Dean&Francis

ISSN 2959-6149

Study on the Correlations Between Social Media Use and Mental Health

Tairan Yang

Abstract:

The extensive influence of social media has transformed the way people interact and communicate in the past two decades. However, as concerns regarding mental health increase alongside the rise of social media, there is growing speculation that correlation exists between the two factors. In the light of this issue, researchers have leveraged machine learning algorithms to examine the potential correlations and understand the health implications. In this paper, we employ three ML models and explore a specific aspect of the issue: the relationship between social media use and sleep, a key indicator of mental health conditions. This investigation can be utilized in medical settings as a preliminary self-assessment, providing access to mental health diagnosis for a wider population.

Keywords: Social Media, Mental Health, self-assessment, medical

Introduction

Prior to the advent of social media, social interactions mainly existed within close circles, bounded by the restraints of geographical location and cultural barriers. With its rapid development in the past two decades, social media has extended its reach to nearly half of the world's population [14] and plays a vital role in connecting people with their communities. However, as its influence diffuses across the globe, concerns about its negative impact on people's mental health have correspondingly grown. A number of previous studies show the potential correlation between social media use and negative emotions. One study suggests individuals often curate an idealized image of themselves on social media to seek validation from others; however, "continuous exposure to positive content posted by others may result in the distortion of perception, lack of control, and frustration in social comparisons" [5].

In spite of the potential negative effects of social media, the technology can also be harnessed for positive purposes. Vast data on social media provides insight into the social interactions in modern societies and allows researchers to leverage this data for predictive analytics, offering an opportunity to identify mental health issues in their early stages. Hence, the implementation of algorithms is key to the prevention of mental health illnesses. Machine learning (ML) is one of the most widely applied approaches within this field [14]. Though broad in its scope, ML can be divided into two general categories: supervised learning, where algorithms are trained based on labeled data, and unsupervised learning, where there are no predefined labels [15]. Once trained, ML algorithms are able to analyze the data, predict the likelihood of an individual experiencing mental illnesses, and offer personalized feedback based on their conditions.

ISSN 2959-6149

Although a multitude of studies have been conducted on the correlations between social media use and mental health using ML algorithm analysis, the majority of them were focused on the most common illnesses such as depression and anxiety disorders [16]; fewer studies explore the relationship between social media use and sleep, a factor that directly reflects the mental health condition of individuals. Therefore, we aim to investigate the correlations between the two factors in this paper. To do this, we employ three ML models — two conventional ML models (logistic regression and random forest) and one DL model (neural network) — and offer a comprehensive evaluation of their performances. This study is statistically crucial as it demonstrates the feasibility of an automated system for identifying risky behaviors and providing timely assistance. Such a system could facilitate access to mental health diagnosis for a wider population, especially when clinical options are unavailable.

Methodology

A. Dataset Description

The dataset (Social Media and Mental Health) used for this study, regarding the correlation between social media use and mental health, is acquired from Kaggle. It contains demographic data of 480 individuals from a randomized population, including age, gender, relationship status, occupation and affiliation, as well as their responses to questions related to social media usage. In our dataset, the demographic data and the question responses were converted into a total of 19 features, while the response to the final question 'how often do you face issues regarding sleep?' is used as the label.

Since the participants' responses to the questions were evaluated on a scale of one to five, where one represents 'strongly disagree' and five represents 'strongly agree', it was first translated to a classification problem to perform any further analysis. We divided the five levels and set the threshold to different values for accuracy comparison. For instance, when the threshold is set at y=3, responses 1, 2, and 3 are categorized as class 0 (negative), and responses 4 and 5 are categorized as class 1 (positive). In the context of this particular study, class 0 represents experiencing no issues falling asleep, and vice versa for class 1.

Despite the randomization of the participant selection, we observed an evident demographic skew in age; a considerable portion of the population were in the 20–30-year age bracket. It is to be noted that this is not the result of an intentionally biased recruitment, but a natural occurrence. In the process of data cleaning, we identified missing values (NaNs) within the dataset. To address this issue, the Simple Imputer strategy was employed, specifically using the 'most frequent' method. This method replaces the missing values with the mode of the respective columns.

