Predicting Self-Reported Stress Levels: The Role of Screen Time, Social Media, and Lifestyle Factors

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Business Problem

Stress affects health, work, and daily life. High stress can lead to lower productivity, poor health, and burnout. Many people spend long hours on screens and social media, which may increase their stress. This project explores how screen time, social media, sleep, and exercise relate to stress and how we can predict a person's stress level from these habits. The goal is to help organizations and individuals use simple data to manage stress before it becomes harmful (American Institute of Stress, 2025).

Background/History

In recent years, stress levels in America have reached record highs (American Institute of Stress, 2025). Constant digital activity and social media use make it harder to disconnect and relax. Financial worries, long work hours, and poor sleep add to the problem. Health experts agree that good sleep and regular exercise help lower stress (Harvard Health Publishing, n.d.), but many people struggle to maintain those habits. Using data about everyday routines—like screen time or sleep quality—can help us understand what drives stress and how to reduce it.

Data Explanation

The dataset came from Kaggle (n.d.) and includes about 500 survey responses. Each person rated their stress level (1–10) and reported daily screen time, social media use, sleep quality, exercise frequency, age, gender, and happiness. The main variable we want to predict is stress level. The data was already clean and ready for analysis, with no missing values. We changed text fields like gender and social media platform into numeric form so they could be used in models.

Methods

I first explored the data through charts and correlations. Then, I tested three predictive models: linear regression, random forest, and gradient boosting. The data was split 80/20 into training and test sets. I measured accuracy using R^2 (how much variation the model explains) and RMSE (average prediction error). The best-performing model would be used to identify which factors most affect stress.

Analysis

The data showed clear patterns. People who spent more hours on screens had much higher stress levels. Those who reported good sleep had lower stress. Exercise and social media use showed weak connections to stress. The strongest relationships were between screen time, sleep quality, and stress. The linear regression model explained about 55% of the variation in stress, while the random forest model improved slightly to 62%. In both, screen time was the top predictor, followed by sleep quality. These results show that screen use and rest play major roles in how stressed people feel.

Conclusion

I found that stress can be predicted fairly well using simple lifestyle data. Longer screen time raises stress, while better sleep lowers it. Exercise and social media use may still matter but were not strong predictors in this dataset. These insights support common advice: get enough rest, reduce screen use, and maintain a balanced lifestyle (Harvard Health Publishing, n.d.). Predictive tools based on these findings could help people and workplaces spot rising stress early and take preventive steps.

Assumptions

I assumed participants answered honestly and that their self-reported stress levels reflected real experiences. I also assumed that the relationships between behaviors and stress were similar across people. Because this was survey data, results show associations, not cause and effect.

Limitations

The data was self-reported, so some people may have misjudged their stress or habits. It was also cross-sectional, meaning it shows one point in time and not long-term changes. Other causes of stress—like finances or relationships—were not included. The sample mainly represented younger adults, so findings might differ for older groups.

Challenges

A key challenge was separating the effects of screen time and sleep, since they were highly related. It was also difficult to measure social media's emotional impact with only basic metrics. We balanced the need for accurate models with the goal of keeping results easy to explain.

Future Uses and Applications

This model could be added to wellness apps or employee health programs. For example, an app could warn users when screen time and poor sleep suggest high stress risk. Over time, more data could make the model smarter, allowing real-time feedback and personalized stress reduction tips.

Recommendations

People should set limits on daily screen time, focus on better sleep routines, and make regular exercise part of their schedule. Companies should educate employees about digital well-being and offer resources like mindfulness sessions or fitness breaks. Predictive data tools can help target support where it's needed most.

Implementation Plan

To apply this research, organizations could collect anonymous lifestyle data through apps or surveys. Models like ours can predict group stress trends and trigger wellness initiatives when stress levels rise. Data must always be voluntary, secure, and used only to support mental health, not to evaluate performance.

Ethical Assessment

Using personal data to predict stress requires strong ethics. People must give clear consent and control how their data is used. The model should never be used to judge or penalize anyone. It must also be tested for fairness to avoid bias. The goal is to promote well-being, not surveillance. Transparency, privacy, and respect are essential for trust and responsible use.

