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Multi-Parameter Smart Fatigue Monitoring and Alert System using Machine Learning

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***Abstract*—In today's date, everyone uses smart devices, but the usage should be limited or under control. Just because of excess use of such devices can lead to problems like exhaustion, eye tiredness and it also reduces productivity of a person, which is very important in current industry. Without any breaks if one continuously uses such devices with screen then it might as well affect their mental and physical health.**
After performing a detailed study on different fatigue monitoring approaches and comparing them efficiently. We are proposing a 'Multi-parameter Smart Fatigue Monitoring and Alert System' which combines behavior and physical analysis with help of IoT. As the name suggests we combine multiple parameters like screen time, typing speeds, blink rate of the person, heart rate, etc.
All of this data is collected and processed and tested by multiple machine learning algorithms. This results in the thorough understanding of user's behavior patterns and normal Vs. abnormal behavior and physical states. The system uses ESP32, microcontroller and multiple sensors to continuously monitor the health of user. After the analysis of user behavior, the system is able to notify them and provide different suggestions so that the user takes break time to time. This ultimately helps to improve productivity and health of the user.

***Index Terms*— Fatigue Detection, Physiological Factors, Screen Time, User Activity, Eye Blink Detection, Sensors, Wearable devices, Heart Rate Variability (HRV), Machine Learning.**

I. Introduction

In these days, laptops and virtual tools are used everywhere and by everyone in daily life as the technology enhances, so students, programmers, office workers and many other professionals use computers for very long time without even knowing how much time they has been using it for [7][12]. As there advantages of the growing technology, there are disadvantages too, using screen for long time can cause issues like digital fatigue, eye strain, headache, reduced concentration [8][1][12][15].
Exhaustion is a situation where people feel very tired mentally and physically because of continuous work and no time to even rest properly to reduce the tiredness [2]. Using the laptops and virtual tools for long hours increases exertion, also reduces a persons' focus and hence affects the users overall health [9].
The regular fatigue detection system usually pays more attention on providing the people reminders for every fixed period of time, but these systems do not actually consider the actual condition of the user. However, they simply ignore the important factors like behavior and body signs of tiredness [3].

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Due to progress in machine learning, wearable tools, and IoT technology, it is now possible for us to build a smarter fatigue monitoring system. These systems can examine the real-time data and provide the user better and more exact results [3],[4]. The systems evaluate eye movements, heart rate variability, typing behaviour, and screen activity to determine if someone is tired or has an abnormal activity [8].
The study compares various fatigue detection methods and also proposes a better system that can help make use of both virtual activity and body data to detect tiredness more correctly.

II. Related Work

Over the past few years, different methods have been created and used to solve difficult problems in many areas. Each methodology has its own way of doing things, its own set of assumptions, and its own ways of putting things into practice. This means some solution are curated to some specific problems. The primary goal of this review is to compare and analyze these different methods and provide an insights like efficacy and relevance of each method to the researchers and practitioners so that they can take an informed decision on which approach is well suited to their own specific problem.