B. Models

Prior to investigating the dataset, we first obtained the accuracy results of the original model. The result serves as a benchmark in predicting the likelihood of an individual feeling distressed due to social media use. The original model reported an accuracy of 58%, setting the baseline for later comparative analysis. Three ML algorithms are investigated in this study to determine the one with the optimal performance when applied to unseen data, thereby enhancing the effectiveness of the results.

1. Logistic Regression

The first model used was logistic regression. This is a statistical model that classifies data into K classes [3], in a way that ensures all data lies within [0,1] and sums up to 1. As it adjusts the data to be bound within the range of 0 and 1, unlike the linear regression model, it does not require the input and output variables to be linearly correlated [10]. The formula for logistic regression takes the form:

\[Fx=\frac{1}{1+{e}^{-{\beta }_{0}+{\beta }_{1}x}}\]

In the case of this study, the model is rather simple; since K=2, there is only one single linear function [3]. This type of predictive model with binary outcomes is extensively used in fields related to biomedicine, as many produce either positive or negative results. Some instances of such classifications include whether a patient died or survived, experienced a heart attack or not, or whether an email is spam or not spam. For predictions with binary outcomes, the threshold of 0.5 is often used to decide the classification. If the predicted value is under 0.5, it will be classified as negative, or class 0; if it is greater than 0.5, then it will be classified as positive, or class 1.

2. Random Forest

The random forest model is the second model employed in this study. A random forest is made up of building blocks known as decision trees. Decision trees are well known for their relatively low bias; however, they are also notorious for their high noise levels [3].

The random forest model mitigates excessive noise by grouping multiple trees together, hence its sylvan name. By combining a multitude of decision trees and averaging the results, the variance of the prediction is greatly reduced [3]. Random forests can be used for both classification and regression [3], and the process for the two varies slightly as the trees sort along their paths. For this particular study, the model is only used for binary classification; the final decision is made by obtaining class votes from each tree and identifying the majority vote [8]. We set the ‘max_depth’ parameter to 3 in the random forest. Although generally considered shallow, it is sufficient for this investigation since the training data is less complex, thus avoiding the risk of overfitting.

3. Neural Network

Contrary to the previous two models, the third model, neural network, falls under the domain of deep learning. We selected this method to provide an alternative to the conventional ML algorithms, as neural networks outperform them in most cases. The essential concept of NN is to mimic the way the human brain functions, specifically how neurons signal to each other, by deriving linear combinations of the original data and introducing a nonlinear function (activation function) into the network [3]. Commonly used activation functions include sigmoid, ReLU, softmax, etc [9].

The model we built for this investigation follows a sequential architecture: it begins with a fully connected input layer that comprises 256 neurons, followed by a hidden layer with 128 neurons, both of which utilize the ReLU function as the activation function. The output layer consists of two neurons, producing a binary classification outcome. We trained the data with ten epochs to prevent overfitting, and optimized the classification results by implementing stochastic gradient descent.

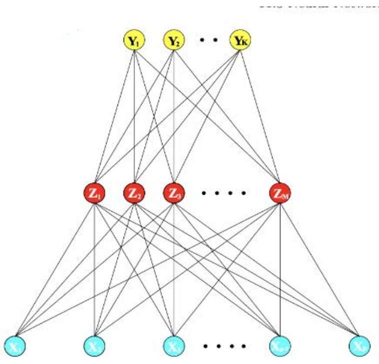

Figure 1. Schematic of a single hidden layer neural network

4. Setup and Metrics

We employed a 75:25 ratio for the train-test split for this experiment. This is a commonly applied ratio when training models as a higher proportion of training data contributes to more accurate predictions. To ensure the comparability among the three models, we used the accuracy metric consistently throughout this study. Accuracy is a more general measurement compared to other metrics (e.g. precision and recall), defined as the ratio of all correct predictions, both positive and negative, to the total number of predictions [11]. The accuracy formula is given as:

$$Accuracy=\frac{tp+tn}{tp+tn+fp+fn}$$

where:

tp (true positives) is the number of correct positive predictions;

tn (true negatives) is the number of correct negative predictions;

fp (false positives) is the number of incorrect positive predictions;

fn (false negatives) is the number of incorrect positive predictions.

