Computer Science

The Relationship Between Social Media and High Schooler Mental Health and the Efficacy of AI Models in Predicting Stress Levels Among High School Students Using Social Media Posts

Investigator:
Daniel Guo, Research Student
STEM Fellowship, St. Mark’s School

Adult Sponsors:
Ms. Lindsey Lohwater, St. Mark’s Science Department
Mr. David Palmer, St. Mark’s Science Department

Abstract

Addressing the critical concern of stress among adolescents, highlighted by health organizations' declaration of a national emergency in children's mental health, this study uses the widespread use of smartphones and social media to predict stress levels in high school students. Traditional psychological assessments like the Perceived Stress Scale (PSS-14) are difficult to consistently use, prompting this study's shift towards digital platforms such as Instagram and Snapchat, where engagement is high among teens. Utilizing Convolutional Neural Networks (CNNs) for prediction and the Statistical Package for the Social Sciences (SPSS) for statistical evaluation, this study develops a predictive model based on data collected through psychological surveys. By focusing on platforms that offer more insight into adolescent life compared to text-based social media, this study also aims to uncover the relationship between social media use and stress levels. By integrating image processing with detailed statistical analysis, the research provides new perspectives on detecting and understanding adolescent stress in relation to social media, offering pathways for targeted mental health interventions.

Keywords

Social Media, Student Stress, Machine Learning

1. Introduction

Stress is an important part of our daily lives. Stress is defined as a state of worry or mental tension caused by a difficult situation by the WHO, and more importantly, especially impacts adolescents. In fact, adolescent stress is such an issue that the American Academy of Pediatrics, American Academy of Child and Adolescent Psychiatry, and Children's Hospital Association have declared a national state of emergency in children's mental health. Preteen and teenage students are overloaded with all sorts of different sources of stress: Schoolwork, an uncertain future, personal problems, difficult relationships, and unexpected accidents. This stress, when kept unchecked, can lead to not only mental and personal issues like anxiety and depression but can affect physical health as well. Chronic stress results in cancer, cardiovascular disease, depression, and diabetes, and thus is deeply detrimental to physiological health and psychological wellbeing. Additionally, especially for adolescent students, too much stress leads to poor academic performance and learning. Therefore, developing methods to rapidly and accurately detect human stress as well as analyzing the biggest sources and reasons of stress is of utmost importance.

Substantial efforts have already been committed to detecting student stress. Psychologists have already developed several subjective measurements, such as the Perceived Stress Scale PSS-14. However, while these measurements are professional and exhibit high accuracy, they require respondents to either fill in a questionnaire or talk to a professional, so these methods are difficult to apply to high school adolescents.

According to Pew Research Center (2022), nearly all adolescents have access to a smartphone. 95% of U.S teens report having access to a smartphone, and 90% have access to a desktop/laptop computer. In 2014-2015, 73% had access to a smartphone, a jump of 22%. Especially teens aged 15 to 17 in high school, as 98% have access to a smartphone. 97% report using the internet daily, and 51% report using Snapchat daily and 50% report using instagram daily. This leap in usage of social media among adolescents shows that more people are interacting with friends and willing to share their daily activities and mood swings through these social media platforms. The information of instagram posts and snapchat data can be used to predict the stress levels and emotional states among adolescent students.

Previous research has primarily focused on twitter, reddit, and other text-based social media platforms, as they have more accessible data and text is much easier to do machine learning on. However, only 23% of U.S teens reported ever using twitter and 14% reported ever using reddit. Compared to the significantly higher numbers of 62% having reported to have ever used instagram and 59% having used Snapchat, twitter and reddit is not an accurate representation of the social use and mental condition of the U.S teen.

In this paper, I explore the use of Instagram and Snapchat data, collected from high school students through psychological surveys, to develop a sophisticated model for predicting emotional and stress levels in this age group. The study utilizes Convolutional Neural Networks (CNNs) to build a predictive model based on the images and stress-related data collected. Additionally, I employ the Statistical Package for the Social Sciences (SPSS) for a detailed statistical analysis to understand the relationship between social media use and stress levels in high school students. This research aims to provide insights into how adolescents interact with social media and the potential impacts on their emotional and stress levels, using a combination of advanced image processing and statistical analysis techniques.

