# Mobile Application for Predicting Stress Levels Using Digital Wellbeing Data

Sharan Sukesh
*School of Computer Science*
*University of Windsor*
Windsor, Canada
sukesh@uwindsor.ca

Aaryen DSouza
*School of Computer Science*
*University of Windsor*
Windsor, Canada
dsouza96@uwindsor.ca

Reuben George
*School of Computer Science*
*University of Windsor*
Windsor, Canada
george2a@uwindsor.ca

Sanjay Suthar
*School of Computer Science*
*University of Windsor*
Windsor, Canada
suthar73@uwindsor.ca

***Abstract*—The increased use of smart-phones and other electronic devices presented today guarantees constant interaction with the digital world and thus leads to unprecedented records in the percentage of screen time and social network activity. These technologies have improved the connectivity and ease of access to information but have presented new problems in terms of mental health, most importantly stress. This project outlines the process of creating a mobile application, with the help of digital wellbeing data such as screen time, frequency and variety of app usage, social activity, and gaming activity predicts the level of stress in a particular person. Not only does the application predict stress levels, but it also suggests appropriate measures to help release stress caused by digital consumption using machine learning algorithm and large language model. After evaluating machine learning models, XGBoost Balanced & Tuned model was chosen to integrate with the application for its superior performance with an accuracy of 0.77. The main purpose is to provide users, mental health workers, and organizations with control, improvement, and prevention of the negative consequences of the problematic use of digital technology devices.**

***Index Terms*—Stress management, Machine Learning, Digital well-being, Large language model**

## I. Introduction

### A. Background and Motivation

In today's digital era, smartphones and other connected devices are the very essentials of daily life, bringing communication, entertainment, and information right to our fingertips. Since these technologies are so convenient and easy to use, it has resulted in a great increase in time spent on digital screens. Recent findings would suggest that one typically spends several hours daily using a smartphone, consuming time on the phone with activities such as browsing social media, watching content, and playing games. Although there are many benefits associated with owning one of these devices, increasing evidence has shown that prolonged screen use and digital communication may be detrimental to mental health[8].

Another important concern is the relationship between long-term use of digital devices and increased levels of stress. Studies have shown that too much exposure to screens is associated with changes in sleep patterns, decreased physical activity, and decreased social contact with friends, all factors that contribute to increased stress. In particular, social media platforms can enhance feelings of anxiety and stress with continued exposure to selective portrayals of other's lives, forms of cyberbullying, and pressure to maintain an online presence. From these facts, it becomes clear how important the development of tools and strategies must be in a way that enables people to execute proper management over their digital wellbeing[9].

### B. Problem Statement

Despite the growing awareness of the possible negative consequences of excessive involvement in

digital media, many users cannot yet successfully monitor and regulate their device use in ways that support mental health[1]. The existing digital wellbeing features provided on most smartphones simply display basic statistics, such as total screen time or app usage information; they do not offer more insightful analytics or tailored suggestions that can address specific user needs. Without personalized feedback or suggestions, it could become overwhelming for the user to interpret this meaningfully and make informed decisions about how to adjust their digital habits to reduce stress[2].
Meanwhile, it also becomes difficult for mental health professionals and organizations trying to solve these problems to access and use digital wellness data to help their clients or employees. There is a clear need for an integrated solution that not only tracks digital usage patterns but also analyzes this information to predict stress levels and suggest specific interventions.

### C. Project Objectives

The goal of this project will be to come up with an Android-based application that could effectively forecast user's levels of stress using provided parameters, which include but are not limited to digital wellbeing information such as screen time usage, app usage frequency, social media activity, and physical activity. The application aims to provide users with a holistic understanding of how their digital behaviors impact their stress levels. The specific goals of the project are as follows:

*1) Stress Level Prediction:* Use machine learning algorithms to analyze digital health data and accurately predict the current stress level of the user[1].

*2) Personalized Recommendations:* Offer tailored advice and strategies to help users reduce stress. These include:

- Suggesting screen time limits.
- Recommend mindfulness activities.
- Encourage physical exercise.

*3) User Engagement:* Foster a user experience that encourages regular interaction with the app, promoting sustained engagement with the stress management tools provided.

### D. Contribution

This project contributes to the field of digital wellbeing and mental health by integrating advanced data analytics and machine learning techniques into a user-centric mobile application. The key contributions include:

*1) Innovative Use of Data:* Combining various sources of digital wellbeing data to create a multifaceted view of the user's digital habits and their correlation with stress levels.

