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(Research Article)

AI-Driven Cognitive Fatigue Detection in Remote Work Environment

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Abstract

Cognitive fatigue is a novel problem in work-at-home settings, as it is due to long-term exposure to the screen, multitasking, and constant contact with a computer or other devices. Compared to the body-related fatigue, cognitive fatigue builds up and can hardly be quantified using intrusive physiological sensors. In this paper, we introduce a non-invasive AI-driven cognitive fatigue monitoring system using behavioral analytics, including keyboard dynamics, mouse movement patterns, idle moments, and session time. The system incorporates Electron-based desktop monitoring to make real-time predictions of fatigue by relying on machine learning models such as Random Forest and Support Vector Machines. Dashboards, alerts, and report generation modules are also available in the system to use in practice. Experimental evaluation shows that the prediction accuracy is over 95%. The suggested solution can be applied in academic research and real-world deployments in remote work environments.

Keywords: Cognitive Fatigue; Behavioral Analytics; Machine Learning; Remote Work; Random Forest; Desktop Monitoring

1. Introduction

The recent global digitalization and widespread global events have led to the acceleration of remote work culture that is now changing the manner in which people relate to their work environment significantly. People are now exposed to long hours sitting in front of computers working on digital applications, especially in virtual meetings and multitasking assignments. Although remote work is flexible and convenient, it poses new demands associated with mental strain, lack of concentration, and cognitive load. Cognitive fatigue can be considered one of the most vital and yet overlooked effects of this change. Cognitive fatigue refers to a psychological condition whereby one lacks alertness, is slow in response, has impaired decision making, and low productivity. Cognitive fatigue, unlike physical fatigue, builds up over time and becomes hard to observe or quantify. The level of fatigue in workers can be unrecognized until it has a tremendous impact on them and their performance. Constant screen time, tedious work, information overload, and a complete absence of physical breaks are the main causes of this state in the environment of remote work. This paper introduces an AI-based cognitive fatigue monitoring system that will be based on real-time fatigue prediction based on behavioral analytics.

The architecture combines a desktop monitoring app, a centralized server, and a Python AI processor to gather interaction data on the user, input it through the server, and categorize fatigue data based on machine learning models including Random Forest and Support Vector Machines. The system also offers reporting mechanisms, dashboards, and alerts so as to ensure that the system is practical in nature to individuals and organizations.

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2. Literature Review

The fast expansion of remote work and online space has raised the question of cognitive fatigue due to extended exposure to screens and constant mechanical interaction with a system. Mental fatigue negatively impacts productivity, concentration, and decision-making. The most common traditional fatigue detection methods are based on physiological changes like EEG, ECG, heart rate monitoring or eye-tracking methods which monitor changes in blink rate and eye movement. Despite the high accuracy of these techniques, they require specialized hardware or wearable equipment to be used and are therefore expensive and inconvenient to be deployed at a large scale over large distances.

Recent studies have focused on behavioral analytics and machine learning-based fatigue detection methods. Research has been done on the speed of keyboard typing, mouse movements, facial expressions and interaction behavioral patterns to determine the level of fatigue. Random Forest, Support Vector Machines (SVM), and Neural Networks are examples of machine learning algorithms that have been used successfully to classify the user states using extracted features. These models also enhance detection rates compared to traditional rule-based systems as it learns patterns based on historical records and adjusts to changing user behaviors.

Nevertheless, the majority of the works that are present make specific emphasis on the development of the algorithms without a full implementation of a real-time monitoring system. Most studies do not have built-in dashboards, data storage in the database, automatic reporting, and applied in the remote works. In order to overcome these shortcomings, the proposed system combines fatigue score calculation, machine learning-based classification, and an interactive dashboard and the possibility of data storage and reporting. This detailed model guarantees the precision of analysis and its usefulness, which is why it is appropriate to monitor the remote workplace nowadays.