2. DATA AND COLLECTION

A dataset consisting of stress data taken from surveys from high school classmates was used, with one survey each week for four weeks. This survey included the Perceived Stress Scale test (PSS), the Positive and Negative Affectations Score test (PANAS), and asking for the participant's snapchat score, snaps sent and snaps received. This study was approved by an Institutional Review Board (IRB) from the St. Mark's School. All participants were given informed human consent forms, and if they were underaged their parents filled out the forms as well. The Instagram stories of the participants were screenshotted and saved in anonymous Google Drive folders every night from 1/7/2024 to 2/5/2024.

The surveys were conducted through the website jotform, where forms can be sent to participants through email. The number of participants in each survey is as follows: 41, 32, 35, 38. The results were then downloaded as excel files and calculated using the scales provided by PSS and PANAS tests.

Code was made using the Python Imaging Library to produce statistical facets of the images manually, with each image labeled numerically to preserve anonymity and avoid bias. Objective information such as Hue, Saturation, Lightness and subjective information such as expressions and whether or not the poster of the story was a subject were considered and recorded manually on a complete excel sheet for all taken images, with the surveyed stress scores, positive and negative emotion scores in relation as well.

3. ANALYSIS

Correlation tests were performed between each feature and the stress level and positive and negative emotional level to uncover the associated features. The statistical application SPSS(Statistical Product and Service Solutions) by IBM was used to perform the correlation tests. Results for the analysis on instagram story images are presented below in table 1, and results for the analysis on snapchat information are presented in table 2. Averages were also run on the various categorical variables, including athletics, repost, expression, and gender.

Numerial Features of Instagram Story Correlations

		Hue	Saturation	Lightness	Warm Colors%	Vivid Colors%	R	G	B	Pos Score	Neg Score	PSS Score
Hue	Pearson Correlation	1	-.062	-.006	-.646**	.045	-.214**	-.052	.189**	-.040	.007	.012
	Sig. (2-tailed)		.341	.928	<.001	.494	<.001	.429	.003	.539	.918	.859
	N	237	237	237	237	237	237	237	237	237	237	237
Saturation	Pearson Correlation	-.062	1	-.170**	.358**	.625**	-.117	-.254**	-.237**	-.048	-.003	.017
	Sig. (2-tailed)	.341		.009	<.001	<.001	.072	<.001	<.001	.465	.962	.798
	N	237	237	237	237	237	237	237	237	237	237	237
Lightness	Pearson Correlation	-.006	-.170**	1	-.040	-.048	.873**	.968**	.927**	.155*	-.176**	-.204**
	Sig. (2-tailed)	.928	.009		.544	.461	<.001	<.001	<.001	.017	.007	.002
	N	237	237	237	237	237	237	237	237	237	237	237
Warm Colors%	Pearson Correlation	-.646**	.358**	-.040	1	.195**	.241**	-.046	-.287**	.011	-.038	.021
	Sig. (2-tailed)	<.001	<.001	.544		.003	<.001	.481	<.001	.861	.556	.744
	N	237	237	237	237	237	237	237	237	237	237	237
Vivid Colors%	Pearson Correlation	.045	.625**	-.048	.195**	1	.034	-.083	-.065	.014	-.089	-.097
	Sig. (2-tailed)	.494	<.001	.461	.003		.599	.203	.317	.833	.171	.135
	N	237	237	237	237	237	237	237	237	237	237	237
G	Pearson Correlation	-.052	-.254**	.968**	-.046	-.083	.878**	1	.919**	.144*	-.150*	-.177**
	Sig. (2-tailed)	.429	<.001	<.001	.481	.203	<.001		<.001	.027	.020	.006
	N	237	237	237	237	237	237	237	237	237	237	237
B	Pearson Correlation	.189**	-.237**	.927**	-.287**	-.065	.741**	.919**	1	.126	-.163*	-.188**
	Sig. (2-tailed)	.003	<.001	<.001	<.001	.317	<.001	<.001		.053	.012	.004
	N	237	237	237	237	237	237	237	237	237	237	237
R	Pearson Correlation	-.214**	-.117	.873**	.241**	.034	1	.878**	.741**	.158*	-.191**	-.189**
	Sig. (2-tailed)	<.001	.072	<.001	<.001	.599		<.001	<.001	.015	.003	.004
	N	237	237	237	237	237	237	237	237	237	237	237
Pos Score	Pearson Correlation	-.040	-.048	.155*	.011	.014	.158*	.144*	.126	1	-.509**	-.647**
	Sig. (2-tailed)	.539	.465	.017	.861	.833	.015	.027	.053		<.001	<.001
	N	237	237	237	237	237	237	237	237	237	237	237
Neg Score	Pearson Correlation	.007	-.003	-.176**	-.038	-.089	-.191**	-.150*	-.163*	-.509**	1	.865**
	Sig. (2-tailed)	.918	.962	.007	.556	.171	.003	.020	.012	<.001		<.001
	N	237	237	237	237	237	237	237	237	237	237	237
PSS Score	Pearson Correlation	.012	.017	-.204**	.021	-.097	-.189**	-.177**	-.188**	-.647**	.865**	1
	Sig. (2-tailed)	.859	.798	.002	.744	.135	.004	.006	.004	<.001	<.001	
	N	237	237	237	237	237	237	237	237	237	237	237