*2) Machine Learning Model Development:* Designing and training a robust machine learning model capable of making accurate stress level predictions based on complex, multidimensional data.

*3) Accessible Technology:* Developing an application that is readily available to a wide audience, with compatibility across major Android devices, thus lowering barriers to access.

*4) Empowering Users:* Providing individuals with the tools and knowledge to take control of their digital wellbeing, leading to improved mental health outcomes.

## II. Literature/Background Study

Recent studies underscore the significant impact of digital habits, particularly screen time, on mental well-being, providing crucial insights into stress management. Francisquini et al. (2024) revealed a clear positive correlation between prolonged screen time and elevated stress levels, with adolescents exceeding four hours of daily screen use showing notably higher stress indicators[2]. This finding highlights the direct psychological toll of excessive digital exposure. Building on this, Ge et al. (2020) explored the combined effects of screen time and physical activity, demonstrating that individuals with high screen time and low physical activity are particularly susceptible to stress[4]. Their work emphasizes the compounded impact of sedentary lifestyles coupled with heavy digital consumption, further reinforcing the importance of monitoring and addressing digital habits to mitigate stress.

The predictive potential of digital data for mental health was explored by Moshe et al. (2021), who utilized smartphone and wearable data to forecast stress, anxiety, and depression[3]. Their approach validated the efficacy of leveraging digital behavior patterns, such as screen usage, sleep disruptions, and activity levels to accurately predict mental health outcomes. Similarly, Dixit et al. (2024) introduced a holistic framework for stress management using machine learning to deliver personalized recommendations and real-time interventions, enhancing user engagement[1]. These findings align closely with the goals of our project, which integrates predictive analytics with actionable insights to address the challenges of digital wellbeing. By building on these foundational studies, our mobile application seeks to provide users with practical tools for monitoring their digital habits, predicting stress levels, and implementing targeted strategies for stress reduction, offering a comprehensive and evidence-based approach to digital wellbeing management.

## III. Project Details and Methodology

### A. Definitions

*1) Digital Wellbeing Data:* Quantitative and qualitative information that reflects a user's interactions with digital devices, including metrics such as screen time duration, frequency of app usage, types of applications used, notifications received, and online activity patterns[1].

*2) Stress Level:* An individual's perceived psychological strain or tension, which can be influenced by various factors including environmental conditions, physical health, and emotional state. In this context, stress level is quantified using validated assessment tools or inferred through behavioral indicators[2].

*3) Machine Learning Model:* A computational algorithm that learns patterns from input data to make predictions or decisions without being explicitly programmed for specific outcomes. Models can range from simple linear regressions to complex random forest[11].

### B. Specification

The project involves developing a mobile application with the following specifications:

*1) Compatibility:* The application must be compatible with major Android devices, ensuring accessibility for a broad user base.

*2) Data Integration:* The app should seamlessly collect and integrate various forms of digital wellbeing data from the user's device, adhering to privacy and security standards.

*3) Machine Learning Integration:* Incorporate a trained machine learning model capable of processing the collected data in real-time to predict stress levels accurately.

*4) User Interface:* Design an intuitive and engaging user interface that allows users to easily navigate between different features, including stress predictions, and recommendations.

*5) Personalization:* Provide personalized recommendations based on the user's unique data profile, enhancing the relevance and effectiveness of the stress reduction strategies offered.

### C. Architecture

The application's architecture is designed to support efficient data processing, real-time predictions, and a seamless user experience. The key components of the architecture include:

*1) Data Collection Module:* Responsible for gathering digital wellbeing data from the user's device, such as screen time logs and app usage statistics. This module interfaces with the device's operating system APIs while ensuring compliance with privacy regulations.

*2) Data Preprocessing Unit:* Cleans and preprocesses the collected data to prepare it for analysis. This includes handling missing values, normalizing data scales, and encoding categorical variables. The preprocessing unit ensures that the data fed into the machine learning model is of high quality and suitable for accurate predictions[12].

*3) Machine Learning Engine:* The core component of the application is the Machine Learning Engine, which powers stress level prediction using advanced machine learning models. Four models were trained and evaluated: Random Forest[10] (Default), Random Forest (Tuned)[10], XGBoost[6] (Default), and XGBoost (Balanced and Tuned)[6]. Among these, the XGBoost (Balanced and Tuned) model was selected for its superior accuracy, precision, recall, and F1-score. This model processes preprocessed user data, such as screen time, social media usage, and sleep hours, to generate precise stress level predictions. The engine is optimized for mobile devices, utilizing on-device computation to minimize latency and reduce dependency on external servers.

