors we needed for our research. SQL language was familiar to all the research conductors and many tools were there available to use to extract data from the BRFSS dataset.

We used Python and analytical python libraries such as Numpy [6] and Pandas [7] as a programming vehicle. We used Jupytor notebook as a tool to write our code to further clean the data, organize it, normalize it, and statistically visualize it.

At this stage, we showed the effect of each factor in each year on all the states and territories of US. We showed the data trend for each factor and compared it with the trend of the status of mental health. From these statistical analysis we drew fascinating conclusions. We added an interactive visualization in which users can pick a year, pick a factor, and visually sees the status of mental health in all states and territories of US. The interactive visualization calculates what proportion of the surveyed population has mental issues and what proportion have the selected behavior. Users can visually feel and see the effect of each factor on various stats and territories. The link to the interactive visualization can be found in [1].

○ *The advanced data modeling*
We brought more innovation and novelty to the table by using ML and DL to provide analytical models to predict the possibility of getting (or having) mental health. Currently our accuracy at its best is 72% and we understand that it is not very high but for the short time of the life of this project, this is a great achievement. We need more time to optimize our models and increase the accuracy. We consider that a future work for this research.[1]

At the start of our analysis journey, we used RandomForest, Gaussian NaiveBayes, Linear Discrimination, KNN, Quadratic Discriminant, AdaBoost, and Gradient Boosting to build the ML models. Based on Decision Tree from Random Forest algorithm, we sorted our features from most important to least important. We used this ranking to tune our algorithms and to make sure we avoid model overfitting. The best accuracy after hyper-parameters tuning for each model was 69% by linear Discrimination. We also tried deep learning (DL) models for classification with various layers of neurons. Yet we got 68% accuracy. Clearly, there was more optimization work needed to increase the accuracy of our models.

○ *Enhancing ML models by tuning features*
At this point, we decide to tune our features and add more features that are meaningful to our analysis. Some examples of added features are: sex (male or female), general health status, employment, income, and more. We also dropped features that are part of this research but were not available in all years such as internet usage or eating vegetables and fruits. Details on these feature and the logic behind our pick and drop features can be seen in the Fig 8. Our accuracy increased to 72% using Random Forest and Gradient Boosting algorithms. We got similar results with our deep learning model.

○ *Distribution of work*
All these tasks are distributed among all the researchers of this paper. Each of us owned a factor, extract it and cleaned for the analysis. The statistical analysis and ML model analysis was done by each member and results reported and generated separately. Different members took some tasks to consolidate the research work. Tasks such as conversion to SQLite, consolidating all visualization into one, optimizing the ML models, and writing the reports and proof writing them. For more details on how tasks were distributed, please refer to 10.

IV. EVALUATION

After cleaning up the data and consolidating it into one place (SQLite database), we evaluated our hypothesis based on the data we collected. With respect to smoking and drinking alcohol, as can be seen from the Figure 1, cross all

[1]Our experience in big corporation show that, some models takes 5 to 7 weeks of full time work to get to an accuracy of 80%.

the years, proportion of smokers was low (less than 20%) and the proportion of drinkers was more than 50%. The interesting part is that they seemed to be in lockstep with mental issues. All three trending to reduce but with spike in drinking and almost seen in smoking, the mental health got worsen. This support our hypothesis and the hypothesis of previous researches that drinking and smoking has direct effect on mental health.

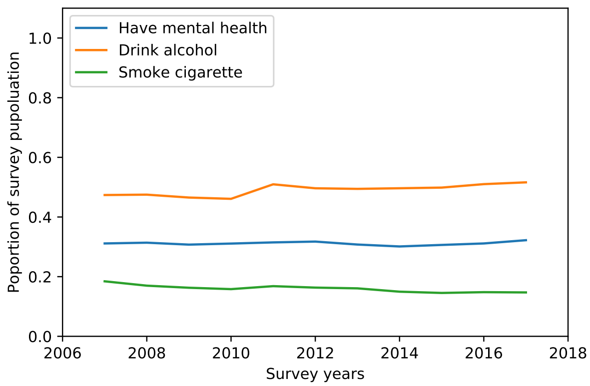

Fig. 1: Smoking and drinking vs. mental issues.

