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A Vision-Based AI Framework for Real-Time Fatigue and Workload Detection in IT Professionals Using MediaPipe and a Fusion Neural Network.

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Abstract*: - In the prevailing work setting of the modern technology sector, screen usage, static positions, and cognitive engagements of the brain contribute to physical and mental exhaustion. Existing solutions to fatigue monitoring and alerting are often computationally complex and wearable and invasive technology. This research work introduces the use of a vision-tracking AI model that is non-invasive and exclusive to the specific requirements of the technical professionals. The model considers the eye movements, body positions, and human interactions to provide an accurate level of physical and mental fatigue. Through the learning concept of fusion learning, the model differentiates between the drastic and short-lived work patterns and the continuous physical and mental states. The proposed model is validated to collectively work in a timely and expert manner with very low computational complexity, thereby imparting expert warning notifications related to physical and mental fatigue. The model adheres to the concepts and requirements of Industry 5.0.

Keywords— Computer Vision, Workload Detection, Mediapipe, Fusion Neural Network, Machine Learning, Artificial Intelligence, MentalFatigue.

I. Introduction

Working on computers has been part of the routine jobs of IT personnel, which include long hours of sitting, screen time, and mental engagement. This will eventually lead to physical and mental fatigue, which might decrease alertness, productivity, and well-being. Symptoms include eye strain, neck, shoulder, or back pain, as well as decreased concentration levels when working on the computer for long hours [1], [2].

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Unfavorable ergonomics add to these implications. The consistent protruding head posture known as "tech-neck" exerts pressure on the neck and muscle tissues in the cervical region because of continuous usage of the computer and related devices [3]. Conversely, eye strain is usually evident with modifications in blinking rates and consequent eye closure and yawning, especially when computer screens are utilized extensively [4] and [5].

Vision-based monitoring is a method for documenting the manifestations of fatigue without disturbing the user's workflow. Modern approaches in pose estimation and facial landmarks, such as MediaPipe, OpenPose, etc., make it possible to extract data on the position of the body and the face with good accuracy using conventional web cameras [6]. At the same time, patterns of behavioural interactions, like keyboard rhythm and mouse movement, were found to be correlated to mental workload and fatigue levels [9], [10].

Most of the current solutions for fatigue detection are based exclusively on one modality, for example, eye movements or physiological signals, primarily intended for transportation or medical fields rather than office work. Wearable solutions are precise but unusable in office environments. There is thus a need for an integrated non-intrusive solution combining both visual and behavioral parameters for fatigue estimation in real time.

In our paper, we present a vision-based AI system encompassing posture analysis, ocular metrics, and interaction behavior to accurately determine fatigue and workload of IT professionals. Our system will run smoothly even on standard edge machines to allow continuous supervision with preservation of privacy.

II. LITERATURE REVIEW

The study of automated fatigue recognition began with visual cues that were very simple and evolved into machine learning. The pioneered work considered such aspects as the extent of your blinking or the movement of your head. Recently, people have been utilizing deep learning and various types of sensors. The research in office and IT environments is aligned at three research areas: eye-based fatigue detection, sitting and ergonomics, and the behavior of people. A lot of articles claim that fatigue accumulates gradually, and thus, to identify it accurately, you should observe the fluctuations over time.

A. Vision-Based Fatigue Indicator.

It is even possible to know whether the person is tired or not by examining the eyes. Individuals would examine things such as the form of the eye to determine whether the individual is drowsy. They do it with the help of the Eye Aspect Ratio (EAR). One of its applications is in a number of systems which operate automatically and independently. EAR is better still when the system is able to pick up when you are yawning. It is normally used together with other tricks in order to obtain a more precise outcome. Sometimes EAR is not compatible at all, when the lighting is not so good, or when you have some task that requires great attention. Although, EAR improves the more sophisticated deep-learning models that track the patterns of blinking with time [1], they are computationally expensive and not very useful in the sense that they constantly observe people at a desk. Blink patterns vary also significantly with whatever you are doing and such a look at the eyes might not be sufficient [5].