*4) Large Language Model:* The application leverages Google Gemini LLM[7] to provide personalized recommendations tailored to each user's digital habits and stress patterns. By integrating this advanced language model, the app offers actionable insights and strategies to help users effectively manage and reduce stress, enhancing the overall digital wellbeing experience.

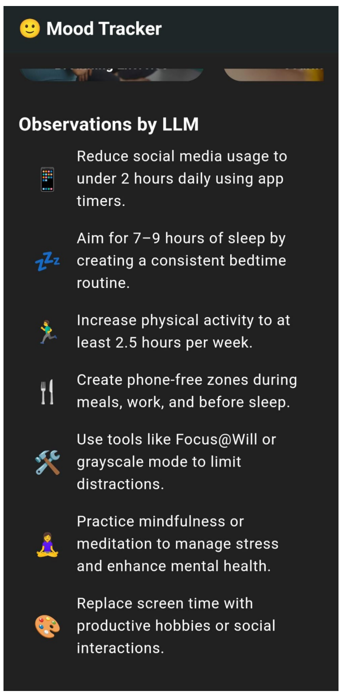



Fig. 1. Suggestions by LLM

*5) Recommendation System:* Based on the predicted stress levels and identified usage patterns, this system generates personalized recommendations aimed at reducing stress. Recommendations are derived from evidence-based strategies and may include suggestions such as taking regular breaks, limiting screen time before bedtime, or engaging in physical activity[13].

*6) User Interface (UI):* The front-end component that interacts with the user. The UI presents stress predictions, recommendations, and data visualizations in an accessible manner. It supports user interactions such as adjusting settings, providing feedback, and navigating between different sections of the app[14].

### D. Platform

The project utilizes the following platforms and technologies:

*1) Operating System:* Android OS, supporting versions commonly used by the target audience to maximize reach.

*2) Development Environment:* Android Studio is used for app development, with programming in Java or Kotlin. The choice of language depends on performance considerations and compatibility with existing libraries.

*3) Machine Learning Framework:* TensorFlow Lite is employed for integrating the machine learning model into the mobile application. TensorFlow Lite is optimized for on-device machine learning, providing efficient inference capabilities on mobile hardware.

### E. Design

The application's design prioritizes usability and aesthetic appeal to enhance user engagement:

*1) User-Centered Design:* The interface is designed with the end-user in mind, featuring clear navigation menus, intuitive controls, and easily accessible features. User feedback is incorporated throughout the design process to refine the interface.

*2) Visual Consistency:* A consistent visual theme is applied across the app, using color schemes and typography that are soothing and promote relaxation. Visual cues and icons help users quickly identify different sections and functions.

*3) Accessibility:* The app adheres to accessibility guidelines, ensuring that users with disabilities can effectively interact with the app. This includes support for screen readers, high-contrast modes, and scalable text sizes.

*4) Feedback Mechanisms:* Interactive elements provide immediate feedback to user actions, enhancing the overall experience. For example, changes in stress levels are highlighted, and users receive notifications when new recommendations are available.

## IV. Experimental Setup

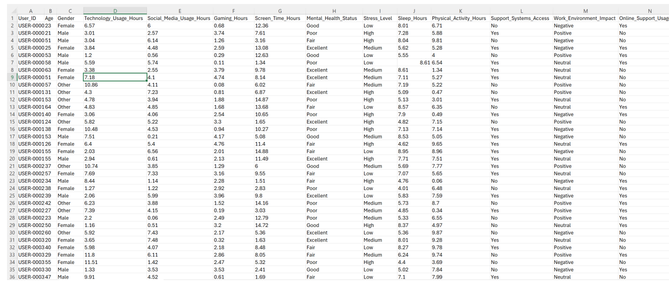
The experimental setup for this project involved carefully curating the dataset and configuring the machine learning model development. The dataset comprised anonymized records of user's digital habits and mental health parameters, including metrics such as screen time, social media usage hours, gaming hours, and sleep patterns, alongside self-reported stress levels. The dataset was divided into an 80:20 training-to-testing split, ensuring a sufficient amount of data for both model learning and performance evaluation[5].