With respect to physical activity in Figure 2, we compared NOT working out and having mental issues. The results are stunning. proportion of people from sample population is almost equal to proportion of those do not have physical activity. In other words, low physical activity can be directly affecting the mental health and deteriorating it.

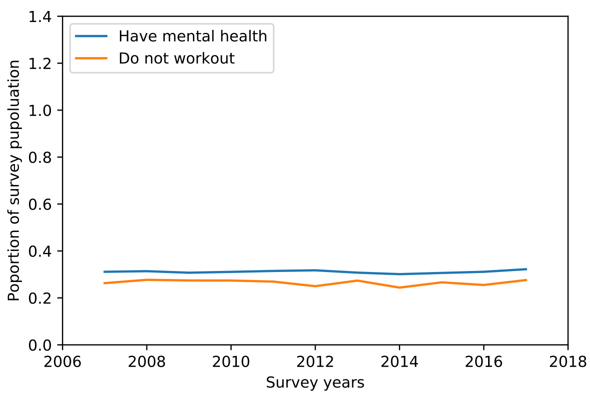

Fig. 2: Physical activity vs. mental issues.

When it comes to fruit and vegetables, the Figure 3 the data shows that vegetable and fruit consumption is high from 2007 to 2017. There is a very small trend of increasing and we see similar such trend but in decreasing the mental issues. Though the data does not show dramatic effect but one cannot help but notice that consuming fruit and vegetables (healthy food) has a slight effect on reducing mental health.

Using technology (in our case internet) Fig 4, on the other hand, shows that increase of usage has increase in mental

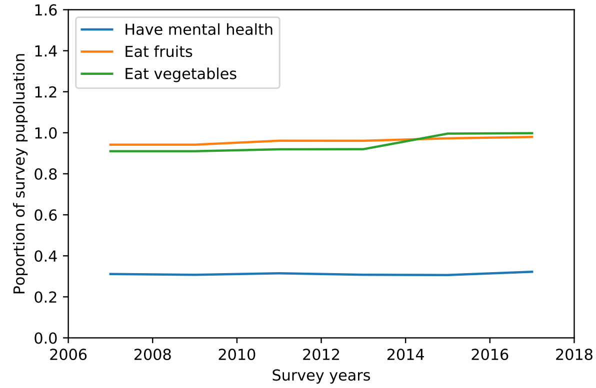

Fig. 3: Eating veggies and fruits vs. mental issues.

issues. The data about internet was available from 2013 and the proportion of sampled population using internet above 70% and increasing. We notice that in that period of time (2013-2017), mental issues are increasing.

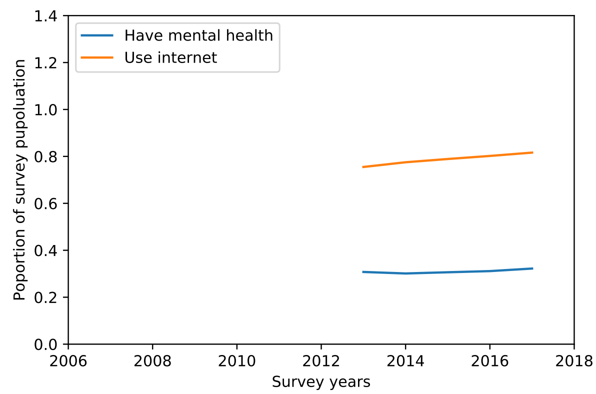

Fig. 4: Using internet vs. mental issues.

Lastly, Fig 5 shows that people of the sampled population were almost 90% had highschool or above degree. And the number of educators were mildly increasing. We notice that mental issues was decreasing toward last few years and it starts to slightly increase. This is very interesting because in our mind, the more you know the better mental health you may have. Nevertheless, this result does not show it that way.

We think that education and knowledge would help prevent mental issues but other factors that comes with it, such as using internet, will offset the good effect of education on mental health and lead to mild increase in the mental issues.