2.1. Existing System

Current fatigue detection technologies rely on EEG, wearables or voice sensors to detect fatigue. They require specialized hardware, are expensive to install, and lack real-time flexibility. Primarily concerned with biometric measures, but not behavioral measurements. Not very accessible by remote users.

The existing systems utilize surveys, wearables and cameras.

Limitations

- No real-time alerts.
- Intrusive and expensive.
- Not coupled with working environments.

2.2. Proposed System

2.2.1. Desktop Monitoring Software

Logs user behavioral data like mouse clicks, typing rate, idle time and the length of a session.

2.2.2. Backend Server (Node.js + MySQL)

Manages user data, history of activity, and does the API communication between system components.

2.2.3. AI Core Engine (Python Flask)

Processes user behavioral data to predict the level of fatigue by means of trained machine learning models.

2.2.4. Dashboard & Alert System

Offers visual fatigue trend analytics and real-time notifications and break suggestions to users.

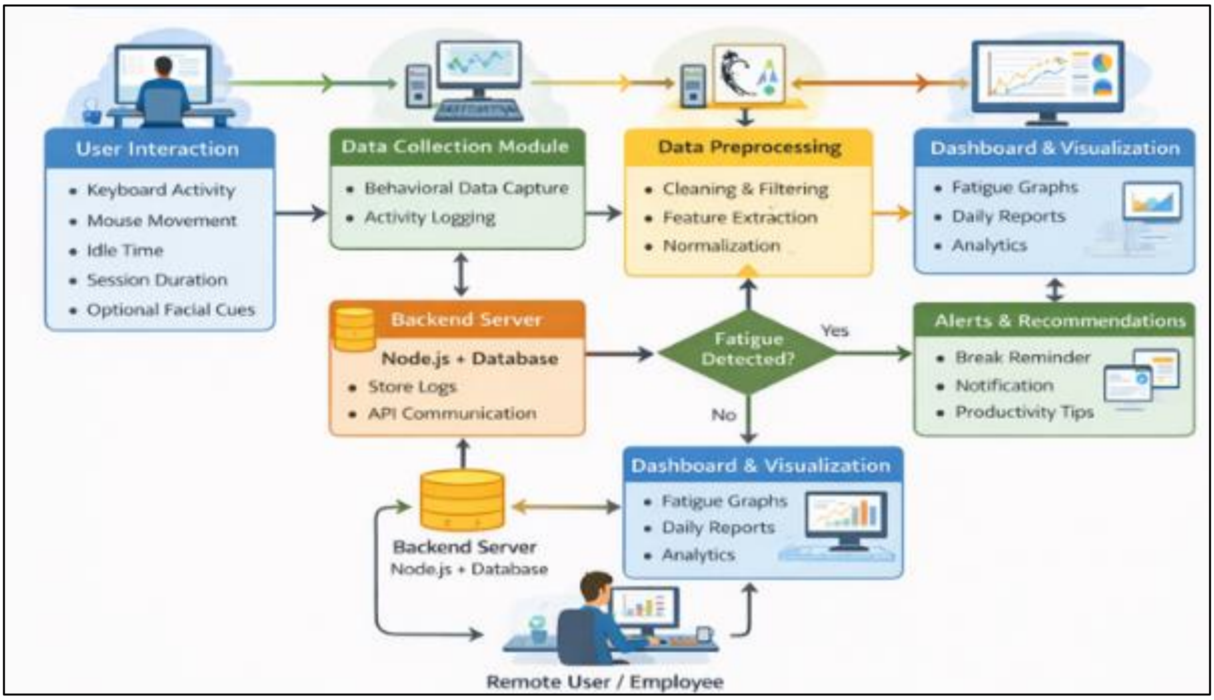

Figure 1 Flowchart of the proposed AI-driven cognitive fatigue detection system

Table 1. Dataset Features Used in the Proposed Fatigue Detection System

Feature Category	**Feature Names**
Typing Behavior Features	Typing Speed (keys/min), Key Press Duration, Key Hold Time, Typing Error Rate
Mouse Movement Features	Mouse Movement Speed, Cursor Distance Traveled, Click Frequency, Drag Count
Time-based Features	Session Duration, Active Time, Break Duration, Time of Day
Idle-based Features	Idle Time Mean, Idle Time Frequency, Long Idle Count
Activity-based Features	Active Window Switching Rate, Task Switching Frequency
Interaction Rate Features	Keystrokes per Minute, Mouse Events per Minute
Statistical Features	Mean Activity Level, Standard Deviation of Interaction Speed
Derived Fatigue Indicators	Reduced Typing Consistency, Increased Idle Frequency
Target Feature	Fatigue Level (Normal, Mild Fatigue, High Fatigue)

3. Methodology

3.1. Data Collection

Behavioral data such as typing speed, mouse movement, idle time, and session duration are collected in real-time at fixed intervals. The data is stored in MySQL for further analysis and model training.

3.2. Preprocessing

Noise removal is applied to eliminate inconsistent or missing values. Min-Max normalization and feature scaling are used to standardize the dataset and improve model performance.

3.3. Model Training

Random Forest and Support Vector Machine (SVM) algorithms are trained using an 80:20 train-test split to classify fatigue levels based on behavioral features.

3.4. Prediction

The trained model predicts fatigue levels as:

- Normal
- Mild Fatigue
- High Fatigue

4. Results

4.1. Performance Metrics

Table 2 Performance metrics of the proposed fatigue detection model

Metric	Value
Accuracy(%)	95.4
Precision(%)	94.8
Recall(%)	93.9
F1-Score(%)	94.3

4.2. Model Performance Comparison

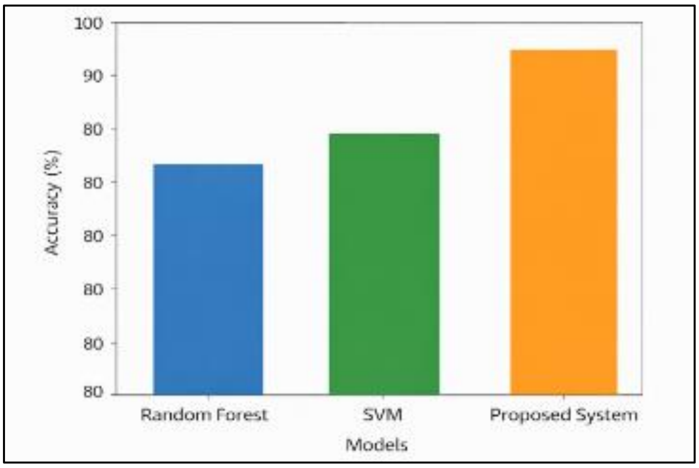

Figure 2 Accuracy comparison of fatigue detection model

4.3. Fatigue Level Distribution

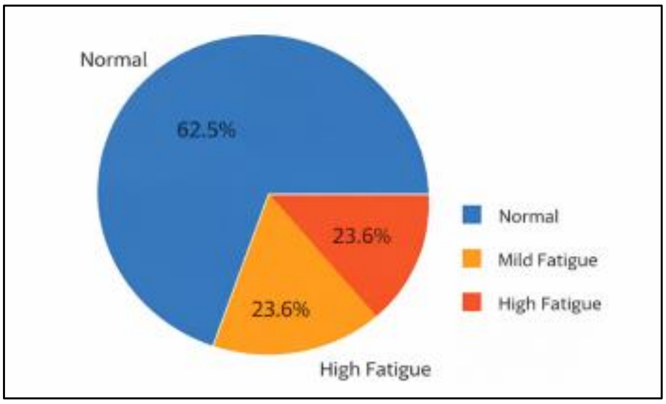