Key components of the experimental setup app are:

1) Dataset Features: The dataset included variables such as Age, Gender, Technology_Usage_Hours, Screen_Time_Hours, Mental_Health_Status, Stress_Level, and more. These features were chosen for their potential to reveal correlations between digital usage and stress levels[5].
2) Preprocessing Steps[12]:
    - Data cleaning: Addressed missing and inconsistent entries.
    - Normalization: Applied Min-Max scaling for numerical features.
    - Encoding: Converted categorical features such as Gender into numerical values.
3) Evaluation Metrics[15]: Performance metrics included accuracy, precision, recall, F1-score, and Mean Absolute Error (MAE). Cross-validation techniques were utilized to ensure the model's robustness.
4) Toolchain[16]:
    - Python libraries like Pandas, NumPy, and Scikit-learn for data preprocessing.
    - TensorFlow for machine learning model training.

## A. Implementation Details

The development of the machine learning model involved exploring multiple algorithms to identify the most effective solution for predicting stress levels. Random Forest and Extreme Gradient Boosting (XGBoost) were thoroughly tested, and Extreme Gradient Boosting with balancing and tuning was selected for its superior ability to handle complex, non-linear relationships within the dataset. The model was trained on an 80:20 data split, ensuring sufficient data for both the training and testing phases. To enhance performance, hyperparameters such as the number of trees and maximum depth were fine-tuned using grid search. Although the final choice remained XGBoost due to its robustness, consistent results. Once trained, the XGBoost model was converted into TensorFlow Lite format, enabling seamless integration into the mobile application while ensuring compatibility with Android devices.