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Tabel 1: *Correlation between Instagram image features and mental health status.*

Snapchat Data Correlation

		Difference_in_Total	Difference_in_sent	Difference_in_recieved	PSS	PanasPositive	PanasNegative
Difference_in_Total	Pearson Correlation	1	.905**	.452**	-.154	-.054	-.184*
	Sig. (1-tailed)		<.001	<.001	.077	.308	.044
	N	87	87	87	87	87	87
Difference_in_sent	Pearson Correlation	.905**	1	.527**	-.183*	.017	-.191*
	Sig. (1-tailed)	<.001		<.001	.045	.437	.038
	N	87	87	87	87	87	87
Difference_in_recieved	Pearson Correlation	.452**	.527**	1	-.018	-.006	-.036
	Sig. (1-tailed)	<.001	<.001		.434	.476	.369
	N	87	87	87	87	87	87
PSS	Pearson Correlation	-.154	-.183*	-.018	1	-.611**	.824**
	Sig. (1-tailed)	.077	.045	.434		<.001	<.001
	N	87	87	87	87	87	87
PanasPositive	Pearson Correlation	-.054	.017	-.006	-.611**	1	-.504**
	Sig. (1-tailed)	.308	.437	.476	<.001		<.001
	N	87	87	87	87	87	87
PanasNegative	Pearson Correlation	-.184*	-.191*	-.036	.824**	-.504**	1
	Sig. (1-tailed)	.044	.038	.369	<.001	<.001	
	N	87	87	87	87	87	87

**. Correlation is significant at the 0.01 level (1-tailed).

*. Correlation is significant at the 0.05 level (1-tailed).

Table 2: Correlation between Snapchat features and mental health status.

4. PREDICTION

Finally, the accuracy of machine learning models in categorizing levels of stress through social media images was investigated. Label Studio was attempted as a tool, but while it was very useful at labeling data the actual neural network aspect proved too difficult to implement. A different folder method was used to label and categorize the data into three categories based on the PSS gradings: low stress, moderate stress, and high stress. This method was implemented on Google Colab. Four different neural network architectures were utilized: A self-written neural network, VGGnet, Resnet with full layers, and Resnet with some layers turned off. Performance is measured using validation accuracy given by the premade functions. Tensorflow, Numpy, CV2, and OS libraries were used for machine learning. Due to issues with the size of the dataset and the inconsistency between categories, as there were substantially more moderately stressed post compared to high or low stress posts, some special tools were used to increase the accuracy within the small-sized dataset, including ImageDataGenerator and resample for the preprocessing and data enhancement. Each model was trained for 500 epochs, with the exception of the fully layered Resnet model, which was trained for 1000 epochs.

5. DISCUSSION

Three distinct architectures of Convolutional Neural Networks (CNNs) were evaluated: two pretrained image classification models, VGG16 and ResNet, along with one custom-designed neural network architecture. The modified ResNet model, with certain layers deactivated, was the most accurate in terms of validation accuracy. The self-written neural network architecture achieved the second best results, while the fully-layered Resnet and the VGGnet followed. The specific accuracies can be found below in figures 1 to 4. The underperformance of the pretrained models with extensive layers compared to the self-written architecture can likely be attributed to their complexity and the small size of the dataset utilized in this study. Especially the VGGnet model, which clearly did not perform successfully due to its inconsistent results. Despite employing strategies such as data augmentation to enhance the dataset, achieving high validation accuracy proved challenging; the highest validation accuracy reached was 62%. This figure, however, still represents a significant improvement, being 29% higher than the 33% accuracy expected from completely random selections, thereby fulfilling the machine learning objectives of the research.