As mentioned previously, the original accuracy reported by the author of the dataset is 58%. This sets the baseline for result comparison among the three models.

Results & Discussion

The experiment was conducted with the three models, and generated the results below:

Table 1: Mean and STD Values of the Three Models

Model	Mean	Standard Deviation
Logistic Regression	0.74	0.11
Random Forest	0.73	0.12
Neural Network	0.53	0.04

ISSN 2959-6149

Table 2: Comparison of Model Performances at a Threshold of 3

Threshold	Model	Accuracy
3	Logistic Regression	0.62
	Random Forest	0.60
	Neural Network	0.53

Table 3: Comparison of Model Performances at Varying Thresholds

Threshold	Accuracy	
	Logistic Regression	Random Forest
1	0.87	0.89
2	0.70	0.65
3	0.62	0.60
4	0.78	0.77

Overall, it can be seen in Table 1 that the logistic regression model produced predictions with the highest accuracy of 74%, while the random forest model and the neural network model produced an accuracy of 73% and 53%. The standard deviations for each model are 0.11, 0.12, and 0.04, respectively. We observe a trend: as the accuracy decreases, the standard deviation values also decrease, suggesting a clear alignment with the Bias-Variance Tradeoff. However, it is significant to note that there is one difference between our experimental outcome and the tradeoff. Typically, as the model complexity is increased, the variance (as shown by STD) increases and the bias (as shown by accuracy) decreases, and vice versa; this trend is reversed in this study. The two conventional ML models, which are thought to be less complex, produced high variance and low bias results, while the opposite behavior occurred for the neural network model. We reach the same conclusion when analyzing the models' performances in a more specific situation, where the threshold is set at y=3: the logistic regression model yielded the highest accuracy at 62%, followed by the random forest model at 60%, with the neural network ranking last at 53%.

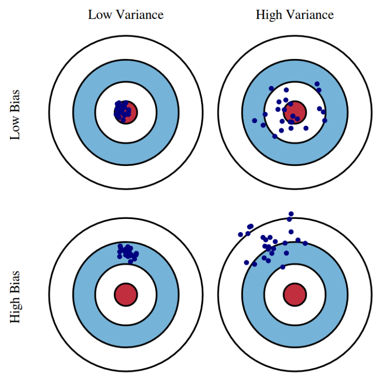

Figure 2. The Bias-Variance Tradeoff

The most probable explanation for this atypical performance is the characteristics of the dataset. The obtained dataset consists of 480 entries and 14 features, which is considered relatively small; simpler models such as the logistic regression model and the random forest model are sufficient for the purposes of this investigation. In contrast, the neural network model generally requires larger and more complex datasets for it to perform well. If the requirement is not fulfilled, it can be prone to learning the noise during training, thus overfitting the unseen data.

Another notable trend observed is the fluctuation in accuracy when testing the models with varying thresholds. Given our aim to perform binary classification, and considering the survey responses are evaluated on a one to five scale, we experimented with multiple threshold values to determine the most suitable one. For both conventional ML models, we found that the accuracy is higher when the threshold is set at y=1 and y=4, and visibly lower when set at y=2 and y=3. The results in Table 3 demonstrate this trend: when y=1, the accuracy is 87% for the logistic regression model and 89% for the random forest regression; however, after changing the threshold to y=3, it dropped to a respective 62% and 60%. This trend can be attributed to imbalanced classes: the majority of responses for question 20 ('how often do you face issues regarding sleep?') clusters around the two extreme ends (1 and 5). Therefore, a model's accuracy might appear high simply due to the frequent occurrence of the extreme values. On the contrary, with less data points located in levels 2, 3 and 4, the models produce seemingly less accurate results. We realize the results do not entirely reflect the prediction abilities of the models and take this factor into account when evaluating.

We also conducted the experiments with variations of the three models above, with the results recorded in Table 4.