| | User_ID | Age | Gender | Technology_Usage_Hours | Social_Media_Usage_Hours | Gaming_Hours | Screen_Time_Hours | Mental_Health_Status | Stress_Level | Sleep_Hours | Physical_Activity_Hours | Support_Systems_Access | Work_Environment_Impact | Online_Support_Usage |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | USER-0000 | 23 | Female | 6.57 | 6 | 0.68 | 12.36 | Good | Low | 8.01 | 6.71 | No | Negative | Yes |
| 3 | USER-0000 | 21 | Male | 3.01 | 2.57 | 3.74 | 7.61 | Poor | High | 7.28 | 5.88 | Yes | Positive | No |
| 4 | USER-0000 | 51 | Male | 3.04 | 6.14 | 1.26 | 3.16 | Fair | High | 8.04 | 9.81 | No | Negative | No |
| 5 | USER-0000 | 25 | Female | 3.84 | 4.48 | 2.59 | 13.08 | Excellent | Medium | 5.62 | 5.28 | Yes | Negative | Yes |
| 6 | USER-0000 | 53 | Male | 1.2 | 0.56 | 0.29 | 12.63 | Good | Low | 5.55 | 4 | No | Positive | Yes |
| 7 | USER-0000 | 58 | Male | 5.59 | 5.74 | 0.11 | 1.34 | Poor | Low | 8.61 | 6.54 | Yes | Neutral | Yes |
| 8 | USER-0000 | 63 | Female | 3.38 | 2.55 | 3.79 | 9.78 | Excellent | Medium | 8.61 | 1.34 | Yes | Neutral | No |
| 9 | USER-0000 | 51 | Female | 7.18 | 4.1 | 4.74 | 8.14 | Excellent | Medium | 7.11 | 5.27 | Yes | Neutral | No |
| 10 | USER-0000 | 57 | Other | 10.86 | 4.11 | 0.08 | 6.02 | Fair | Medium | 7.19 | 5.22 | No | Positive | No |
| 11 | USER-0001 | 31 | Other | 4.3 | 7.23 | 0.81 | 6.87 | Excellent | High | 5.09 | 0.47 | No | Positive | No |
| 12 | USER-0001 | 53 | Other | 4.78 | 3.94 | 1.88 | 14.87 | Poor | High | 5.13 | 3.01 | Yes | Neutral | No |
| 13 | USER-0001 | 64 | Other | 4.83 | 4.85 | 1.68 | 13.68 | Fair | Low | 8.57 | 6.35 | No | Neutral | Yes |
| 14 | USER-0001 | 40 | Female | 3.06 | 4.06 | 2.54 | 10.65 | Poor | High | 7.9 | 0.49 | Yes | Negative | Yes |
| 15 | USER-0001 | 24 | Other | 5.82 | 5.22 | 3.3 | 1.65 | Excellent | High | 4.82 | 7.15 | No | Positive | No |
| 16 | USER-0001 | 38 | Female | 10.48 | 4.53 | 0.94 | 10.27 | Poor | High | 7.13 | 7.14 | Yes | Negative | No |
| 17 | USER-0001 | 53 | Male | 7.51 | 0.21 | 4.17 | 5.08 | Good | Medium | 8.53 | 5.05 | Yes | Negative | No |
| 18 | USER-0001 | 26 | Female | 6.4 | 5.4 | 4.76 | 11.4 | Fair | High | 4.62 | 9.65 | Yes | Neutral | Yes |
| 19 | USER-0001 | 55 | Female | 2.03 | 6.56 | 2.01 | 14.88 | Fair | Low | 8.95 | 8.96 | Yes | Negative | No |
| 20 | USER-0001 | 55 | Male | 2.94 | 0.61 | 2.13 | 11.49 | Excellent | High | 7.71 | 7.51 | Yes | Neutral | No |
| 21 | USER-0002 | 37 | Other | 10.74 | 3.85 | 1.29 | 6 | Good | Medium | 5.69 | 7.77 | Yes | Positive | No |
| 22 | USER-0002 | 57 | Female | 7.69 | 7.33 | 3.16 | 9.55 | Fair | Low | 7.07 | 5.65 | Yes | Neutral | No |
| 23 | USER-0002 | 34 | Male | 8.44 | 1.14 | 2.28 | 1.51 | Fair | High | 4.76 | 0.06 | No | Negative | Yes |
| 24 | USER-0002 | 38 | Female | 1.27 | 1.22 | 2.92 | 2.83 | Poor | Low | 4.01 | 6.48 | No | Neutral | Yes |
| 25 | USER-0002 | 39 | Male | 2.06 | 5.99 | 3.96 | 9.8 | Excellent | Low | 5.83 | 7.59 | Yes | Negative | Yes |
| 26 | USER-0002 | 42 | Other | 6.23 | 3.88 | 1.52 | 14.16 | Poor | Medium | 5.73 | 8.7 | No | Positive | Yes |
| 27 | USER-0002 | 27 | Other | 7.39 | 4.15 | 0.19 | 3.03 | Poor | Medium | 4.85 | 0.34 | Yes | Positive | Yes |
| 28 | USER-0002 | 23 | Male | 2.2 | 0.06 | 2.49 | 12.79 | Poor | Medium | 5.33 | 6.55 | No | Positive | Yes |
| 29 | USER-0002 | 50 | Female | 1.16 | 0.51 | 3.2 | 14.72 | Good | High | 8.37 | 4.97 | No | Neutral | Yes |
| 30 | USER-0002 | 60 | Other | 5.92 | 7.43 | 2.17 | 5.36 | Excellent | Low | 5.36 | 9.87 | No | Negative | No |
| 31 | USER-0003 | 20 | Female | 3.65 | 7.48 | 0.32 | 1.63 | Excellent | Medium | 8.01 | 9.28 | Yes | Neutral | No |
| 32 | USER-0003 | 40 | Female | 5.98 | 4.07 | 2.18 | 8.48 | Fair | Low | 8.27 | 9.78 | Yes | Positive | No |
| 33 | USER-0003 | 29 | Female | 11.8 | 6.11 | 2.86 | 8.05 | Fair | Medium | 6.24 | 9.74 | No | Positive | Yes |
| 34 | USER-0003 | 55 | Female | 11.51 | 1.42 | 2.47 | 5.32 | Poor | High | 4.4 | 3.69 | No | Negative | No |
| 35 | USER-0003 | 30 | Male | 1.33 | 3.53 | 3.53 | 2.41 | Good | Low | 5.02 | 7.84 | No | Negative | Yes |
| 36 | USER-0003 | 47 | Male | 9.91 | 4.52 | 0.61 | 1.69 | Fair | Low | 7.1 | 7.99 | Yes | Neutral | No |

Fig. 2. Data Used to train the ML Model

The mobile application itself was developed using Android Studio, with Dart serving as the primary programming language and Flutter as the framework. The app's architecture consisted of multiple interconnected modules designed for efficiency and usability. The Data Collection Module extracted information such as screen time logs and app usage statistics from the user's device, forming the foundation for subsequent predictions. The Prediction Engine, powered by the TensorFlow Lite model, provided real-time stress level predictions based on user data. A dynamic Recommendation System was also integrated, offering actionable insights tailored to individual stress profiles, such as reminders to schedule device-free hours or improve sleep hygiene.

