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# Mindcare360 - A Mental Fatigue Detector and Personality Based Relief Planner

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**Abstract- Within the contemporary digital landscape, individuals often encounter mental fatigue stemming from extended screen time, disrupted sleep cycles, and occupational stressors. The early identification of mental fatigue is crucial for sustaining productivity, emotional equilibrium, and overall health. Conventional wellness applications typically offer broad suggestions that do not account for individual variations in personality and lifestyle. This constraint diminishes the efficacy of these systems in mitigating mental fatigue[1]. This study introduces MindCare 360, an intelligent wellness framework that employs machine learning and explainable artificial intelligence (XAI) to identify mental fatigue and formulate personalized strategies for relief planner. The proposed system employs dual Random Forest classifiers to predict fatigue levels and personality types based on behavioral and lifestyle attributes such as sleep duration, stress levels, physical activity, social interaction, and screen time. Customized daily wellness strategies, segmented into morning, afternoon, evening, and night routines, are generated by integrating the outputs of these models through a rule-based decision-making process. Predictions, confusion matrices, and analyses of feature impact are presented via a Streamlit dashboard, designed with user experience as a priority. Furthermore, the Explainable AI component enhances transparency and builds user trust by elucidating the influence of various lifestyle factors like sleep hours ,sleep quality, and stress score based on their reactions to various situvations on fatigue predictions. Experimental assessments indicate that the proposed system accurately predicts fatigue levels while offering actionable and personalized relief suggestions. The MindCare 360 framework underscores the potential of integrating predictive analytics with personalized wellness planning to aid proactive mental health management.**

**Keywords: Machine Learning, Mental Fatigue Detection, Explainable AI, Personality Prediction, Digital Wellness, Random Forest, Streamlit Dashboard.**

## I. INTRODUCTION

The increasing academic demands, professional responsibilities, and digital lifestyle choices characteristic of modern society have engendered a greater emphasis on mental health. Mental fatigue, a state of cognitive depletion resulting from prolonged mental activity, can significantly diminish productivity and cognitive performance [1]. Therefore, the early identification of fatigue symptoms is crucial for mitigating the risk of chronic psychological distress and burnout.

Presently, numerous digital wellness applications prioritize the monitoring of physical health indicators, including step counts, heart rate, and sleep cycles. Nevertheless, these systems frequently neglect the assessment of behavioral and psychological patterns that contribute to mental fatigue. Moreover, the majority of platforms provide generalized recommendations that fail to consider the user's unique personality characteristics or lifestyle.

For example, the coping mechanisms that prove beneficial for an extroverted person might differ significantly from those suitable for an introverted individual.

Recent advancements in machine learning and data analytics have facilitated the creation of intelligent systems capable of identifying behavioral trends and predicting mental health challenges [3]. Machine learning models can aid in the early identification of mental fatigue by analyzing variables such as sleep quality, stress levels, social interactions, and daily routines.

To overcome the limitations of current systems, this research introduces MindCare 360, a machine learning-based framework designed to predict mental fatigue and provide personalized wellness recommendations. The system employs two Random Forest classification models: one for fatigue evaluation and the other for personality assessment. The outputs generated by these models are subsequently used to develop tailored daily relief strategies.

## II. LITERATURE REVIEW

Several studies have explored the use of machine learning techniques for detecting mental health conditions and predicting behavioral patterns. These approaches demonstrate the potential of data-driven methods in identifying early indicators of psychological stress and fatigue.

S. Kumar et al. (2021) proposed a machine learning model for stress detection using physiological signals such as heart rate variability and sleep patterns. The study used Support Vector Machine and Random Forest algorithms to classify stress levels. While the system achieved high prediction accuracy, it relied heavily on wearable sensor data and did not provide personalized coping strategies.
J. Smith and R. Lee (2020) investigated the use of social media behavior for personality prediction. Their model analyzed online interaction patterns and applied logistic regression and Random Forest classifiers to identify personality traits. Although the research demonstrated effective personality classification, the system focused solely on personality detection and did not consider mental health indicators.

A. Sharma et al. (2022) developed a digital wellness platform that monitors user activity patterns such as screen time, work hours, and sleep habits to detect mental fatigue. The system utilized machine learning algorithms to identify fatigue levels. However, the recommendations provided by the platform were generic and not tailored to individual personality characteristics.

M. Patel and K. Shah (2019) introduced a stress prediction model using behavioral data collected from smartphone sensors. Their research highlighted the effectiveness of machine learning models in detecting stress patterns. Despite achieving promising results, the study lacked an explainability mechanism to interpret the model predictions.

L. Wang et al. (2023) explored the use of Explainable Artificial Intelligence (XAI) techniques to improve transparency in mental health prediction systems. The study applied feature importance analysis to explain the contribution of different variables in predicting stress levels. However, the system did not incorporate personalized intervention strategies.

From the literature review, it is evident that many existing systems focus primarily on prediction of mental health conditions but rarely provide personalized relief strategies based on personality traits. Furthermore, transparency in machine learning predictions is often limited [4].