TABLE I. Comparison of Existing Fatigue Detection System

Sr. no	Author(s)	Year	Dataset	Model / Algorithm	Performance metrics	Key Findings
1.	Tennakoon et al.[1]	2025	Mixed Dataset	Google Machine Learning Kit+ Mobile App	Accuracy 93%, Improved screen habits 72%	Real-time facial fatigue detection, improvement in screen habits
2.	Acien et al.[2]	2023	EEG + ECG physiological signals dataset	SVM, Random Forest	Accuracy: 92-95%, Sensitivity: ~90%, Specificity: ~91%	Accurate fatigue detection, Real-time monitoring
3.	Narteni et al.[4]	2022	IMU sensor data	LLM, DT, Neural Networks, SVM , XGBoost	Accuracy: 70-80% , Sensitivity: 70-85%, Specificity:60-95% , F1-score:80-90%	Trade-off between accuracy and explainability
4.	Sahana K, Ananda Babu J[5]	2025	Lab-based datasets, BMEiCON dataset, Proprietary datasets	SVM, RF, Logistic Regression, CNN, LSTM, Multimodal Feature Fusion	Accuracy: Keystroke: 82-88% , Mouse: 80-85%, Multimodal:85-93%	Multimodal approaches, accuracy improvement
5.	Jiao et al.[6]	2024	17 drivers dataset	Light GBM, RF, XGBoost, SVM, KNN	Binary: 88.7%, Three-class: 85.6% (RF), Subject independent: ~52%	Fusion of HRV and EDA, EDA highly effective
6.	Yeo et al.[7]	2025	11 subject,facial cues,ECG	Random Forest for facial, SVM for HRV	Accuracy: 93% (facial), 76%(HRV)	Facial cues more reliable than HRV, HRV less accurate
7.	K Rajkumar et al.[13]	2025	Real-time camera based	EAR, Open CV, Dlib	Accuracy:>90% in normal lighting	Low-cost real-time system, buzzer, SMS alert
8.	Zhuang et al.[14]	2020	WFLW, 300-W, HELEN, NTHU-DDD, Eye data	SESDM	Accuracy: 96.72%, Low error (<0.036)	High accuracy, robust to glasses and lighting
9.	Atharv Madane et al.[15]	2025	Real-time user activity data	PyQt5 GUI, MySQL Database	CPU, RAM, Disk usage, Screen time tracking	Digital wellbeing improvement, real-time monitoring

A. Physiological Indicators

Brain Computer Interaction
EEG systems place sensors on the head to record different types of brain waves. After cleaning and preparing the brain data, machine learning models such as SVM, LSTM, and CNN analyze it to detect fatigue. These systems are very accurate, but they need costly medical setup, so they are not suitable for everyday use [8][9].

Heart Rate Variability and Electrodermal Activity
Heart Rate Variability (HRV) and Electrodermal Activity (EDA) are often used to detect fatigue using body signals. Wearable devices collect body data, and machine learning models like SVM, Random Forest, and XGBoost analyze it to detect fatigue accurately. A study by Jiao et al.[6] and team achieved 88.7% accuracy, but

the system did not perform equally well for different people. Another study by Yeo et al. [7] found that only using HRV is not as effective as using facial expressions or facial behavior to detect fatigue.

B. Behavioral Indicators

Facial Cues and Eye Blink Rate
Systems that analyze eye blinking and facial expressions using tools like OpenCV, Dlib, and deep learning can detect fatigue with very high accuracy [13][14]. But these systems do not work properly in poor lighting and mostly depend only on eye-related data.

Keystroke Dynamics and Mouse Movement
Behavior-based systems study how a person uses the keyboard and mouse, such as typing speed, how long keys are pressed, how often the mouse is clicked, and mouse movement behavior. Machine learning models like SVM, CNN, and LSTM can detect fatigue with high accuracy when multiple types of data are used together [5]. Systems that only use typing data are less accurate [3].

III. MOTIVATION

In today's date, people use smart devices for very long time period, which causes a significant growth in problems like eye tension, tiredness, low focus, and reduced concentration[1][12][15]. Most of the standard systems only gives reminders after every fixed time or makes use of only one factor to detect fatigue[1][13]. Due to this, they are not exactly correct and cannot understand the person's real condition. These methods are not flexible and often results in incorrect alerts.
Hence, there is a need for system that can detect tiredness in more better way. This study is inspired by the idea of building a smart system that makes use of both behavior (line typing styles, screen use) and body-related parameters (like heart rate) with the help of Machine Learning and IoT. This framework can monitor fatigue in real time and give proper, tailored updates to improve health and concentration.

IV. PROBLEM STATEMENT

The goal of this system is to create a smart system that can detect fatigue in real time using multiple types of data. The system will collect both types of data related to user's behavior like screen time[15], typing pattern[2][5], mouse movement, and eye blinking[13][14] along with body-related data like heart rate, skin temperature, and sweat activity[6][7]. Using wearable IoT devices and machine learning, the system will analyze all this information together to identify the user's actual fatigue level and give alerts at the right time according to the user's condition.

