



# Artificial Intelligence for Detecting Mental and Cognitive Fatigue During Computer Use: A Comprehensive Review of Webcam-Based and Nonverbal Behavior Approaches

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## Abstract

Mental and cognitive fatigue have become more common with prolonged computer use or prolonged sitting in front of smart device screens in modern digital environments, significantly impacting concentration, individual performance, and overall health. This comprehensive review covers the scientific literature published from 2012 to 2025, examining AI-based approaches for detecting mental and cognitive fatigue using webcam data and nonverbal behavioral cues. Recent innovations in artificial intelligence and computer vision have led to the design of intelligent systems capable of detecting fatigue through behavioral and visual cues. This literature review examines some studies on AI-generated fatigue detection, focusing on approaches that use webcams to analyze nonverbal behavior. It also highlights the main trends in detection methods—physiological, visual, and dual—with an emphasis on the growing importance of deep learning models and multi-source data fusion in improving the efficiency and accuracy of detection. Research indicates a significant evolution from traditional feature extraction methods to intelligent network models that automatically learn features, which can recognize subtle indicators of fatigue such as eye blink rate, head movement and direction, and subtle facial expressions. This study represents a fundamental step towards building a sophisticated intelligent system based on nonverbal behavior analysis that can continuously analyze nonverbal behavior to detect fatigue during actual computer use. This review aims to analyze and compare AI-based approaches for detecting mental and cognitive fatigue through nonverbal behavior and computer vision techniques, including recent methodological progress and important discoveries to inform future research directions.

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## 1. Introduction

Because of the digital evolution that our world is seeing, people spend long amounts of time using digital devices, adding risk to mental and cognitive fatigue, two of the most significant factors. Prolonged use of computer results in a loss of focusing capabilities, inattention, and decreased alertness, which are prominent contributors to

declining general performance [1][2]. Fatigue not only harms productivity, but also places workers in a dangerous position in workplaces that require sustained attention and accuracy [3][4]. Traditional methods have relied mainly on subjective measures of fatigue like questionnaires and fatigue scales [5]. Although these are widely used, they are simple to

implement, yet often unpredictable and individualized, limiting their reliability [6] (see **Figure 1a**). To combat the aforementioned challenges, recent works of research have been based on physiological signals like EEG, ECG, EMG, and heart rate variability to scientifically evaluate fatigue levels [7][8] (see **Figure 1b**). However, monitoring physiological signals can be invasive to users due to the need for tactile devices like sensors, which are usually placed for very long periods or unfeasible for regular computer use. Hence, nonverbal cues analysis using computer vision methods assisted by artificial intelligence has developed as an advanced method for efficiently identifying mental fatigue in an easy and non-invasive manner for persons [1] [9]. Micro-facial expressions, Eyes on screen, head orientation, and body posture are appropriate markers of fatigue detection, which can be captured via cameras or embedded sensors[10] (see **Figure 2**). When fatigue is detected, Internet of Things (IoT) systems can be used to take early response actions, such as adjusting the lighting and alerting the user, in order to lessen the risks of fatigue [11] [12]. Linking AI detection with IoT response also allows for an automatic smart intelligent device to monitor, detect, and respond to users' mental fatigue in real time. The purpose of this review is to identify mental and cognitive fatigue through nonverbal behavior using webcams, based on an analysis of

alternative artificial intelligence approaches and a comparison of conventional physiological methods and modern computer vision techniques in terms of applicability, accuracy, and usability. It also covers databases, algorithms, and performance metrics from established studies to identify areas for further research and future challenges for real-time fatigue detection using intelligent non-contact systems. This review contributes at the core by building an integrated analytical perspective about mental and cognitive fatigue detection through computer vision, physiological analysis, and nonverbal behavioral interpretation. This work emphasizes non-contact, webcam-based models used as a feasible solution over traditional sensor-dependent systems, to provide a comparative review on recent progress of multimodal data fusion techniques that are applied using deep learning paradigms and visual transformer (Vision Transformer) architectures and hybrid CNN–LSTM networks. In addition, the review furnishes an analytical framework for studies published between 2012 and 2025, highlighting methodological and technical evolution in feature extraction algorithms—both advantages and disadvantages—in terms of interpretability, real-time efficiency, as well as privacy concerns. In doing so, it plays a positive role in directing future research towards designing AI systems that are better adapted to more functional, real-world settings.

**Fatigue Assessment Scale (FAS)**

The following ten statements refer to how you usually feel. Per statement you can choose one out of five answer categories, varying from Never to Always. Please circle the answer to each question that is applicable to you. Please give an answer to each question, even if you do not have any complaints at the moment.  
 1 = Never, 2 = Sometimes (about monthly or less); 3 = Regularly (about a few times a month); 4 = Often (about weekly) and 5 = Always (about every day).