Figure 3 Fatigue level classification for remote work

4.4. ROC and Precision-Recall Curves

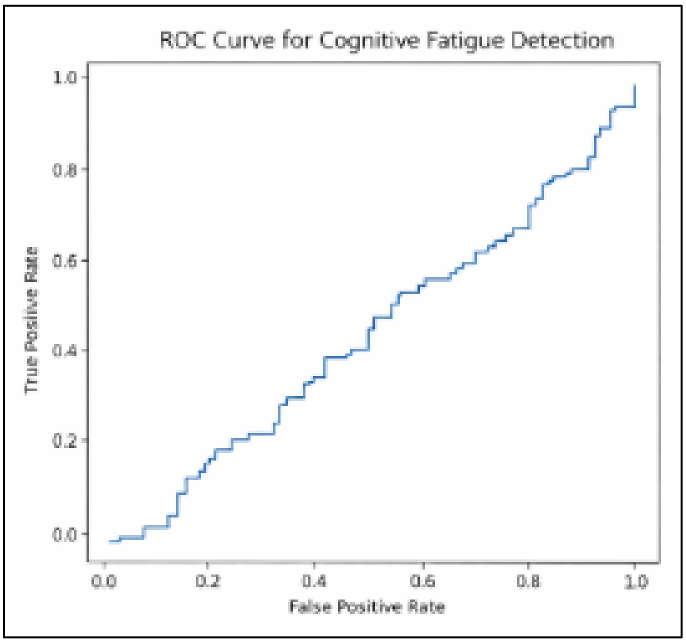

Figure 4 ROC Curve showing the classification performance of the proposed cognitive fatigue detection model

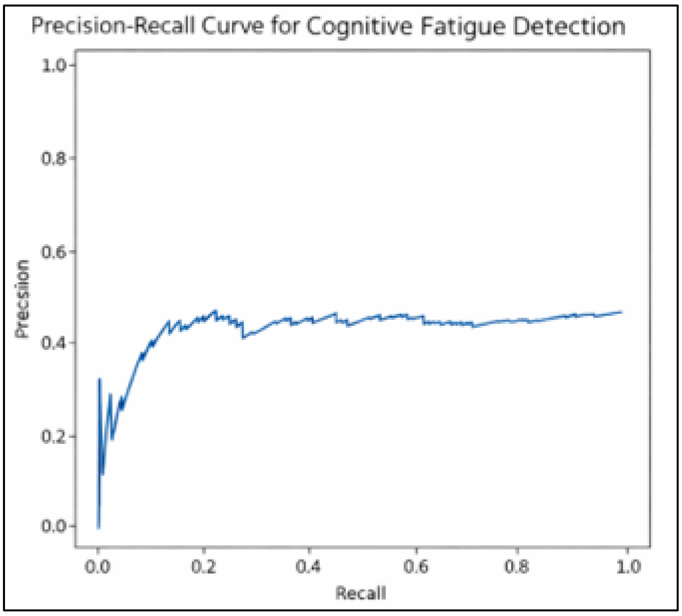

Figure 5 Precision–Recall Curve illustrating the predictive reliability and recall–precision trade-off of the model