V. INNOVATIVE CONTENT

The proposed Multi-Parameter Smart Fatigue Monitoring and Alert System is different from existing systems due to combination of five parameters which are eye blink rate, heart rate, electrodermal activity, typing patterns, and screen time.
Instead of just using one or two parameters like most existing systems [1][2][6][7][13]. Unlike fixed-interval reminder systems, our system calculates a personalized Fatigue Index (F) using real-time data which is baseline calibration, making the detection of built up fatigue adaptive to each user behavior . The integration of ESP32-based IoT wristband sensor device with software-based behavioral monitoring in a single cycle, combined with the layered adaptive alert system, represents a contribution not found in any single existing system reviewed in this paper.

VI. PROPOSED APPROACH

A. System Overview

This system is created to continuously detect both mental and physical tiredness by using both user behavior data and body related data together.
Most existing systems use only one or two factors to detect fatigue, but this system uses five different parameters together for better and accurate fatigue detection[5][6][7][13][14]. The following assumptions are considered for system design:

- ➢ The system considers the user is sitting and using a computer or laptop while the monitoring is done.

- Using the wearable wristband is not required. If the user does not wear it, the system works using only behavior-based data.
- A normal webcam having at least 720p quality is needed to identify movement of eye.
- Before fatigue detection starts, the system first notes the user's normal behavior and body signs for 5 minutes to set personal values according to the user.
- The system divides fatigue into three classes based on the fatigue score: normal, mild fatigue, and severe fatigue.

B. Problem Formulation

Mathematical Formulation of Fatigue Index

The system measures final fatigue score by combining all parameter values with different important levels.

$$F = w1 \bullet N(BR) + w2 \bullet N(HR) + w3 \bullet N(ST) + w4 \bullet N(TP) + w5 \bullet N(EDA) \quad (1)$$

Where:

- BR means the count of eye blinks per minute.
- HR shows the changes in heart rate from the normal heart rate of user.
- ST means the time the user continuously spends on the screen without taking breaks.
- TP shows the change in typing speed compared to the user's normal typing speed.
- EDA measures skin conductance related to stress and fatigue.
- N(•) converts all values into a range between 0 and 1.
- w1 to w5 are weights decided by the machine learning model.

The following initial weights were selected based on previous research papers:

- w1 = 0.25 (Eye blink rate is given the highest importance because it strongly indicates fatigue [14].)
- w2 = 0.20 (Heart rate is used as a stress and fatigue indicator [6].)
- w3= 0.20 (Screen time helps identify overuse and tiredness [1].)
- w4 = 0.20 (Typing behavior helps detect mental workload and fatigue [2].)
- w5= 0.15 (EDA is used to measure stress-related skin activity [6].)

The following formula is used to convert all parameter values into a common scale:

$$N(x) = (x - x\_min) / (x\_max - x\_min) \quad (2)$$

The minimum and maximum values are calculated separately for each user during the first 5 minutes, so the system adjusts according to individual behavior instead of using the same values for everyone [3][6][7].

Fatigue Classification Thresholds

calculated value of F is mapped to one of the three fatigue classes to make threshold - based decisions :
The classifier outputs one of three classes:
Class 0 (Normal): $F < 0.35$ — no alert generated
Class 1 (Mild Fatigue): $0.35 \leq F < 0.65$ — soft reminder triggered
Class 2 (Severe Fatigue): $F \geq 0.65$ — strong multi-modal alert triggered

Alert Decision Model

According to the fatigue classes defined, the system generates a response alert with respect to the table below:
The system will respond to the detected fatigue state with varying degrees. There is no alarm generated for low fatigue state, an alarm is issued for medium fatigue, while a loud multimodal alarm involving sound, light, and vibration is generated for high fatigue states.