B. Postural Ergonomics

It does get tiresome to sit in one position too long. Researches indicate that a significant number of office employees and those who work at home suffer neck and back pain [16], [15]. This is why it is extremely important to pay attention to posture. Ergonomic checker technology new pose-estimation technology allows you to scan ergonomics without actually touching the body, with standard cameras [8]. And many of the systems use video data to compute risk scores [5], [6] though the majority are designed to do a check later, rather than provide real-time assistance.

C. Interaction Cues Behavioural

The experience of being mentally exhausted also alters the way you use the computer. The trends of mouse movements and typing speed change when you are exhausted and the work load is high [10], [12]. These are behaviour cues that come into play when eye signals are not clear as in the situation where you are reading a lot and your body remains very still.

D. Motivation for a Multimodal Approach

Majority of the existing fatigue detection systems simply rely on a single means of determining whether an individual is tired or not and this is when shaky when individuals are sitting at the desks. Unless it takes time to check to see how people are engaging with their surroundings, it will be shortchanged. Behaviour based models do not take into account the space surrounding the individual. Some such as NASA-TLX require individuals to rate the intensity at which they believe they are working, but it does not work well to provide a quick test. We require systems that are user friendly and that monitor the use of eyes, posture and behaviour in a time based fashion- exactly what the Industry 5.0 people first thing is all about. An excellent fatigue system would be highly useful. The proposed paper fills this gap by suggesting one real-time work fatigue and workload system in relation to IT pros.

III. METHODOLOGY

A. Data Acquisition Pipeline

Every information is gathered locally on the machine of the user. This prevents the network delay and stores user data in the device. There are three types of data that are registered simultaneously.

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The RGB video is captured at 640×480 at 30 frames per second with a webcam. Facial and upper-body landmarks are extracted with the aid of MediaPipe Face Mesh and Pose models [6].

These models extract 468 facial landmarks for eye and mouth tracking and 33 body key points for posture analysis. OpenCV is used for frame capture and basic pre-processing.

Landmark coordinates are only processed. Raw video frames are not recorded to preserve user privacy. A background process based on *pynput* library is used to log and monitor keyboard and mouse activity. The time of keystroke and movement of mouse are logged and clustered in brief time intervals. The values are then utilized as workload indicators [10]. The overall system architecture of the proposed framework is as shown in [Fig. 1].

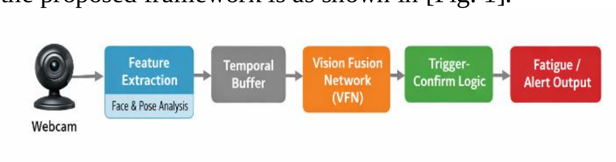

Fig. 1. *Overall system architecture of the proposed vision-based fatigue detection framework.*

B. Extracting Posture Feature

There are three pose landmarks that are used to estimate posture-related fatigue.

The angle of forward rotation of the head is defined with the help of the angle of inclination of the neck (θ). An equation is used to calculate a posture score as follows:

$$PS_i = \min\left(100,\ \max\left(0,\ 100 \cdot \frac{\theta_i - \theta_0}{\theta_{max} - \theta_0}\right)\right) \qquad (1)$$

In this case, $\theta_0$is 15° in which the $\theta_{max}$is 45° which is a severe forward tilt [3].

The slouching of the laterals is estimated by taking the difference between the right and the left shoulders that are in a vertical position. The score of the shoulder symmetry is obtained using the equation below:

$$SS_i = \min\left(100,\ 100 \cdot \frac{\Delta y}{\delta_{max}}\right) \qquad (2)$$

Where, $\Delta y = |y^{L}_{sh} - y^{R}_{sh}|$

Constant changes in positions are regarded as natural movement. An event of change of posture is registered when θ varies by a change of more than 5° per second. The change frequency score in the posture is determined with the help of the following equation:

$$PCS_i = \min\left(100,\ 100 \cdot \frac{N_i}{30}\right) \qquad (3)$$

Reduced PCS values signify extended sitting in the stature.

C. Ocular and Blink-Based Fatigue Estimation

Fatigue in the eyes is assessed based on the behaviour of blinking and eye closing.