All above mentioned analysis show the results of six factors on US as a whole. We wanted to show the effect more visually and in more details for each state. Therefore, we grouped the data based on year, state, and behavior factor in a website available here [3]. The visualization consist of map of united states colored based on the proportion of reported mental health. The higher the mental issue the

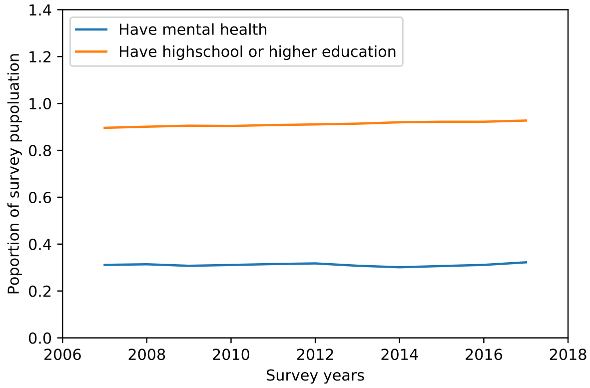

Fig. 5: Education vs. mental issues.

darker the color would show. This an interactive visualization in which user can select a factor, pick a year, and by pointing to each state, it provide details of about the that state such as percentage of mental issues and the selected factor reported for that state. Figure 9 shows one page of this this visualization.

This visualization provides a summary of the effects of the six factors on each state from year 2007 to 2017. By selecting a year, the map extracts data from that year and shows proportion of mental health issues in all states using the visual choropleth map. Users can visually notice which states reported more mental health issues and by hovering the mouse over that state, get the status of picked factor in form of pop up. The visualization is written in D3 [2] and it is portable across all operating systems. The visualization can be publicly reached online [1].

As part of this research, we examined multiple machine learning models to create predictive models for predicting mental health. We evaluated six ML models, and examined multiple DL model layer setups. The accuracy of our models were very low at the beginning. Using hyper-parameters option from scikit-learn [8] package, we managed to increase the accuracy to 69%. We also to used DL models for classifications using Keras [5]. Though DL techniques are used in image recognition, we build a DL classification model and after hours of trainings and neuron layers and density modification, we yet got 68%.

To enhance our analysis, we took our research one step up and re-evaluated features we used in our analysis. We only focused on Random Forest, Gradient Boosting, and Deep Learning models. We added features such as income, general health, details on education, BMI, and few others into our model and evaluated the importance of these features. We dropped features that was not present in all years between 2007 and 2017. We used MinMax to normalize our features and get them between 0 and 1. We took logarithm on some feature (such as BMI) to confine their value to 0 and 1. We applied PCA using the first 24 principle components to

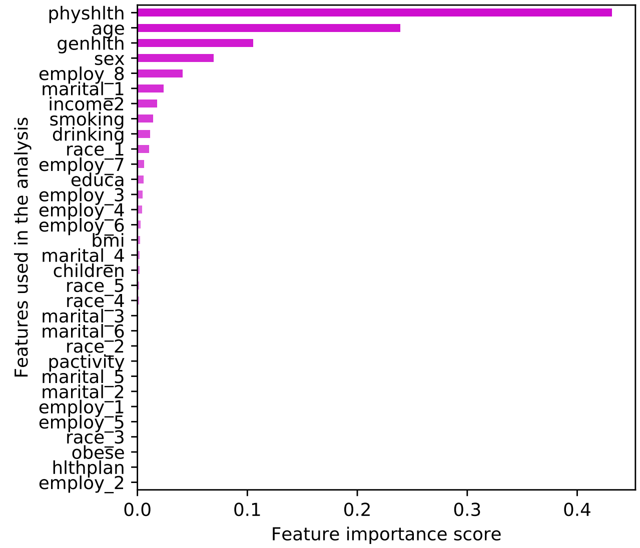

Fig. 6: Feature importance.

capture 97% variance and to reduce dimensionality of our model for training speedup. The result of this effort was that the accuracy of our model for both Random Forest and Gradient Boosting increased to 72%. Our DL model with the new feature selected, also produced a model with accuracy 72%.