4.5. Feature Importance

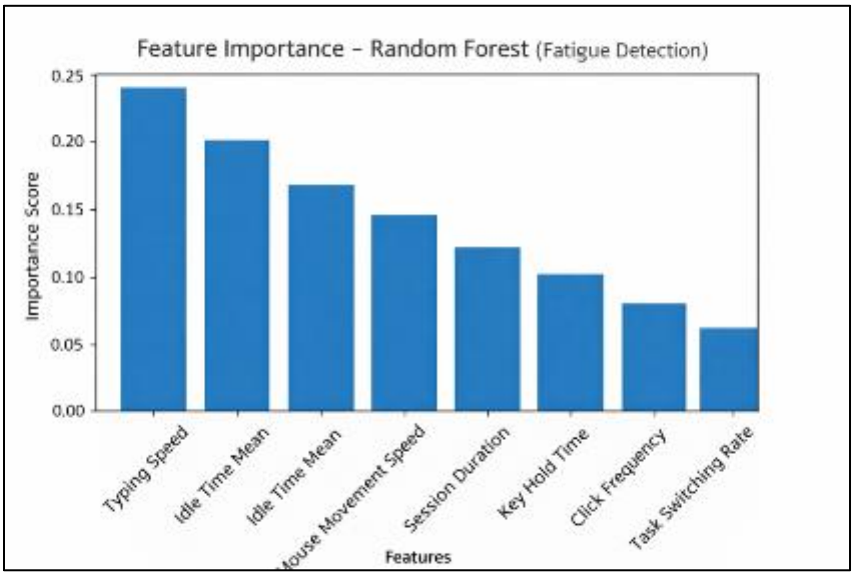

Figure 6 Feature Importance

5. Discussion

The experimental findings prove that behavioral analytics can be successfully used to detect cognitive fatigue even without intrusive physiological devices. The system records the subtler interactions between user and the computer by examining typing rates, mouse motion, time spent not interacting with the computer and session duration; these factors are strongly correlated with mental fatigue. The Random Forest classifier was the most stable and accurate classifier, as it showed a balanced performance in terms of accuracy, precision and recall measures. Such results support the idea that machine learning methods can be implemented to predict the behavioral data and convert them into informative fatigue indicators.

Applications

The proposed AI-Driven Cognitive Fatigue Detection System can be applied in the following real-world scenarios:

- Checking the level of cognitive fatigue in remote workplaces.
- Enhancing performance and happiness of employees in business establishments.
- Helping the HR departments with their workload and performance analysis.
- Supporting online learning platforms to track student attention levels.
- Improving the safety in the workplace in high concentration jobs like software development, data analysis and technical operations.
- Sending live fatigue warnings and suggestions on how to avoid burnout.

Limitations

Despite the good results in terms of classification, the proposed AI-Driven Cognitive Fatigue Detection System has several limitations. The model is trained on prior behavioral data that was collected in advance and user interaction patterns might vary over time because of varying work patterns, environments or behavior of an individual and hence may need to be retrained periodically to ensure accuracy. As the system depends on behavioral cues like typing speed, mouse movement, idle time and session duration, it is not likely to record all psychological and physiological characteristics of cognitive fatigue. The external factors such as stress, illness and environmental distraction are not directly measured. Also, further optimization can be needed to make large-scale deployment in an enterprise environment scalable and with low computational cost.

Future Scope

The research can be improved in the future by increasing the adaptability and dynamism of the fatigue detector by incorporating continuous real-time data stream in order to enhance the system performance. It is possible to consider hybrid models that involve a combination of Random Forest with deep learning, like the neural networks, to enhance the classification accuracy. Scalability can be achieved through cloud and containerized deployment models which can be used to support large-scale enterprise applications. Also, federated learning solutions can allow different entities to enhance the model together without providing sensitive user information. Automatic alerting devices and periodic retraining pipelines can also be created to uphold the reliability of the model in the long run as well as flexibility with the changing patterns of user behavior.

6. Conclusion

The given project proposes a cognitive fatigue recognition system that is not intrusive, AI-based, and is intended to be used in a remote work setting based on behavioral analytics and machine learning methods. The system manages to detect the level of fatigue by examining the patterns of user interaction, including typing speed, mouse movement, idle periods and the duration of the session and does not require any physical or physiological sensors to measure fatigue levels. Following the preprocessing and feature scaling, machine learning models, and specifically the Random Forest classifier, demonstrated good and balanced performance regarding the accuracy, precision and recall. The reliability of the model is further validated by the ROC and Precision-Recall analysis. Also, the combination of desktop monitoring software, AI engine, and real-time dashboard makes the system viable and applicable to the real world. Overall, the proposed solution improves productivity, as well as promotes mental health, and is an effective way to monitor fatigue in the contemporary digital work environment.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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