The Eye Aspect Ratio (EAR) is used to perform Blink detection [8]. The eye configuration used for detecting blinks is shown in [Fig. 2] The blink duration has a relationship with the blink score as shown in equation:

$$BS_i = \min\left(100,\ 100 \cdot \frac{D_i - D_{\text{norm}}}{D_{max} - D_{\text{norm}}}\right) \qquad (4)$$

where D_{norm} = 200 ms (normal blink) and D_{max} = 500 ms (drowsy blink). Persistently high BS_i indicates heavy eyelids.

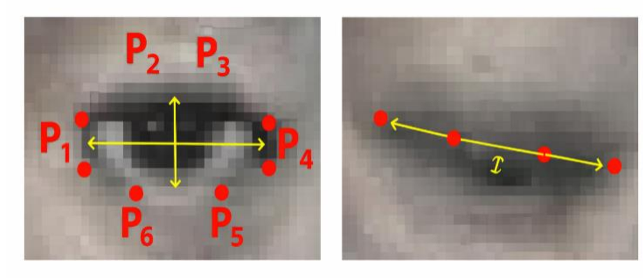

Fig. 2. *Eye landmark points used for blink detection (EAR).*

PERCLOS is used to measure protracted eye closure in a one-minute time frame [11].

The Mouth Aspect Ratio (MAR) is used to detect yawning. The CANDIDE grid of the mouth landmark configuration for yawning detection is presented in [Fig. 3]. The score of the yawning is obtained as:

$$YS_i = \min\left(100,\ 100 \cdot \frac{Y_i}{10}\right) \qquad (5)$$

The occurrence of microsleep is signaled by closure of eyes taking more than 500 ms or upon detecting a head nod, and the microsleep indicator $MS_i$is set to 100 for the current window.

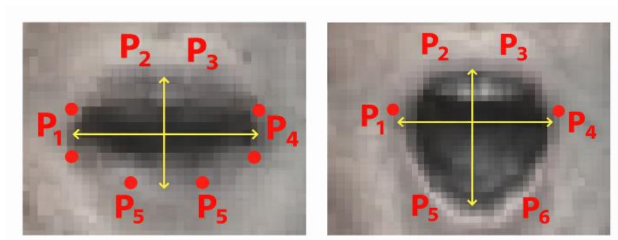

Fig. 3. *Mouth landmark points for yawning detection (MAR).*

D. Sitting Time and Behavioral Metrics

The continuous sitting is measured in minutes. The sitting time score is determined by using the equation:

$$TS_i = \min\left(100,\ 100 \cdot \frac{t_{\text{sit}}}{60}\right) \qquad (6)$$

E. Vision Fusion Network

A Vision Fusion Network is used to add individual scores. The input is a 30-second box of posture, eye, and behavioural characteristics. Each of the streams of features is operated by parallel layers of one-dimensional convolution. The results are added together and sent to a fully connected layer to create a probability of fatigue.

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This method enables the differentiation between short-term behavior, e.g. blinking, and long-term fatigue patterns.

F. Fatigue Feature Vector Construction and Decision Logic
At each time step t, individual fatigue metrics are combined into a feature vector:

$$\mathbf{f}_t = [PS_t, SS_t, PCS_t, BS_t, YS_t, TS_t] \qquad (7)$$

Feature vectors are aggregated into a sliding window tensor:

$$\mathbf{X}_t \in \mathbb{R}^{T \times F} \qquad (8)$$

with $T = 30$seconds and update stride of one second.
The Vision Fusion Network computes the instantaneous fatigue probability:

$$P_{\text{fatigue}}(t) = \text{VFN}(\mathbf{X}_t) \qquad (9)$$

A fatigue trigger is generated when:

$$P_{\text{fatigue}}(t) > \tau, \tau = 0.7 \qquad (10)$$

To reduce false positives, confirmation requires sustained fatigue over a historical window:

$$\frac{1}{W} \sum_{k=t-W}^{t} P_{\text{fatigue}}(k) > \tau \qquad (11)$$

where $W = 5$minutes.