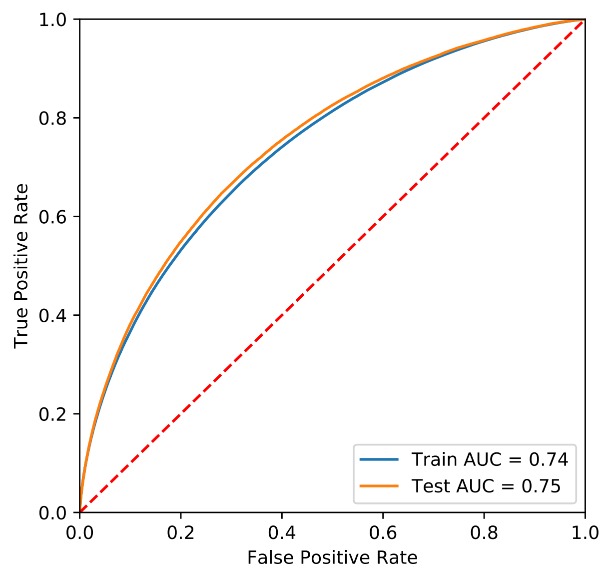

Fig. 7: Probability Curve (ROC).

Fig 7 shows feature importance score (between 0 to 0.5) of our models. In this figure, the higher a feature score, the more effective a feature is to the model. Fig 8 shows more details on the features we used for our models. The ROC (Receiver Operating Characteristics) curve for train and test data set shows that The test AUC (Area Under The Curve) is higher than the train AUC (0.75 vs 0.74) which could indicate an underfitting problem. Clearly there is a room for feature selection improvement.

We are not pleases with this accuracy but not disappointed either. We are planning to put more time and effort as a follow up on this research to increase the accuracy to above 90%.

V. CONCLUSION AND DISCUSSION

The research showed that behavioral habits has effect on mental health particularly on depression and anxiety. It showed a direct relationship between mental health and the six habit factors. The six factors are: smoking, drinking, physical activity, eating disorder (in form of not eating healthy at all), social media (internet), and education.

The research conducted set of analysises to extract the data from BRFSS dataset from 2007 to 2017. The analytics activities included, data conversion, cleaning, normalization, aggregation, and applying machine and deep learning algorithms. The best accuracy achieved was 69% with the six features of the research and got enhanced to 72% after tuning the model by adding new features and removing some features. The accuracy is not breathtaking but, at this stage of research, is a good starter. The analytics model is based on Random Forest method for classification and prediction.

The research also produced an interactive visualization that showed the effects of the six factors on mental health in the form of choropleth map in which user can visually interact with the map and get information on the proportion of BRFSS takers who has mental health and one of the six factors for year 2007 to 2017.

Figure 8: Enhancing the statistical model by tuning features.