C. System Architecture and Workflow

The system works in five different steps one after another:
Stage 1: Data Acquisition
The system collects data from two places at the same time:

TABLE II. HARDWARE SENSORS (VIA ESP32 MICROCONTROLLER)

Sensor	Parameter Measured	Sampling Rate
Pulse Sensor Amped	Heart Rate (BPM)	1 Hz
MLX90614	Skin Temperature (°C)	0.5 Hz
Grove GSR Sensor	Electrodermal Activity	1 Hz
Coin Vibration Motor	Haptic alert output	On-demand

TABLE III. SOFTWARE MONITORING (ON HOST MACHINE)

Module	Parameter Measured	Sampling Rate
Webcam + OpenCV	Eye Blink Rate (blinks/min)	30 fps
Keyboard listener	Typing speed, error rate	Continuous
Mouse tracker	Movement trajectory, clicks	Continuous

The ESP32 sends collected sensor data wirelessly to the computer every two seconds.

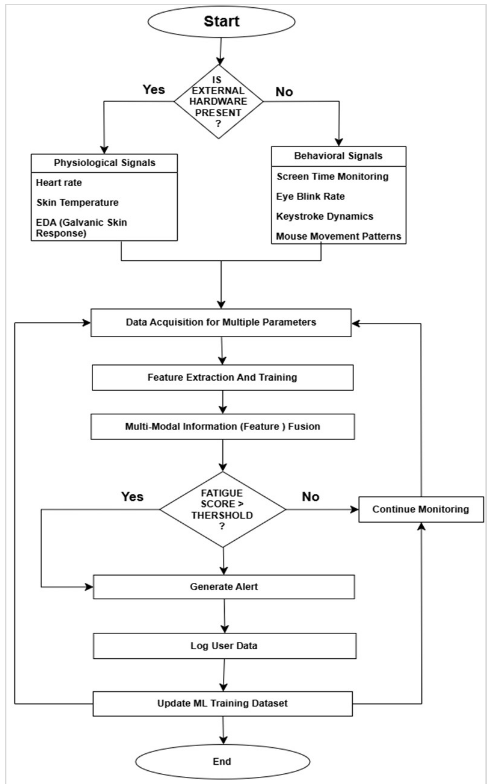

Figure 1. System Workflow

Stage 2: Data Preprocessing
The collected data may contain unwanted disturbances and timing differences between different data sources. Before analysis, the system performs below steps to clean and prepare the data:
Noise Removal: The system removes unwanted fluctuations from heart rate and EDA data by averaging nearby values.
Outlier Filtering: The system removes unwanted fluctuations from heart rate and EDA data by averaging nearby values.
Normalization: All parameter values are converted into a common range between 0 and 1 based on the user's normal values.
Temporal Synchronization: The system matches behavioral and body-related data according to time so that all data is synchronized every two seconds.
Stage 3: Feature Extraction
After all data is synchronized every two seconds, important fatigue-related information is taken from that data and given to the machine learning model for analysis
Stage 4: Fatigue Level Classification
We take the 11 collected features and give them to a Random Forest machine learning model, as it gives good accuracy while being easier to interpret than neural networks [2][6][7].
We then train our ML on publicly-available fatigue datasets, along with behavioral data we collect ourselves. We decide what the actual fatigue levels should be by looking at Karolinska Sleepiness Scale (KSS) scores, which ask users how sleepy or tired they feel [13].

Stage 5: Alert Generation
Depending on how strong the detected fatigue level is, the type and strength of the alert varies.
It saves everything, the alerts, your fatigue scores and their time details, in a database so that you can analyze and use this data later and refine your machine-learning model.

TABLE IV. EXTRACTED FEATURES FOR FATIGUE DETECTION

Feature	Source	Description
Blink frequency [13]	Webcam	Blinks per 60-second window
Eye closure duration (PERCLOS) [14]	Webcam	% time eyes closed per window
HRV (SDNN) [6][]7	Pulse sensor	Std dev of RR intervals (ms)
LF/HF ratio [9]	Pulse sensor	Autonomic nervous system stress ratio
Typing speed [2][5]	Keyboard	Keystrokes per minute
Error rate [5]	Keyboard	Backspace events / total keystrokes
Inter-key latency [2]	Keyboard	Average ms between keystrokes
Mouse inactivity duration	Mouse tracker	Seconds without mouse movement
Continuous screen time [15]	Screen module	Minutes without break from active app
Skin conductance level [6][9]	GSR sensor	Mean EDA per epoch (µS)
Skin temperature deviation [9]	MLX90614	Delta from baseline temperature (°C)