G. Proposed Fatigue Detection Algorithm
The overall workflow followed to estimate fatigue and generate system outputs is outlined in Algorithm. Rather than relying on isolated measurements, the procedure incrementally transforms visual observations into normalized fatigue indicators, models their evolution over time, and validates fatigue events before reporting them.
Algorithm:
a. The system continuously captures video from the webcam and extracts facial and upper-body landmarks using MediaPipe models.
b. From these landmarks, posture-related, ocular, and sitting-time fatigue metrics are computed and normalized using Eq. (1)–Eq. (6).
c. The resulting fatigue metrics are combined into feature vectors and organized into a sliding temporal window $X_t$to preserve recent fatigue history.
d. The Vision Fusion Network processes this window to estimate the current probability of fatigue.
e. To avoid reacting to short-lived or accidental behaviours, a Trigger–Confirm logic is applied, ensuring that only sustained fatigue patterns are accepted.
f. Once validated, the fatigue probability is mapped to the Combined Fatigue Index.
g. Based on this index, the system issues real-time alerts when required and generates a summary report at the end of the session.
H. Output & Reporting
The validated fatigue probability is mapped to the **Combined Fatigue Index**:

$$CFI_i = 100 \cdot P_{\text{fatigue}}(i) \qquad (12)$$

The Combined Fatigue Index is used for visualization, comparison, and evaluation in the Experimental Results section. Real-time alerts are triggered when fatigue exceeds predefined thresholds, and an end-of-session summary report is generated.

IV. SYSTEM IMPLEMENTATION

A practical prototype was created and tested on standard consumer-grade laptop hardware to determine its practical feasibility of the proposed framework. The processing workflow of the proposed vision-based fatigue detection system is shown in [Fig. 4].

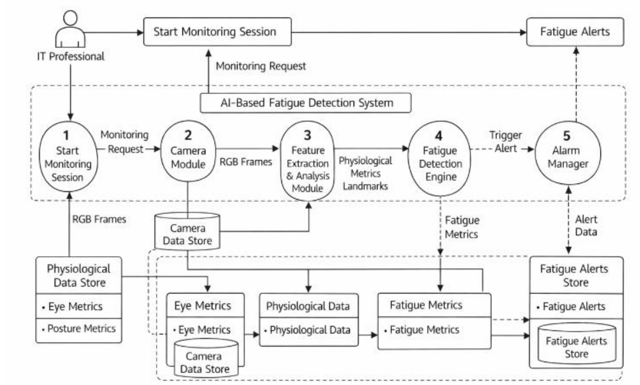

Fig. 4. *Processing workflow of the proposed vision-based fatigue detection system.*

A. Hardware and Software Stack

The system was installed on a laptop with an Intel Core i5-12450H (12th generation) processor that has 16 GB of DDR4 RAM. The hybrid design of the processor comprising of four performance cores and four efficiency cores also enabled the video processing tasks that are compute-intensive in nature to take place without interacting with the background systems, thus preventing resource contention.

Video frames were recorded with the help of OpenCV (v4.8) and landmarks of faces and poses were obtained with the help of MediaPipe that was fully run on the CPU. In any case where possible, the Intel OpenVINO backend was selected to optimize inference behavior [6], [11].

Vision Fusion Network was written in PyTorch and quantized to INT8 and then deployed in the ONNX Runtime ecosystem. This minimized inference time and allowed the CPU to be used in real-time and without having a special GPU.
B. Latency Analysis

Continuous fatigue monitoring must utilize real-time performance. The average time spent on each frame, which is represented by T_{proc}, was measured during 60 minutes of continuous run of the deployed system.

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The mean end-to-end processing latency was 20.4 ms/frame or an effective throughput of about 48 frames per second. This is higher than the normal webcam capture rate of 30 FPS which guarantees a smooth and unobtrusive operation in the normal office environment even in the presence of background tasks.

Table 1: *System Latency Analysis*

Component	**Avg. Latency (ms)**	**Description**
Landmark Extraction	14.2 ms	Face Mesh + Pose (Performance Cores)
Feature Calculation	0.4 ms	EAR, θ, and vector math
VFN Inference	5.8 ms	Forward pass of 1D-CNN (ONNX)
Total System Latency	~20.4 ms	~48 FPS

V. EXPERIMENTAL RESULTS

The experimental results presented in this section were obtained by executing the procedure described in Section III, where raw multimodal inputs were transformed into normalized fatigue metrics using Eq. (1)–Eq. (6), fused temporally using the Vision Fusion Network, and validated using the Trigger–Confirm logic before final index computation.