Features	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**Notes**
Label to predict 88=0, 1-30->1	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	MENTHLTH	
sleep difficulty 1-5, 8=0	ASNOSLEP										ASNOSLEP	Many blank
general health 1-5	GENHLTH										GENHLTH	
Marital Status 1-6 **CAT**	MARITAL										MARITAL	
Education 1-6	EDUCA										EDUCA	
employment 1-8 **CAT**	EMPLOY	EMPLOY	EMPLOY	EMPLOY	EMPLOY	EMPLOY	EMPLOY1	EMPLOY1	EMPLOY1	EMPLOY1	EMPLOY1	
INCOME 1-8	INCOME2										INCOME2	
INTERNET 1=Yes, 2=No							INTERNET	INTERNET	INTERNET	INTERNET	INTERNET	REMOVE
SEX 1=Male 2=Female	SEX										SEX	
Smokers 1=No, 2=Yes	_RFSMOK3										_RFSMOK3	
Binger drinker 1=No, 2=Yes	_RFBING4	_RFBING4	_RFBING4	_RFBING4	_RFBING5	_RFBING5	_RFBING5	_RFBING5	_RFBING5	_RFBING5	_RFBING5	
Physical activity 1=Yes, 2=No	_TOTINDA										_TOTINDA	
Fruit 2=No Fruit											_FRTLT1A	REMOVE
Vege											_VEGLT1	REMOVE
Race 1-5 **CAT**	_RACEGR2	_RACEGR2	_RACEGR2	_RACEGR2	_RACEGR2	_RACEGR2	_RACEGR3	_RACEGR3	_RACEGR3	_RACEGR3	_RACEGR3	
Age 1-13	_AGEG5YR										_AGEG5YR	
Poor Physical or Mental Health 88=0, 1-30	POORHLTH										POORHLTH	Many blank
Health Care coverage 1=Yes, 2=No	HLTHPLAN	HLTHPLAN	HLTHPLAN	HLTHPLAN	HLTHPLN1	HLTHPLN1	HLTHPLN1	HLTHPLN1	HLTHPLN1	HLTHPLN1	HLTHPLN1	
High blood pressure 1=No, 2=Yes											_RFHYPE5	REMOVE
OW or Obese 1=No, 2=Yes	_RFBMI4	_RFBMI4	_RFBMI4	_RFBMI4	_RFBMI5	_RFBMI5	_RFBMI5	_RFBMI5	_RFBMI5	_RFBMI5	_RFBMI5	
Body Mass Index (BMI) 1-9999	_BMI4	_BMI4	_BMI4	_BMI4 (1-999	_BMI5	_BMI5	_BMI5	_BMI5	_BMI5	_BMI5	_BMI5	
Num of children 1-87, 88=0	CHILDREN										CHILDREN	
Number of Days Physical Health Not Good 1-30, 88=0	PHYSHLTH										PHYSHLTH	

Figure 9: Six factors vs. mental health for all states.