During the deployment phase, the app was rigorously optimized for Android devices to ensure compatibility across a wide range of hardware configurations. Special attention was paid to minimizing resource consumption, resulting in a lightweight design that preserved battery life and ensured smooth operation during continuous monitoring.

## B. Testing

The testing process for the machine learning models focused on evaluating multiple algorithms to identify the one that delivered the best predictive performance for stress level analysis. The models tested included Random Forest (Default and

Tuned) and XGBoost (Default and Balanced & Tuned). Each model was assessed using metrics such as Accuracy, Precision (Weighted Average), Recall (Weighted Average), and F1-Score (Weighted Average). The dataset was split into training and testing subsets, ensuring the models were rigorously validated on unseen data.

The initial testing of the Random Forest Default model yielded an accuracy of 0.66, with Precision, Recall, and F1-Score averaging at 0.65. A tuned version of the Random Forest model improved the Precision metric slightly to 0.66 but did not significantly outperform its default counterpart. XGBoost Default achieved an accuracy of 0.65, with a corresponding F1-Score of 0.64, falling slightly below the Random Forest results[14]. However, the Balanced and Tuned XGBoost model demonstrated significant improvements, achieving the highest accuracy of 0.77 across all metrics. This performance boost, combined with its ability to handle imbalanced datasets effectively, made XGBoost the optimal choice for the project.

| Model | Accuracy | Precision (Weighted Avg) | Recall (Weighted Avg) | F1-Score (Weighted Avg) | Support |
|---|---|---|---|---|---|
| Random Forest (Default) | 0.66 | 0.65 | 0.66 | 0.65 | 4100 |
| Random Forest (Tuned) | 0.66 | 0.66 | 0.66 | 0.66 | 4100 |
| XGBoost (Default) | 0.65 | 0.63 | 0.65 | 0.64 | 4100 |
| XGBoost (Balanced & Tuned) | 0.77 | 0.77 | 0.77 | 0.77 | 6580 |

TABLE I
ML RESULT COMPARISON TABLE

After selecting XGBoost as the best-performing model, it was integrated into the mobile application using TensorFlow Lite. The integration process ensured seamless compatibility between the model and the app's backend architecture. Real-world testing involved adding various input combinations into the app to simulate diverse user scenarios. The app accurately predicted stress levels based on the provided inputs and offered recommendations aligned with the predictions. For instance, users with high screen time and low sleep hours received suggestions to reduce device usage before bedtime and improve sleep hygiene. These recommendations were consistent with expected outputs, validating the integration's success.

By leveraging XGBoost's predictive capabilities and ensuring accurate recommendations, the app effectively delivered a reliable tool for stress management and digital wellbeing enhancement.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.79 | 0.74 | 0.76 | 2178 |
| 1 | 0.75 | 0.80 | 0.78 | 2198 |
| 2 | 0.77 | 0.77 | 0.77 | 2204 |
| accuracy | | | 0.77 | 6580 |
| macro avg | 0.77 | 0.77 | 0.77 | 6580 |
| weighted avg | 0.77 | 0.77 | 0.77 | 6580 |

Fig. 3. XGBoost Result in Testing

### C. Discussion of findings, and challenges

The testing and evaluation phase provided significant insights into the performance of the machine learning models and their integration into the mobile application. Among the models tested, In Fig.3, the Balanced and Tuned XGBoost algorithm demonstrated superior performance, achieving an accuracy of 0.77 and consistent Precision, Recall, and F1-Score values of 0.77. These results highlighted the model's ability to effectively handle the complexities of the dataset, which included diverse features such as screen time, sleep hours, and stress levels. The improvements seen in the XGBoost model were attributed to its ability to manage imbalanced data distributions, a common challenge in datasets with varying stress level categories.

The integration of the XGBoost model into the mobile application further validated its practical utility. The app seamlessly utilized the model to analyze user inputs and generate accurate stress level predictions. During real-world testing, the application provided actionable recommendations based on these predictions, showcasing its effectiveness in addressing user-specific digital wellbeing challenges. For example, users with high stress levels due to excessive technology usage hours were advised to schedule device-free periods and engage in physical activities, while those with insufficient sleep hours received tailored suggestions for improving sleep patterns.

The user feedback gathered during the testing phase underscored the app's ability to deliver meaningful insights and recommendations. Users reported that the predictions aligned with their experiences, and the recommendations were practical and easy to implement. This alignment between the model's outputs and user expectations highlighted the robustness of the machine learning approach and its value in real-world scenarios. Additionally, the app's ability to present data visually through dashboards enhanced users' understanding of their digital habits and motivated behavioral changes, such as reducing social media usage during work hours or improving physical activity levels.