Appendix

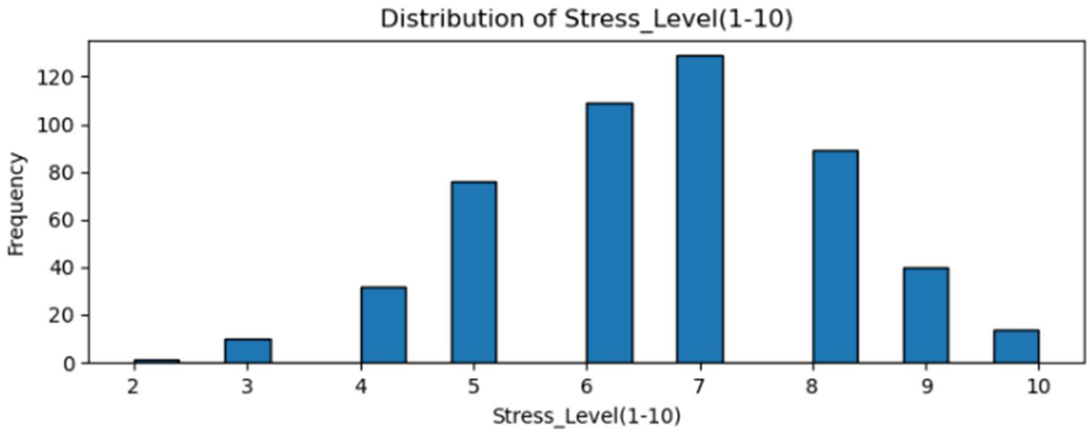

Figure 1: Stress Level Distribution

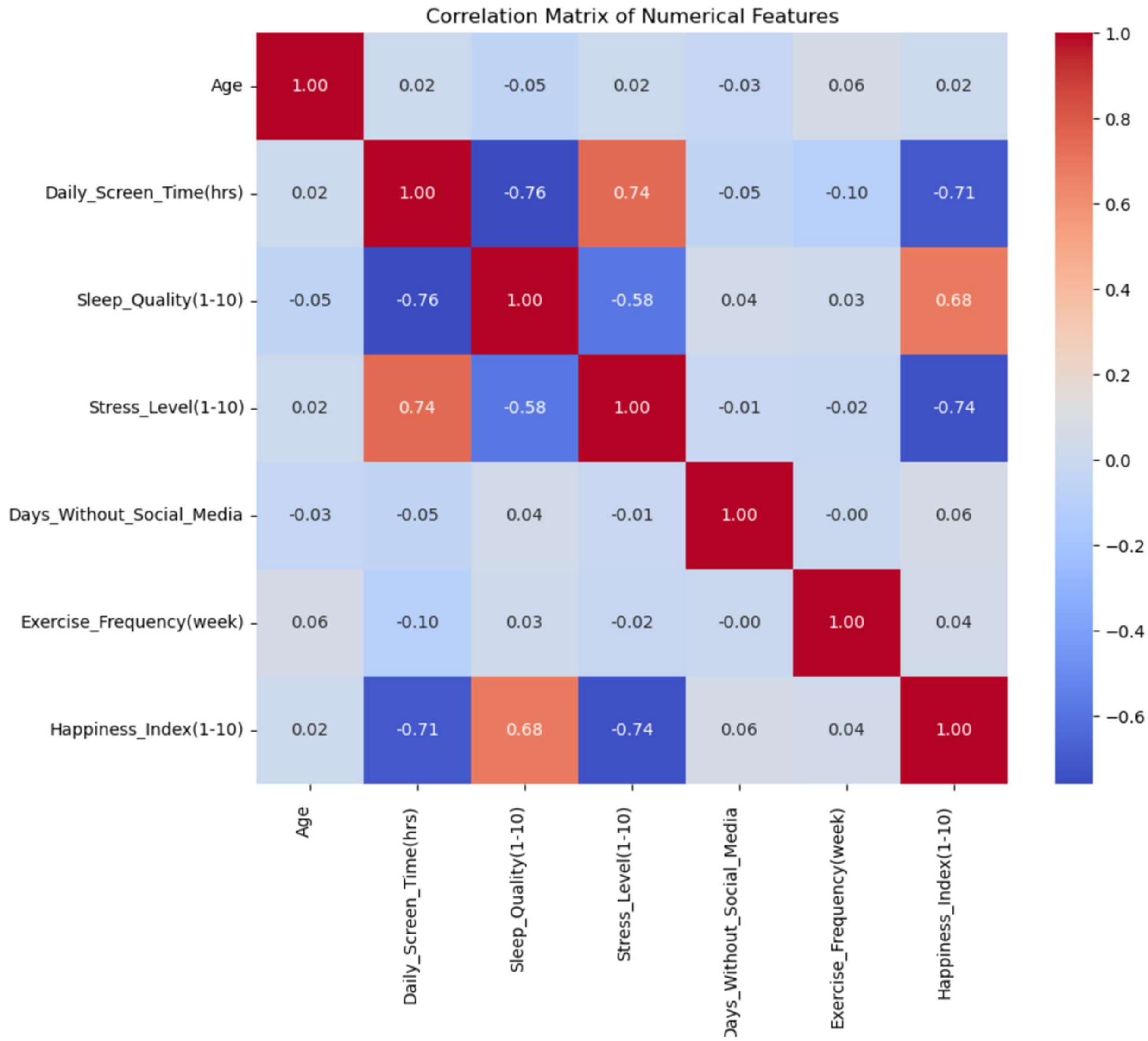

Figure 2: Correlation Heatmap

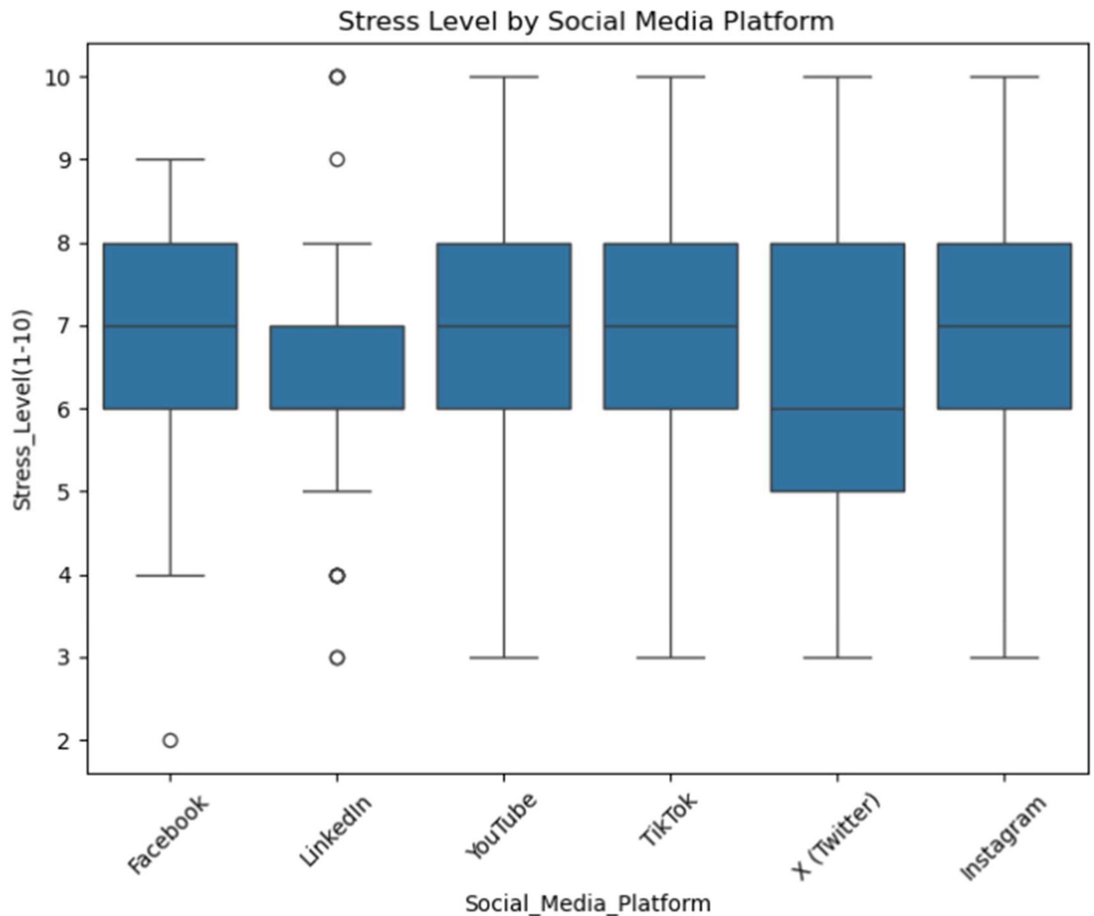

Figure 3: Boxplot Stress Level by Social Media Platform

References

American Institute of Stress. (2025). *What the latest reports say about stress in America*. https://www.stress.org/news/what-the-latest-reports-say-about-stress-in-america/

Harvard Health Publishing. (n.d.). *Exercising to relax*. https://www.health.harvard.edu/mind-and-mood/exercising-to-relax

Kaggle. (n.d.). *Screen Time vs Mental Wellness Survey (2023)*. https://www.kaggle.com/datasets/adharshinikumar/screentime-vs-mentalwellness-survey-2023