The proposed MindCare 360 framework addresses these gaps by combining fatigue detection, personality prediction, and explainable AI to generate customized daily wellness plans.

## III. METHODOLOGY / PROPOSED SYSTEM

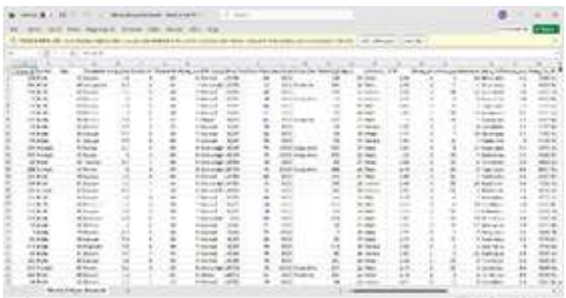
This study's main contributions involve creating a dual-system approach. The proposed system uses a structured framework, including data input, machine learning predictions, and personalized relief generation. The MindCare 360 architecture combines behavioral data analysis with machine learning models to offer personalized mental wellness guidance.

**DATA COLLECTION AND PREPROCESSING**
**The system uses two datasets:**
- Mental_Fatigue_Balanced Dataset
- Personality classification dataset

The fatigue dataset comprises several attributes, specifically:
- Age
- Gender

- Sleep Hours
- Sleep Quality
- Physical Activity
- Stress Score

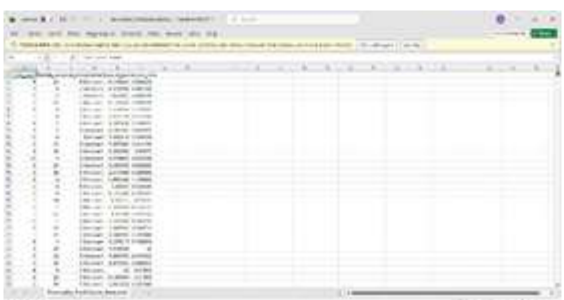
These characteristics serve as the basis for classifying fatigue levels into Low, Medium, and High categories [5].



Conversely, the personality dataset encompasses behavioral attributes, including:

- Time spent alone
- Number of close friends
- Participation in social events
- Social interaction score
- Screen time usage

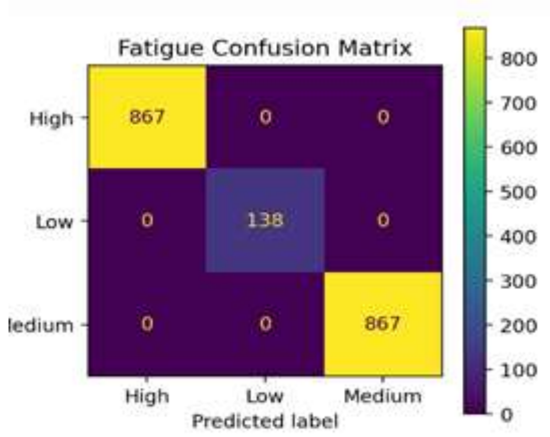
These features are utilized to categorize individuals as Introvert, Ambivert, or Extrovert.



Data preprocessing steps, including the handling of missing data, dataset balancing [6], and the normalization of numerical features, are implemented to improve model efficiency.

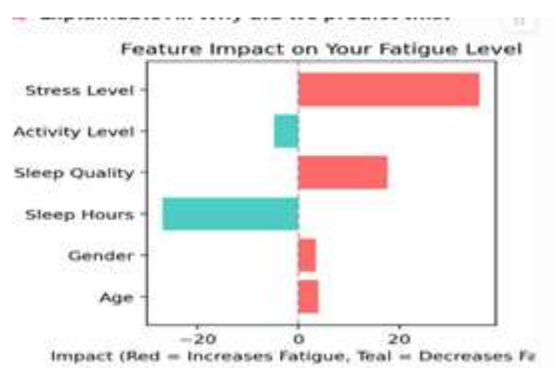
## IV. MACHINE LEARNING MODEL

The system employs Random Forest classifiers for the tasks of fatigue detection and personality prediction [7]. Random Forest was selected due to its capacity to manage complex datasets, reduce overfitting, and provide insights into feature importance. The fatigue model predicts the level of mental fatigue, utilizing lifestyle and behavioral data. Conversely, the personality model categorizes the user's personality type, based on their social interactions and behavioral tendencies.




**EXPLAINABLE AI COMPONENT**

To enhance transparency, the system derives feature importance values from the Random Forest model [8]. These values elucidate the impact of each input factor on the ultimate prediction. For instance, diminished sleep quality or elevated stress scores may substantially elevate fatigue levels.




**PERSONALIZED RELIEF PLANNER:**

The outputs from the fatigue and personality models are subsequently processed via a rule-based system, which generates tailored wellness strategies. These recommendations are organized into four daily segments [9]:

- Morning routine
- Afternoon activities
- Evening relaxation
- Night recovery plan

The strategies are contingent upon the specific combination of fatigue level and personality type [10].