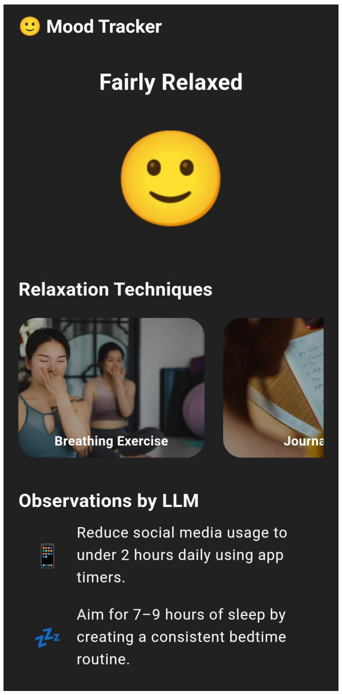



Fig. 4. Result is displayed on the frontend

## V. Conclusion

This project successfully developed a mobile application that predicts user stress levels based on digital well-being data using advanced machine learning techniques. After evaluating four models, the XGBoost (Balanced and Tuned) model was chosen for its superior accuracy, precision, recall, and F1 score. The application integrates this model with a user-friendly interface, and actionable recommendations, enabling users to better understand their digital habits and their impact on mental health. The app not only identifies stress levels but also provides tailored suggestions through LLM to help users manage and reduce stress effectively.

The project demonstrates the potential of combining technology and machine learning to address real-world challenges like mental health management. While the app achieved high accuracy and usability, future work could focus on expanding the dataset, improving recommendation algorithms, and integrating wearable device data for more comprehensive stress analysis. With these enhancements, the application could further support individuals and organizations in fostering digital well-being and mental health awareness.

## VI. Future Work

To enhance the application's performance, we aim to focus on improving the accuracy of the machine learning model by training it with larger and more diverse datasets. This will help the model better understand complex patterns in user data and provide more reliable stress predictions. Additionally, fine-tuning the algorithms will ensure the predictions are both precise and personalized to individual user behaviors.

Key areas for future work include expanding the dataset to include biometric data from wearable devices, such as heart rate variability and sleep quality, which will enrich the dataset and improve the model's predictive power. Cross-platform development is another priority, with plans to introduce an iOS version of the app to reach a broader audience and facilitate data collection from a more diverse user base. Additionally, we aim to implement predictive analytics and proactive interventions, enabling the app to forecast future stress trends and provide timely recommendations to prevent critical stress levels.

To deepen user engagement, the app will integrate advanced personalization techniques that adapt recommendations based on user feedback and behaviors over time. Collaborations with mental health professionals and organizations are also under consideration to offer access to expert resources and integrate the app into broader wellness programs.

## References

[1] Dixit, R., Raj, P., Raj, R., & Garg, P. (2024, May). Your Sanctuary in the Digital Age: A Stress Management Solution Redefining Wellbeing. In 2024 International Conference on Intelligent Systems for Cybersecurity (ISCS) (pp. 1-7). IEEE.

[2] Francisquini, M. C. J., Silva, T. M. D. S., Santos, G. C. D., Barbosa, R. D. O., Dias, P. H. G., Ruiz, A. B., ... & Stabelini, A. (2024). Associations of screen time with symptoms of stress, anxiety, and depression in adolescents. Revista Paulista de Pediatria, 43, e2023250.