The investigation also encountered challenges related to the dataset's composition. Manual review revealed a skew in the data, with some individuals posting more frequently than others. Furthermore, unique posting habits and decisions among users complicated the model's ability to identify predictive patterns. Mandatory and non-personal posts, such as birthday and college acceptance announcements, also distorted the analysis due to their uniform nature across different users. The collection of data at a singular school with only 40 students also limited variety.

Analysis of the data revealed several trends: see table 3 below for specific figures. For instance, a slight negative correlation was observed between Snapchat activity metrics (such as snap score total and snaps sent) and both Perceived Stress Scale (PSS) and Panas Negative Score, suggesting that increased Snapchat activity is associated with a reduction in negative emotions and stress. This trend might be attributed to Snapchat's primary function as a photo-sharing application, where individuals experiencing stress or negative emotions may feel less inclined to share images of themselves. Conversely, analysis of Instagram posts indicated a slight positive correlation between image brightness (lightness and RGB values) and positive emotion scores, along with a slight negative correlation with negative emotion scores and stress levels. This suggests that brighter images are associated with happier and less stressed states. Additionally, Instagram stories that were reposts displayed lower average stress and negative emotion scores and higher average positive emotion scores compared to original posts, possibly reflecting the reduced stress associated with sharing others' content compared to personal posts. Moreover, stories featuring individuals with serious expressions were found to be the least stressed and most positive emotionally, a finding that warrants further investigation to understand the underlying reasons. It should also be noted that Instagram stories related to athletics were associated with lower stress levels and higher positive emotion scores, which could be linked to the social popularity of athletically involved individuals. Stories that included images of the poster were associated with higher stress, positive, and negative scores, suggesting a relationship between self-presentation and emotional state on social media. Another interesting relationship include event and non-event posts, which had the same average score, showing that whether the post involved a special event or not did not influence the stress score. However, event posts had a significantly higher positive score and a slightly lower negative score, indicating that while the stress of students did not change due to special event, the emotions of these students did improve.

	Average of PSS	**Average of Pos Score**	**Average of Neg Score**
Contains Poster(y/n)			
No	19.2828947	33.9868421	26.4342105
Yes	22.3411765	33.6705882	28.9882353
Gender			

Female	24.5223881		
Male	14.9902913		
Athletics(y/n)			
no	22.3231707	32.7317073	29.1036585
yes	16.0136986	36.4383562	23.4109589
Repost(y/n)			
no	23.3818182	32.4636364	30.2272727
yes	17.7795276	35.0944882	24.8582677
Expressions			
Happy, Smiling	20.1230769	33.3846154	27.0615385
No face	21.5671642	33.5970149	28.5671642
Serious	19.9166667	34.9305556	26.6527778
Comments			
Non-Event	20.3615024	33.629108	27.2957746
Event	20.5416667	36.0416667	27.8333333
Captioned	25.84	31.28	32.52
has a @	17.4861111	35.3611111	25.1666667
Picture	22.9722222	34.0555556	29.4722222

Table 3: *Mental health averages of non-numerical image features.*

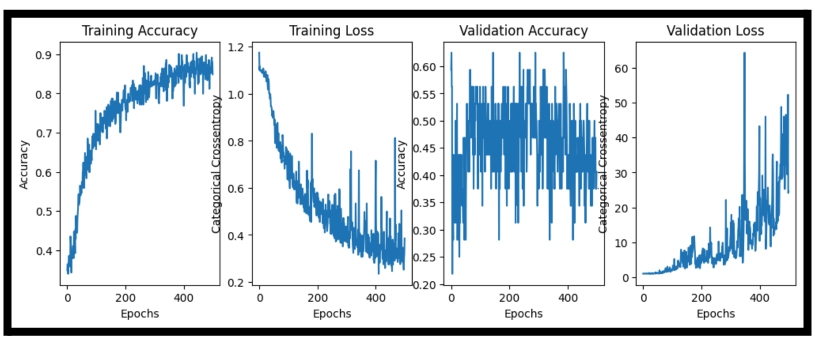

Figure 1: *Self-Written Neural Network Architecture trained for 500 epochs, validation accuracy reached high of 61%.*