Table 4: Performance Comparison of Model Variations

Y cut	Model	Accuracy	Balanced Accuracy
3	Variations of Logistic Regression		
	LinearDiscriminantAnalysis	0.60	0.60
	QuadraticDiscriminantAnalysis	0.49	0.51
	Variations of Random Forest		
	BaggingClassifier	0.53	0.52
	ExtraTreeClassifier	0.53	0.53
	Variations of Neural Network		
	Perceptron	0.58	0.58
	LabelPropagation	0.58	0.58
	XGBClassifier	0.58	0.59
	LGBMClassifier	0.58	0.58
	AdaBoostClassifier	0.54	0.54

The derived outcome provides considerable insight into the correlation between social media use and mental health. However, it is critical that we also address the limitations that exist within our study. As mentioned previously, although unintentional, the data used for this experiment was demographically skewed; the majority of the participants were in the 20–30-year age range. The results would be more reliable if the data was evenly distributed. In addition, while gathering data through surveys fulfills the purpose of this study, it can be complicated and resource-intensive to do so in real life applications. To enhance the effectiveness of its application, alternative methods of data collection would be needed.

Conclusion

As the influence of social media continues to expand across the world, it is key to understand both its positive and negative implications. It can be utilized as a channel for fostering connections and expressing thoughts; however, excessive use of social media can also lead to poor mental health. We attempted to investigate the correlation between the two in this paper. Our objective was to investigate the relationship between social media use and mental health by employing various models including logistic regression, random forest and neural network. After conducting the experiment, contrary to consensus, we found that the two conventional ML models both outperform NN, with logistic regression yielding the most accurate predictions. Through evaluating the data and the three models, we concluded that this atypical performance is due to the relative simplicity of the dataset - it only consists of 480 entries and 14 features. Therefore, the two conventional ML models would be more suitable to employ for the sole purpose of this study, although results may differ when applied in another scenario.

References

[1] Sinnott, R. O., Duan, H., & Sun, Y. (2016). A Case Study in Big Data Analytics. Elsevier EBooks, 357–388.

[2] Hastie, T., Tibshirani, R., & Friedman, J. (2008). Springer Series in Statistics The Elements of Statistical Learning Data Mining, Inference, and Prediction Second Edition.

[3] Chancellor, S., & Munmun De Choudhury. (2020). Methods in predictive techniques for mental health status on social media: a critical review. Npj Digital Medicine, 3(1).

[4] Safa, R., & Sorourkhah, A. (n.d.). Predicting mental health using social media: A roadmap for future development.

[5] Chung, J., & Teo, J. (2022). Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges. Applied Computational Intelligence and Soft Computing, 2022, 1–19.

[6] Breiman, L. (2001). Machine Learning, 45(1), 5–32.

[7] Lior Rokach, & Maimon, O. (2006). Decision Trees. Springer EBooks, 165–192.

[8] Dubey, S. R., Singh, S. K., & Chaudhuri, B. B. (2022). Activation functions in deep learning: A comprehensive survey and benchmark. Neurocomputing, 503, 92–108.

[9] Machine Learning Guide for Oil and Gas Using Python. (2021).

[10] Hercules Dalianis. (2018, May 15). Evaluation Metrics and Evaluation.

[11] Ortiz-Ospina, E., & Roser, M. (2023, December 28). The

ISSN 2959-6149

rise of social media. Our World in Data.
[12] Lin, H., Jia, J., Nie, L., Shen, G., & Chua, T.-S. (2016). What Does Social Media Say about Your Stress?
[13] Digital 2023: Global Overview Report — DataReportal – Global Digital Insights. (2023, January 26). DataReportal – Global Digital Insights. DataReportal – Global Digital Insights.
[14] Chen, S., Li, H., Pang, L., & Wen, D. (2023). The Relationship Between Social Media Use and Negative Emotions Among Chinese Medical College Students: The Mediating Role of Fear of Missing Out and the Moderating Role of Resilience. Psychology Research and Behavior Management, Volume 16, 2755–2766.
[15] Ngumimi Karen Iyortsuun, Kim, S.-H., Jhon, M., Yang, H.-J., & Pant, S. (2023). A Review of Machine Learning and Deep Learning Approaches on Mental Health Diagnosis. Healthcare, 11(3), 285–285.
[16] World Health Organization. (2022, June 8). Mental disorders. Who.int; World Health Organization: WHO.
[17] Social Media and Mental Health. Kaggle.com. https://www.kaggle.com/datasets/souvikahmed071/social-media-and-mental-health