The proposed system was tested on a controlled synthetic fatigue progression model given that there is no publicly available dataset that simultaneously records postural behavior, ocular cues, and desk-based fatigue patterns unique to IT professionals. This simulation was created to model realistic physiological and behavioral variability that occurs during a standard eight-hour working day in the office which was adjusted by workload and work fatigue data that were reported in the NASA-TLX research [15].

The time-series data has been produced in terms of results of the ergonomic and human-computer interaction sources according to the standard working schedule 09:00-17:00. To capture the natural variation of alertness throughout the day the simulated work shift was sub-divided into three phases. In the morning (09:00 -12:00), the user was supposed to be in a high-alert position that is characterized by upright sitting position (neck inclination which is less than 15) with normal blink rates of 12-15 blink per minute and short blink rates which are less than 250 ms.

The afternoon (13:0015:00) was to be modeled to represent the popular circadian alertness drop. During this stage the introduced simulation mode added frequency of yawning, occasional incidences of microsleep and slow but steady deterioration of the upright position, with the neck inclination escalating to about 35. During the last stage of the day (15:0017:00), the cumulative effects of fatigue were more severe, as they were reflected in the maintenance of ocular strain revealed by the increased duration of blink over 350 ms, as well as in the maintenance of the slouched posture.

Proposed Vision Fusion Network (VFN) was compared to a traditional linear weighted moving average baseline, which is widely used in fatigue monitoring systems [11]. As Fig. 5 illustrates, the baseline approach is very sensitive to isolated events which tend to result in sudden spikes in the fatigue score due to a yawn or short change of position. Contrary to this, the VFN is characterized by a decreased temporal responsiveness with less focus on the immediate anomalies and more focus on the long-term trends of fatigue. It is interesting to note that the VFN fatigue index increases steadily and steadily during the post-lunch period (around 13:30) as an indication of simulated onset of cumulative fatigue, and not behavioural period changes.

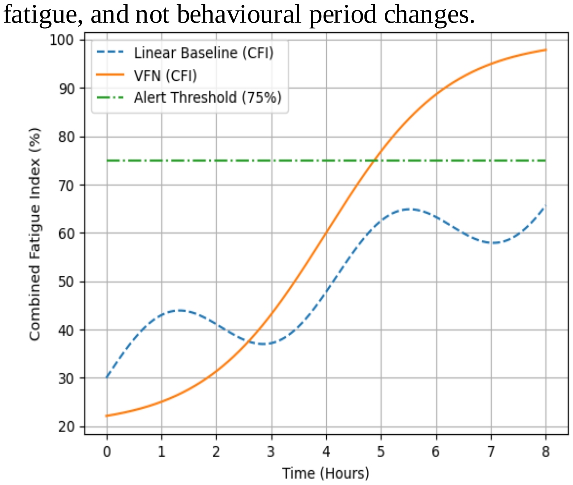

Fig. 5. *Comparison of CFI over time for the proposed VFN and a linear baseline.*

The strength of the Trigger Confirm logic was also tested by inserting 50 transient non-fatigue events and 50 actual fatigue occasions in the data stream. As in Table 2, the findings show that the false-positive rate decreased by over 16 percent when using a historical context of five minutes. This demonstrates the need to apply temporal validation in the monitoring of fatigue at continuous desk-based working conditions.

The results confirm that the temporal validation process is quite effective in filtering short-term behavioral variability and capturing actual fatigue patterns. This is invaluable for ensuring that alerts are generated correctly without responding to actual non-fatigue events.

Table 2: *False Positive Rate (FPR) Comparison*

Methodology	**Detection Accuracy**	**(FPR)**	**Implication**
Naive Threshold-Based Detection [2]	93.8%	18.4%	High alert noise due to sensitivity to isolated events such as single blinks or yawns.
Vision Fusion Network	96.2%	8.7%	Improved detection stability, but still

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(VFN) without Temporal Validation			sensitive to short transient behaviours.
VFN with Trigger–Confirm Logic (Proposed)	**98.1%**	**2.1%**	Demonstrates improved robustness by suppressing transient non-fatigue events within the simulated evaluation.