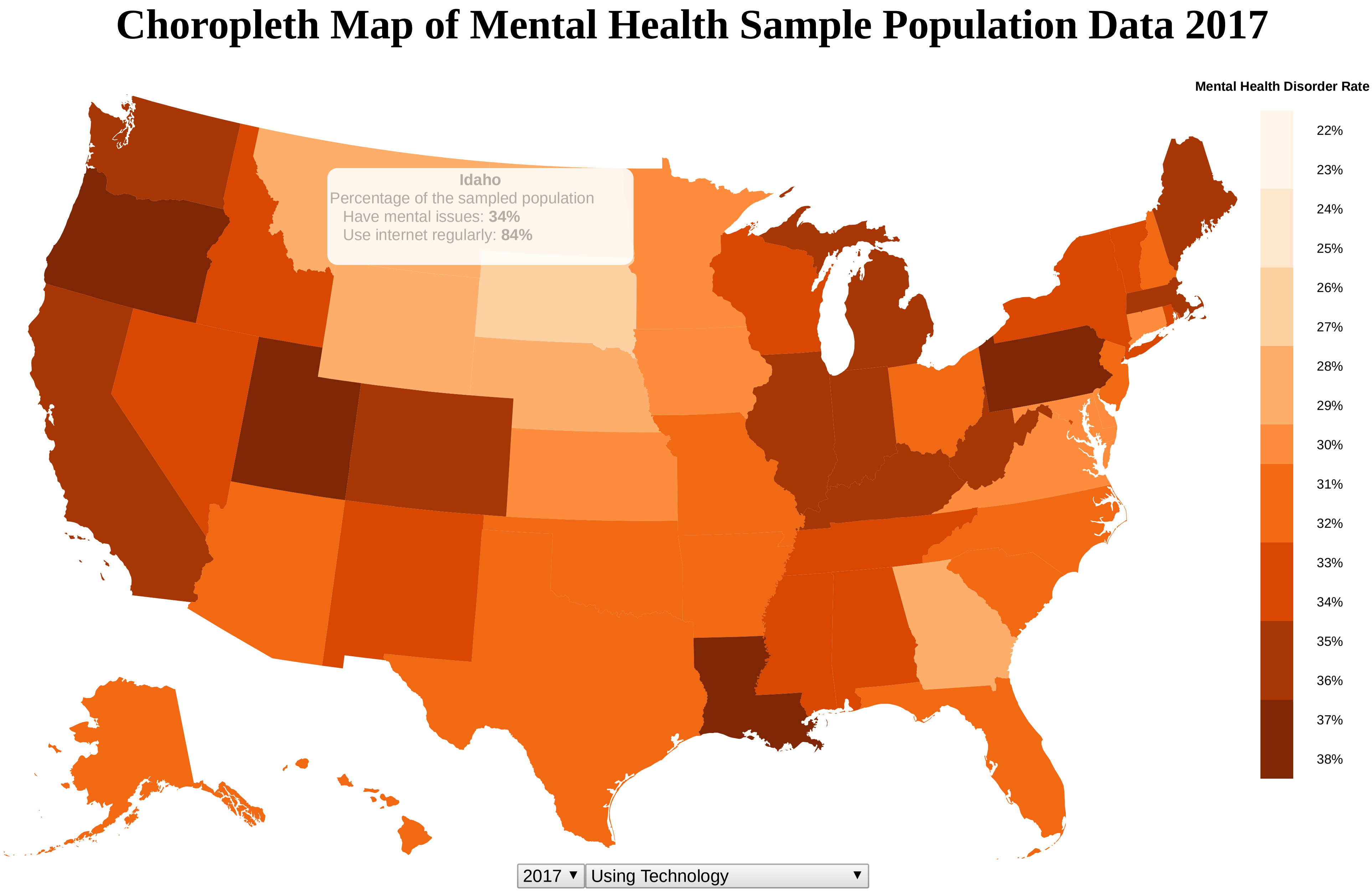

Figure 10: The schedule of the team for the research.

CSE6242 Project

DataLovers (Dang Quang Hoang, Karthikeyan Marikrishnan, Yuqing Ran, Muhammad Hamza Raza, Hadi Sharifi)

SIMPLE GANTT CHART by Vertex42.com
https://www.vertex42.com/ExcelTemplates/simple-gantt-chart.html

Project Start: Fri, 2/15/2019

Display Week: 1

TASK	ASSIGNED TO	PROGRESS	START	END
Lieteratur Review on Relationship between Six Habit Factors and Anxiety/Depression				
Smoking and Drinking Alcohol	Hadi Sharifi	100%	2/15/19	2/23/19
Binge Eating Disorder	Karthikeyan Marikrishnan	100%	2/15/19	2/23/19
Social Media	Muhammad Hamza Raza	100%	2/15/19	2/23/19
Technology/Education	Yuqing Ren	100%	2/15/19	2/23/19
Physical Activity	Quang D Hoang	100%	2/15/19	2/23/19
Prepare a Proposal, Presentation, and Video Presentation				
Proposal/Presentation	Collaboration Among All	100%	2/21/19	2/28/19
Video Recording	Karthikeyan Marikrishnan	100%	2/21/19	2/28/19
Extract Related Data and Clean them (based on year or month)				
Smoking and Drinking Alcohol	Hadi Sharifi	100%	3/1/19	3/16/19
Eating Fruit and Vegetable	Karthikeyan Marikrishnan	100%	3/1/19	3/16/19
Using internet	Muhammad Hamza Raza	100%	3/1/19	3/16/19
Level of Education	Yuqing Ren	100%	3/1/19	3/16/19
Physical Activity	Quang D Hoang	100%	3/1/19	3/16/19
Consolidate Results	Collaboration Among All	100%	3/16/19	3/31/19
Prepare The Progress Report	Hadi Sharifi	100%	3/16/19	3/31/19
Plot The Data, Analyze them, and Drive conclusion				
Plot The Consolidated Results	Collaboration Among All	100%	3/31/19	4/3/19
Draw Conclusions/Guidelines	Collaboration Among All	100%	3/31/19	4/3/19
Prepare The Poster	Collaboration Among All	100%	4/3/19	4/16/19
Prepare the Final Report	Collaboration Among All	100%	4/3/19	4/16/19
Prepare Poster Video	Collaboration Among All	100%	4/3/19	4/16/19