[3] Moshe, I., Terhorst, Y., Opoku Asare, K., Sander, L. B., Ferreira, D., Baumeister, H., ... & Pulkki-Råback, L. (2021). Predicting symptoms of depression and anxiety using smartphone and wearable data. Frontiers in psychiatry, 12, 625247.
[4] Ge, Y., Xin, S., Luan, D., Zou, Z., Bai, X., Liu, M., & Gao, Q. (2020). Independent and combined associations between screen time and physical activity and perceived stress among college students. Addictive behaviors, 103, 106224.
[5] Ali, W. (2024). Mental Health & Technology Usage Dataset. Kaggle.com. https://www.kaggle.com/datasets/waqi786/mental-health-and-technology-usage-dataset
[6] Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. (2016). Experimenting XGBoost algorithm for prediction and classification of different datasets. International Journal of Control Theory and Applications, 9(40), 651-662.
[7] Liu, L., Meng, J., & Yang, Y. (2024). LLM technologies and information search. Journal of Economy and Technology, 2, 269-277.
[8] Kar, S. S., Pradhan, H. S., & Mohanta, G. P. (2010). Concept of essential medicines and rational use in public health. Indian Journal of Community Medicine, 35(1), 10-13.
[9] Kar, S. S., Pradhan, H. S., & Mohanta, G. P. (2010). Concept of essential medicines and rational use in public health. Indian Journal of Community Medicine, 35(1), 10-13.
[10] Rigatti, S. J. (2017). Random forest. Journal of Insurance Medicine, 47(1), 31-39.
[11] Mahesh, B. (2020). Machine learning algorithms-a review. International Journal of Science and Research (IJSR).[Internet], 9(1), 381-386.
[12] Famili, A., Shen, W. M., Weber, R., & Simoudis, E. (1997). Data preprocessing and intelligent data analysis. Intelligent data analysis, 1(1), 3-23.
[13] Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. Egyptian informatics journal, 16(3), 261-273.
[14] Stone, D. (2005). User interface design and evaluation.
[15] Rainio, O., Teuho, J., & Klén, R. (2024). Evaluation metrics and statistical tests for machine learning. Scientific Reports, 14(1), 6086.
[16] Saabith, A. S., Vinothraj, T., & Fareez, M. (2020). Popular python libraries and their application domains. International Journal of Advance Engineering and Research Development, 7(11).

## APPENDIX A
## LIST OF FIGURES AND TABLES

### A. *Figures*



### B. *Tables*



## APPENDIX B
## FULL FORMS AND NOTATIONS

### A. *Full Forms*

- **LLM:** Large Language Model
- **ML:** Machine Learning
- **API:** Application Programming Interface
- **UI:** User Interface
- **MAE:** Mean Absolute Error
- **XGBoost:** Extreme Gradient Boosting

### B. *Notations in the Comparison Table*

- **Accuracy:** Proportion of correctly classified instances out of the total instances.
- **Precision (Weighted Avg):** Weighted average of precision scores for each class.
- **Recall (Weighted Avg):** Weighted average of recall scores for each class.
- **F1-Score (Weighted Avg):** Harmonic mean of Precision and Recall, averaged across all classes.
- **Support:** Number of instances in the test dataset.

## APPENDIX C
## MATHEMATICAL NOTATIONS AND DEFINITIONS

- **Accuracy:** $\text{Accuracy} = \frac{\text{True Positives}+\text{True Negatives}}{\text{Total Instances}}$
- **Precision:** $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$
- **Recall:** $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$
- **F1-Score:** $\text{F1-Score} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$

## APPENDIX D
## MODEL PARAMETERS AND TUNING DETAILS

### A. *XGBoost Parameters*

- Learning Rate: Randomly chosen from [0.01, 0.05, 0.1]
- Max Depth: Randomly chosen from [4, 6, 8]
- Subsample: Randomly chosen from [0.8, 1.0]
- Colsample by Tree: Randomly chosen from [0.8, 1.0]
- Balancing Strategy: Weighted class balancing using `scale_pos_weight`

### B. *Randomized Search Hyperparameter Tuning*

- Number of Trees (`n_estimators`): Randomly chosen from [100, 200, 300]
- Max Depth (`max_depth`): Randomly chosen from [4, 6, 8]

- Learning Rate (`learning_rate`): Randomly chosen from [0.01, 0.05, 0.1]
- Subsample (`subsample`): Randomly chosen from [0.8, 1.0]
- Colsample by Tree (`colsample_bytree`): Randomly chosen from [0.8, 1.0]
- Weight Balancing (`scale_pos_weight`): Randomly chosen from [1, 2, 3]
- Cross-Validation Folds (`cv`): 3
- Scoring Metric: Weighted F1 Score (`f1_weighted`)
- Number of Iterations (`n_iter`): 20
- Random State: 42

### *C. Implementation Details*

- `RandomizedSearchCV` was used to optimize the hyperparameters with `n_jobs = -1` for parallel processing.
- The model was trained using a balanced dataset to mitigate class imbalance effects.

## APPENDIX E
## DATASET DETAILS

- Total Records: 20,000
- Training Split: 80%
- Testing Split: 20%
- Features: Age, Gender, Technology Usage Hours, Screen Time Hours, Mental Health Status, Stress Level, Sleep Patterns
- Source: Mental Health & Technology Usage Dataset [5]