In addition to real-time monitoring, a session-level summary is also produced at the end of the work-day by the system which points out the overall fatigue trends and postural behaviour. During the simulated session, total sitting duration was 6.8 hours which is higher than the recommended ergonomic hours, and the average posture score was moderate slouching. There were four posture related warnings and three of them were adhered to and the compliance was 75.

Figure 5 shows the real-time dynamics of Combined Fatigue Index in normal and fatigued conditions. In general, the experimental findings suggested the experimental framework can be used to generate consistent and understandable fatigue estimates because it focuses on long-term patterns and no single events. Such behavior aids persistent fatigue consciousness and ergonomic intervention in accordance with the human-related aims of Industry 5.0 [14].

Fig. 6. *Example snapshot of the prototype interface for real-time fatigue monitoring*

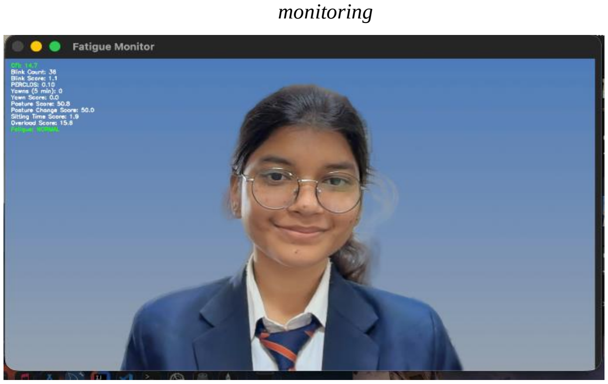

Fig. 7. *Example snapshot of the prototype interface for real-time fatigue monitoring*

VI. COMPARATIVE ANALYSIS AND DISCUSSION

The proposed system was tested within the framework of the representative fatigue detection methods found in literature. analysis of eye reactions and it is hard to differentiate between brief voluntary blinks and long-term eye closure unless thresholds are manually adjusted [5], [8]. The Vision Fusion Network is able to model temporal sequences by using one-dimensional convolutions, which provides information of how fatigue-related events evolve over time, enhancing resistance to transient behaviours [7].

There are a number of previous systems that work on one modality. Vision-only methods [4], [11] can be mistaken in focus reading or slowed motion as fatigue and behaviour-based methods [9] are not effective in low-interaction work. By contrast, the proposed structure combines postures and visual indicators which allow interpreting the state of a user in the context and minimizing false alarms.

High accuracy can be achieved in wearable-based fatigue monitoring techniques based on EEG or EMG signals [13], although these are unfeasible when used in a long office environment. The suggested system uses a standard webcam and processes everything locally, which facilitates continuous monitoring, and the use of human-centric design principles in Industry 5.0 addresses privacy issues highlighted in the human-centric design principles [14].

VII. CONCLUSION & FUTURE WORK

This paper has introduced a vision-based and non-intrusive fatigue monitoring framework to be used in desk-based IT based work environments to monitor continuous fatigue. In comparison with the traditional drowsiness detection methodology, the proposed system is based on a more liberal definition of fatigue since it will consider ocular behaviour, postural ergonomics and temporal consistency. The design enables the framework to have slow development of fatigue instead of responding to single or temporary occurrences.

Vision Fusion Network can fuse temporal parts of multimodal feature, whereas Trigger-Confirm validation mitigates spurious alerts due to transient behaviour including a brief yawn or change of posture. During the simulated assessment, the system was capable of steady fatigue prediction and real-time execution on commodity hardware and did not require any custom sensors, wearable gadgets, or GPU acceleration. Local processing also contributes to preservation of privacy, which is vital in realistic deployment of the same at the workplace.

The use of a synthetic fatigue progression model is the main limitation of the research since publicly available, annotated datasets of fatigue at the office are not available. Future efforts will then focus on longitudinal field research in actual field office settings in order to test the framework against the subjective measure of fatigue like the Karolinska Sleepiness Scale. Other future research paths are the incorporation of the contactless physiological cues and the

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formulation of contextually adaptive and context-sensitive micro-break predictions to facilitate proactive fatigue management.