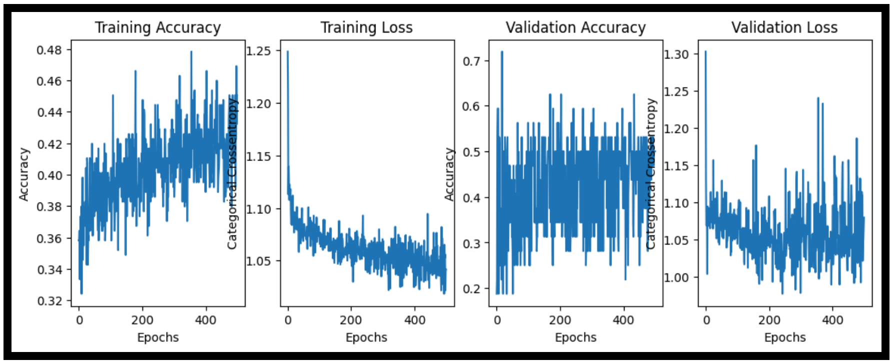

Figure 2: *Resent Model with layers taken off for 500 epochs, validation accuracy reached high of 62%.*

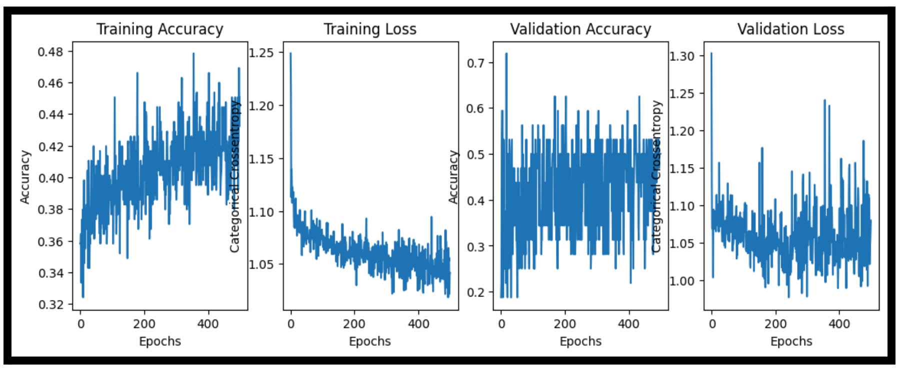

Figure 3: *Full Layered Resnet model trained for 1000 epochs, validation accuracy reached high of 56%.*

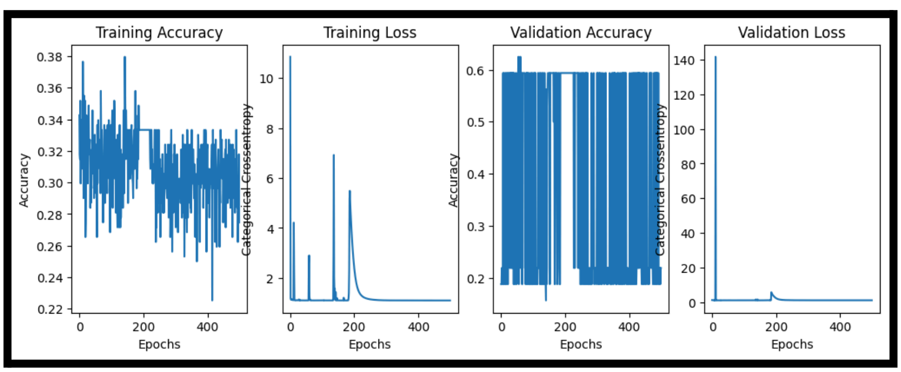

Figure 4: *VGG16 model trained for 500 epochs, results highly sporadic.*

6. LIMITATIONS AND FUTURE WORK

For future research directions, a key focus will be on acquiring a larger and more comprehensive dataset. Many challenges faced in the data analysis and the application of Convolutional Neural Networks (CNNs) can be attributed to the limited dataset. Having a greater dataset could significantly increase the accuracy of the model in classifying the stress categories of the social media posts. However, the ability to create a greater dataset was deeply limited considering all the work was manually done. Having around 30 participants was already a significant struggle to keep track of and record. Future studies could benefit from collaborative efforts, involving more researchers in the manual data collection process to facilitate the gathering of a more extensive dataset. Furthermore, expanding the scope of data collection to include individuals from different educational institutions, cultural backgrounds, and age groups, beyond just high school students from a specific school, could provide valuable insights. Such diversification in the dataset would allow for a better understanding of the relationship between social media usage and emotional well-being across various demographics. This broader approach could uncover significant trends and patterns that are not limited to a single student demographic, thereby enhancing the generalizability and applicability of the research findings.