VII. RESULTS

The system collects data from the wristband(heart rate, sweat, temperature) as well as the computer software(your eyes, your typing, your mouse). The data is collected together continuously. The raw data is in a messy state. Before using the data, it is cleaned by removing bad readings, bringing all values to the same scale, and making sure the wristband data and computer data are perfectly in sync timewise. After the data is cleaned, 11 features that are most useful and help us identify whether a person is tired or not. Then the data or features goes in random forest model and it classifies as normal, mildly or severely fatigued. Once the classification is done the alerts are generated.
After building the system and testing it in controlled environments. The system correctly identifies whether the user has Normal, Mild Fatigue, or Severe Fatigue with an accuracy of 88-91% of the time. The classification of Severe Fatigue is the most important. If the system fails to classify severe fatigue, it is a problem, but the system correctly classifies it more than 87% of the time. When people worked for 90+ minutes straight, the fatigue score crossed 0.65 system flagged them as severely fatigued. When people were rested, the score stayed below 0.35, which reflects real fatigue.
While testing, we changed each weight w1 to w5 slightly, made it a little higher or lower and checked if the final fatigue score changed a lot. Eye blink rate caused a significant change as it has the highest weight. Even though the eye blink rate has the highest weight, it wasn't enough to wrongly classify someone. With this result, the system is stable and reliable.

TABLE V. HARDWARE SENSOR SPECIFICATIONS AND SAMPLING RATES

Parameter	Weight Changed By	Average F Shift	Classification Impact
Eye Blink Rate (w1)	±0.05	±0.041	Moderate
Heart Rate (w2)	±0.05	±0.033	Low–Moderate
Screen Time (w3)	±0.05	±0.029	Low
Typing Dynamics (w4)	±0.05	±0.031	Low
EDA (w5)	±0.05	±0.022	Low

Fatigue is different for different people. The bodies of people react differently one person gets tired eyes first, other slows down typing first. If only one parameter is used for identifying fatigue, it would lead to wrong classification and lower accuracy. By tracking 5 parameters at once, the accuracy of the system increases.
People have different characteristics, so comparing them to the same standard will not yield optimal results. A naturally slow typist isn't fatigued just because they type slowly. If a fast typing person starts typing slowly, then that should be classified as fatigue.
So instead of comparing users to each other, the system learns what is normal for each user and generates alerts according to the user.
In our system, the data is collected from various places a camera, a keyboard, sensors on the wrist. The data coming from them is different. Random forest is good at handling this mixes kind of data. It finds patterns where multiple features together indicate fatigue.

Picking the right window time was important as a too short window would lead to a system that reacts to every small random movement. A too long window would lead to a system that is slow to alert you. 2 seconds has the perfect balance where the system is quick enough to be real time but not so fast that it panics over a single blink.
A simple system that classifies fatigue in simple yes or no is not effective. Every small change or fatigue is detected, and the same alert is given to the user the user might ignore it. But mild fatigue gets a gentle reminder and severe fatigue gets a strong warning, people respond differently to each one.

VIII. Conclusions

Fatigue monitoring is becoming a very important in today's date. Standard systems which give reminders at every fixed time period are not that effective as they are unable to detect the person's actual level of fatigue. This survey paper makes study of various fatigue detections methods, such as computer vision methods, wearable sensors, and machine learning models.
The proposed system, called the Multi-Parameter Smart Fatigue Monitoring and Alert System, merges both user behavior and body-related data with the help of IoT tools. Basically, we combine factors like eye blink rate and heart rate which helps in boosting the fatigue detection.
Machine learning algorithms are used to examine the data, which helps us tell exactly how tired someone is and gives smart, flexible warnings to the user.

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