All in all, this paper helps move in the right direction of practical, people-centric fatigue monitoring systems that can help achieve the well-being and sustainability goals of Industry 5.0.

REFERENCES

[1] G. D. Nousias, K. K. Delibasis, and G. Labiris, "Blink Detection Using 3D Convolutional Neural Architectures and Analysis of Accumulated Frame Predictions," *Journal of Imaging*, vol. 11, no. 1, p. 27, Jan. 2025.

[2] Y. Nie, T. Liu, and L. Han, "Eye Fatigue Detection System Design and Implementation," *Computer Life*, vol. 12, no. 2, pp. 326–329, 2024.

[3] W.-H. Chuah, S.-C. Chong, and L.-Y. Chong, "The Assistance of Eye Blink Detection for Two-Factor Authentication," *Journal of Informatics and Web Engineering*, vol. 2, no. 2, pp. 45–58, Sep. 2023.

[4] A. A. Abusharha, "Changes in Blink Rate and Ocular Symptoms During Different Reading Tasks," *Clinical Optometry*, vol. 9, pp. 133–138, 2017.

[5] J. Patil, S. Joshi, and R. Mulla, "Intelligent Posture Detection System for Improved Ergonomics," in *Proc. 2025 International Conference on Intelligent Control, Computing and Communications (IC3)*, 2025, pp. 892–899.

[6] G. D. Goutham and S. Saravanasankar, "Real-Time AI-Driven Fatigue Monitoring & Ergonomic Risk Assessment," *SSRN Preprint*, Oct. 2025.

[7] M. Calzavara, M. Faccio, I. Granata, and A. Trevisani, "Achieving productivity and operator well-being: a dynamic task allocation strategy for collaborative assembly systems in Industry 5.0," *The International Journal of Advanced Manufacturing Technology*, vol. 134, pp. 3201–3216, 2024.

[8] Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheikh, "OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, no. 1, pp. 172–186, Jan. 2021.

[9] J. Xiong, W. Dai, Q. Wang, X. Dong, B. Ye, and J. Yang, "A review of deep learning in blink detection," *PeerJ Computer Science*, vol. 11, p. e2594, Jan. 2025.

[10] R. Hagimoto, E. Kamioka, C. M. Tran, and P. X. Tan, "Fatigue Detection Using Computer Mouse Operation Patterns," in *Proc. 2025 15th International Workshop on Computer Science and Engineering (WCSE)*, 2025, pp. 195–200.

[11] A. F. Campoya Morales, J. L. Hernández Arellano, E. L. González Muñoz, and A. Maldonado Macias, "Development of the NASA-TLX Multi Equation Tool to Assess Workload," *International Journal of Combinatorial Optimization Problems and Informatics*, vol. 11, no. 1, pp. 50–58, 2020.

[12] A. R. Gowda and S. Merikapudi M, "Keystroke Pattern Analysis for Cognitive Fatigue Prediction Using Machine Learning," *Advanced International Journal for Research*, vol. 6, no. 5, pp. 1–9, 2025.

[13] R. Lee, C. James, S. Edwards, and S. J. Snodgrass, "Differences in upper body posture between individuals with and without chronic idiopathic neck pain during computerised device use: A 3D motion analysis study," *Gait & Posture*, vol. 95, pp. 30–37, 2022.

[14] S. Karoria, S. Mishra, and P. Verma, "Driver Drowsiness Detection with Mediapipe and Deep Learning," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 6, no. 4, pp. 1–5, Apr. 2024.

[15] M. Shah and R. Desai, "Prevalence of Neck Pain and Back Pain in Computer Users Working from Home during COVID-19 Pandemic: A Web-Based Survey," *International Journal of Health Sciences and Research*, vol. 11, no. 2, pp. 26–31, Feb. 2021.

[16] L. Gosain, I. Ahmad, M. R. Rizvi, A. Sharma, and S. Saxena, "Prevalence of musculoskeletal pain among computer users working from home during the COVID-19 pandemic: a cross-sectional survey," *Bulletin of Faculty of Physical Therapy*, vol. 27, no. 1, p. 51, 2022.

10.5281/zenodo.18149292