7. CONCLUSION

This study presents a focus into the relationship between social media usage and mental health among high school students, focusing on the potential of Artificial Intelligence, specifically Convolutional Neural Networks (CNNs), in predicting stress levels from social media posts. This study leveraged data from Instagram and Snapchat, platforms widely used by adolescents, to develop a predictive model that goes beyond traditional psychological assessments, which often pose challenges in terms of consistent application among high school students.

The findings offer insights into how digital footprints on social media can be indicative of an individual's emotional and stress levels. The utilization of CNNs showcased a promising direction in accurately categorizing stress levels through the analysis of social media images, achieving a significant improvement in validation accuracy over random selection. This success underscores the potential of machine learning in enhancing our understanding of adolescent mental health.

However, this study faced challenges related to the dataset's size and composition, highlighting the necessity for a broader and more diverse data collection in future work. Expanding the research to include a wider range of participants from different schools and backgrounds would likely yield more generalizable and insightful results.

As we conclude, it is clear that this study represents only the beginning of what could be a deeply impactful area of research. The relationship between social media use and adolescent mental health is complex and multifaceted, necessitating continued exploration. By harnessing the power of technology, we move closer to understanding and mitigating the impacts of stress on the youth, paving the way for healthier, happier teenager lives.

8. REFERENCES

Ahmed, Arfan, et al. “Machine Learning Models to Detect Anxiety and Depression through Social Media: A Scoping Review.” Computer Methods and Programs in Biomedicine Update, Elsevier, 9 Sept. 2022, https://www.sciencedirect.com/science/article/pii/S2666990022000179.

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). *Perceived Stress Scale* [Database record]. APA PsycTests. https://doi.org/10.1037/t02889-000

Deng, Y., Cherian, J., Khan, N. U. N., Kumari, K., Sial, M. S., Comite, U., Gavurova, B., & Popp, J. (2022). Family and Academic Stress and Their Impact on Students' Depression Level and Academic Performance. *Frontiers in psychiatry*, *13*, 869337. https://doi.org/10.3389/fpsyt.2022.869337

Febriansyah, Mochamad Rizky, and Nicholas Nicholas. “Stress Detection System for Social Media Users.” 10 Jan. 2023, https://www.researchgate.net/publication/366998523_Stress_detection_system_for_social_media_users.

Guntuku, Sharath Chandra, et al. “What Twitter Profile and Posted Images Reveal about Depression and Anxiety.” ArXiv.org, 4 Apr. 2019, https://arxiv.org/abs/1904.02670.

King, W. (n.d.). *Abnormal psychology*. Lumen. https://courses.lumenlearning.com/wm-abnormalpsych/chapter/reading-correlational-research/#:~:text=Correlation%20means%20that%20there%20is,changes%2C%20so%20does%20the%20other.

Label studio documentation - overview of Label Studio. Label Studio Documentation - Overview of Label Studio. (n.d.). https://labelstud.io/guide/get_started.html

Li, R., Liu, Z. Stress detection using deep neural networks. *BMC Med Inform Decis Mak* 20 (Suppl 11), 285 (2020). https://doi.org/10.1186/s12911-020-01299-4

Pandey, P. (2021a, August 31). *Creating custom image datasets for deep learning projects.* Medium. https://towardsdatascience.com/creating-custom-image-datasets-for-deep-learning-projects-6e5db76158d4

Pew Research Center, August 2022, “Teens, Social Media and Technology 2022”

Renu. (2020b, August 19). *Loading Custom Image Dataset for Deep Learning Models: Part 1*. Medium. Loading Custom Image Dataset for Deep Learning Models: Part 1

Social Media and Its Relationship with Mood ... - Wiley Online Library. https://onlinelibrary.wiley.com/doi/full/10.1111/acps.12953.

Watson, D., Clark, L. A., & Tellegen, A. (1988). *Development and validation of brief measures of positive and negative affect: The PANAS scales*. Journal of Personality and Social Psychology, 54(6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063

Yaribeygi, H., Panahi, Y., Sahraei, H., Johnston, T. P., & Sahebkar, A. (2017). The impact of stress on body function: A review. *EXCLI journal*, *16*, 1057–1072. https://doi.org/10.17179/excli2017-480

"50 Current Student Stress Statistics: 2023 Data, Analysis & Predictions." Research.com, 17 Mar. 2023, https://research.com/education/student-stress-statistics.