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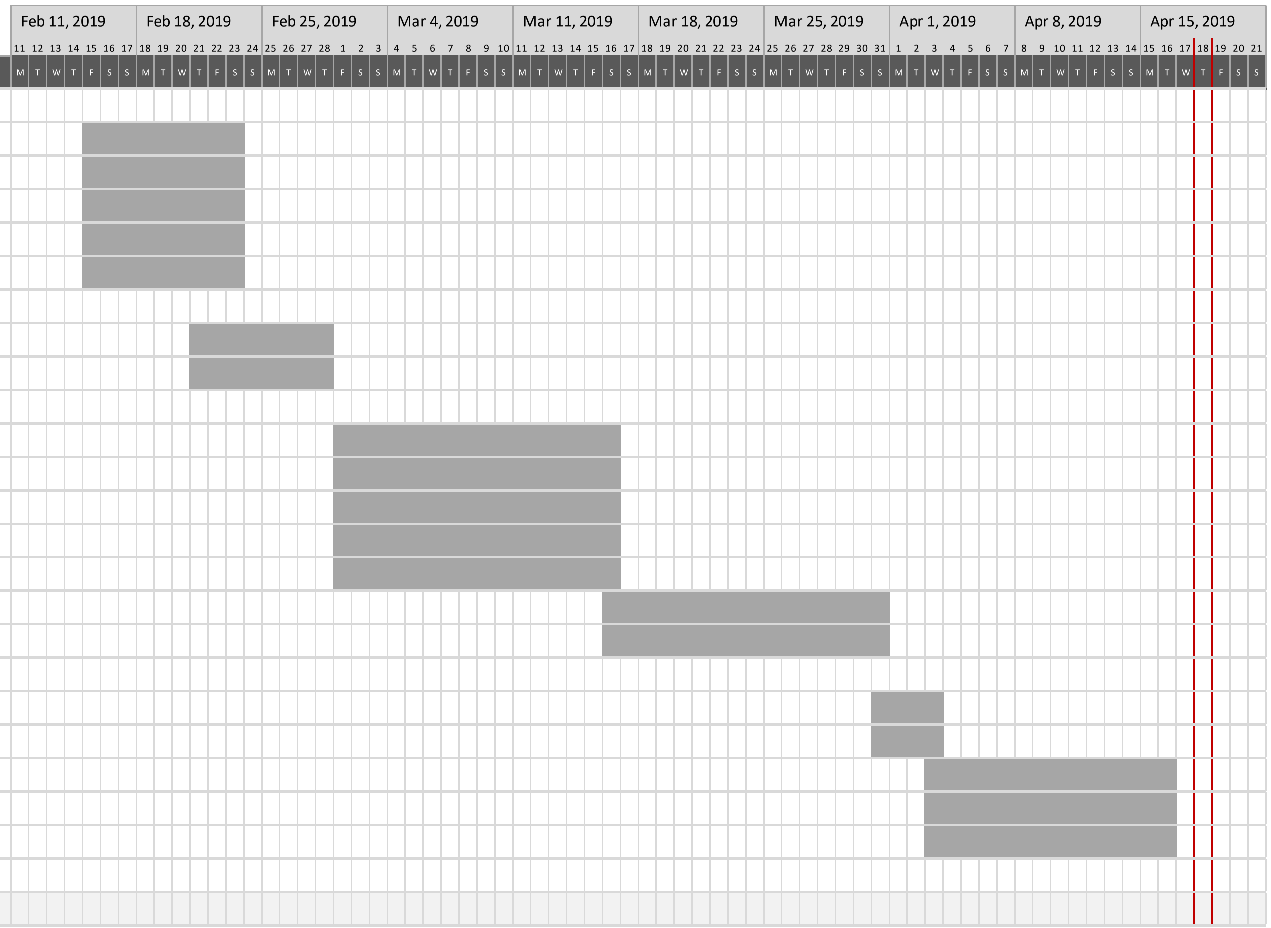

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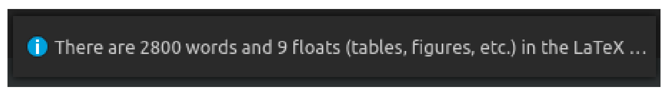
VI. Appendix



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