## V. SYSTEM ARCHITECTURE

The system architecture of the proposed MindCare 360 framework is designed to analyse behavioral data analysis, machine learning prediction, and personalized wellness recommendation. The architecture consists of several interconnected modules that work together to detect mental fatigue and generate customized relief planer generation for users.

The first stage of the system involves data collection and preprocessing. Behavioral and lifestyle data such as sleep duration, stress levels, physical activity, social interaction frequency, and screen time are collected from the datasets. This data is cleaned to remove missing values and normalized to handle categorical value across different features. Data preprocessing improves the quality of the datasetby process like data cleaning and normalizing and enhances the performance of the machine learning models.

The second stage involves machine learning prediction models. Two Random Forest classifiers are used in the system. The first model predicts the user's mental fatigue level, categorizing it into low, medium, or high fatigue. The second model predicts the personality type of the user, classifying individuals as introvert, ambivert, or extrovert based on behavioral data. Random Forest was selected because of its high accuracy, ability to handle complex relationships between variables, and to avoid overfitting.

The third stage includes the Explainable Artificial Intelligence module. Feature importance analysis is used to identify which lifestyle factors have the greatest impact on the fatigue prediction. This helps users understand how variables such as sleep quality, stress levels, and physical activity influence their mental fatigue. Providing transparency in the prediction process improves user trust and interpretability of the system.

The fourth stage is the Personalized Relief Planner. The outputs from the fatigue detection model and personality classification model are combined using a rule-based decision mechanism. Based on the predicted fatigue level and personality type, the system generates relief planner based on their personality and fatigue level, to reduce mental fatigue and improve well-being.

Finally, the system results are displayed through an Streamlit dashboard. The dashboard visualizes model predictions, confusion matrices, feature importance charts, and fatigue level distributions. This interface enables users to easily monitor their fatigue status and understand the factors influencing their mental wellness.

The overall architecture enables the integration of predictive analytics, explainable AI, and personalized wellness planning within a single intelligent framework.

## VI. RESULTS AND DISCUSSION

The proposed models underwent evaluation utilizing performance metrics, including accuracy, precision, recall, and F1-score. The Random Forest classifier exhibited robust performance in predicting both fatigue levels and personality traits.

The system dashboard presents a variety of visualizations, encompassing confusion matrices, correlation heatmaps, and personality radar charts [11]. These visualizations facilitate the analysis of the relationships between diverse behavioral factors and fatigue levels.

Feature importance analysis indicated that sleep quality, stress score, and physical activity were among the most influential variables in predicting fatigue levels. Similarly, the frequency of social interaction and the amount of time spent alone were critical in personality classification [12].

## VII. CONCLUSION

This research introduced MindCare 360, an intelligent framework engineered to identify mental fatigue and deliver personalized wellness strategies through the application of machine learning methodologies. The system incorporates dual Random Forest classifiers for both fatigue detection and personality prediction, alongside explainable AI to augment transparency within the decision-making process.

Empirical evidence supports the framework's effectiveness in identifying fatigue patterns and developing personalized relief strategies, which are tailored to individual personality traits. Moreover, the inclusion of an interactive dashboard improves user engagement through the visualization of predictions and model performance metrics.

Future research can expand the system by incorporating real-time wearable sensor data, advanced deep learning models, and larger datasets to improve prediction accuracy. Additionally, integrating natural language processing for mood analysis from user journals may further enhance personalized mental health support. The MindCare 360 framework demonstrates how machine learning and explainable AI can be leveraged to develop proactive and personalized digital wellness solutions.

## VIII. FUTURE WORK

Although the proposed MindCare 360 framework demonstrates promising results in detecting mental fatigue and providing personalized relief strategies, several improvements can be made in future research.

One potential enhancement is the integration of real-time sensor data like watches which gives further information like such as heart rate, sleep tracking, and physical activity from smart devices. By giving physiological signals can significantly improve the accuracy of fatigue detection by combining behavioral data with biological indicators.
Another improvement involves the use of advanced deep learning models, such as neural networks or hybrid machine learning techniques, to capture more complex relationships between lifestyle factors and mental fatigue. These models may further enhance prediction performance when trained on larger datasets.

Future work can also explore the use of natural language processing (NLP) techniques to analyze user-generated text data such as personal journals, daily reflections, or chat interactions. Sentiment analysis and emotion detection can provide deeper insights into the user's psychological state and improve personalized wellness recommendations.
We can also improve by going deep into the relief planner by adding psychological medicines and techniques so that it can help more in the field of healthcare.

Additionally, the system can be expanded by developing a mobile application version that allows users to receive real-time fatigue predictions and daily relief plans directly on their smartphones. Integrating notification systems and personalized reminders could further encourage users to follow healthy routines.

By incorporating these improvements, the MindCare 360 framework can evolve into a more comprehensive digital mental wellness platform capable of supporting proactive mental health management.

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