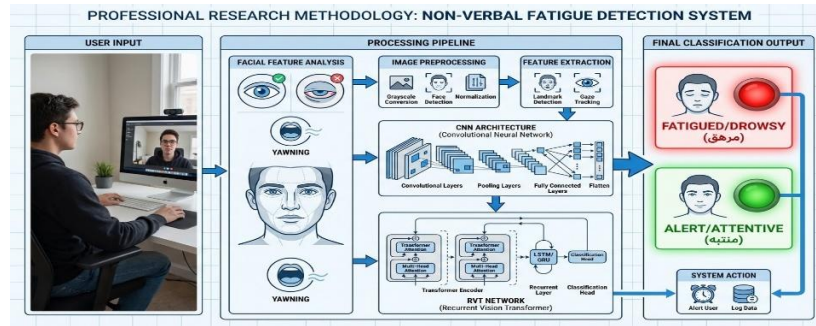
(a)

	Never	Sometimes	Regularly	Often	Always
1. I am bothered by fatigue	1	2	3	4	5
2. I get tired very quickly	1	2	3	4	5
3. I don't do much during the day	1	2	3	4	5
4. I have enough energy for everyday life	1	2	3	4	5
5. Physically, I feel exhausted	1	2	3	4	5
6. I have problems to start things	1	2	3	4	5
7. I have problems to think clearly	1	2	3	4	5
8. I feel no desire to do anything	1	2	3	4	5
9. Mentally, I feel exhausted	1	2	3	4	5
10. When I am doing something, I can concentrate quite well	1	2	3	4	5

(a)



**Figure 1. (a) Traditional subjective fatigue assessment tools, represented by the Fatigue Assessment Scale (FAS). (b) Physiological methods for fatigue detection, including EEG, ECG, EMG, and HRV.**



**Figure 2.** Pipeline of the proposed nonverbal fatigue-detection system.

Facial frames captured by a webcam undergo face detection and landmark extraction to obtain eye and mouth cues. These features are analyzed by deep learning models (CNN and RVT) to determine whether the user is Fatigued or Attentive.

#### Key contributions of this review:

- Developing an integrated analytical perspective for detecting mental and cognitive fatigue through computer vision, physiological analysis, and the interpretation of nonverbal behavior. It focuses on contactless, webcam-based models, which serve as a practical alternative to traditional sensor-based systems.

.Comparison of analytical and methodological studies in terms of models, databases, feature extraction algorithms, and achieved accuracy.

- A comparative analysis of the databases used in these studies, examining their characteristics and suitability for detecting nonverbal fatigue.

- An examination of research patterns influenced by signal type (eye, head position, mouth) on the performance of detection models.

- An analysis of the evolution of fatigue detection algorithms, from manual feature analysis to deep neural networks and Transformer-based architectures.

- An assessment of challenges such as the lack of real-time evaluation, weak generalization, and varying database quality.

- Proposals for future directions based on advanced transformative models, multimedia integration, and improved real-world testing environments.

## 2.Mental fatigue

Mental fatigue is defined as a psychophysiological state caused by repeated mental effort and has a direct effect on performance, attention, and decision-making. Psychological studies have explained it as happening due to an imbalance between effort and mental activity [13] [14] [15]. Fatigue in recent times has been construed as decreased functional activity in associated forebrain networks with

decision making and focus[16]. New research shows mental fatigue is not limited to a subjective feeling of tiredness. This can also be detected through the analysis of nonverbal behaviors such as gaze direction, blink rate, and subtle head movements. Behaviors can be filmed with webcams and analyzed with AI and deep learning algorithms. Studies have proved that fatigue correlates with a real drop in performance accuracy and sustained attention[17].

Using EEG and ECG signals was the method for[18]. It allowed researchers to detect and predict fatigue objectively by means of machine learning models. [8] incorporates supervised learning systems with physiological signals to analyse drivers, to a very high degree of accuracy in laboratory conditions but of little use in real-world environments. [1] studied behavioral performance for prolonged cognitive load and showed strong correlation with physiological and cognitive indicators of fatigue. Facial recognition algorithms have yet to evolve to address the problem of facial expressions, which is a big barrier to data collection and analysis. In the same vein,[19] introduced non-contact approaches for facial assessment. With webcam-based CNN models, facial expressions and eye movements get to be analyzed instantly. [20] [12] based hybrid Transformer architecture integrates facial, ocular, and postural cues, achieving higher reliability and performance in the detection of mental fatigue with respect to accuracy.

## 3.Computer Vision

Computer vision is one of the largest branches of artificial intelligence (AI) which allows computers and computer systems to understand, interpret, and perceive images and videos in just the same way as human vision. This technology is fundamentally a process of extraction, moving and using visual features that you see in digital data, like movements, edges, and shapes. Neural networks and machine learning analyze nonverbal signals to detect fatigue, including facial expressions, gaze direction, and head movement ([21],[10]). Transformational vision models and convolutional neural networks fine-tune convolutional neural networks to recognize and capture more subtle features in images and videos for the early detection

of the real-time early signs of cognitive fatigue [11] [12]. These methods allow non-intrusive monitoring of user behavior, therefore paving the way to build intelligent systems with privacy and productivity in digital workplaces.

Computer vision is used in many non-contact methods to diagnose mental and cognitive exhaustion. Among the previous research, non-invasive computer vision methods were used to analyze the facial characteristics via webcam footage to detect changes in blink rate and subtle facial expressions to estimate fatigue levels. [21] took this trajectory to the next level by training a CNN model on the NTHU-DDD dataset which showed that visual cues including eyelid movement and facial muscle relaxation can constitute valid predictors of cognitive fatigue. [22] designed and developed a hybrid CNN-LSTM model with spatial features (face) and also temporal features (movement of head) in order to dynamically observe fatigue transitions. Meanwhile [12] leveraged a Transformer architecture to integrate facial and ocular signals from multiple types of signals along a multimodal framework, enhancing the precision of the detection in semi-realistic environments. [20] reported that integrating Transformer encoders with multimodal video data facilitates real-time mental fatigue interpretation via visualization analysis, efficiently bridging the gap between lab precision and real-world applicability.

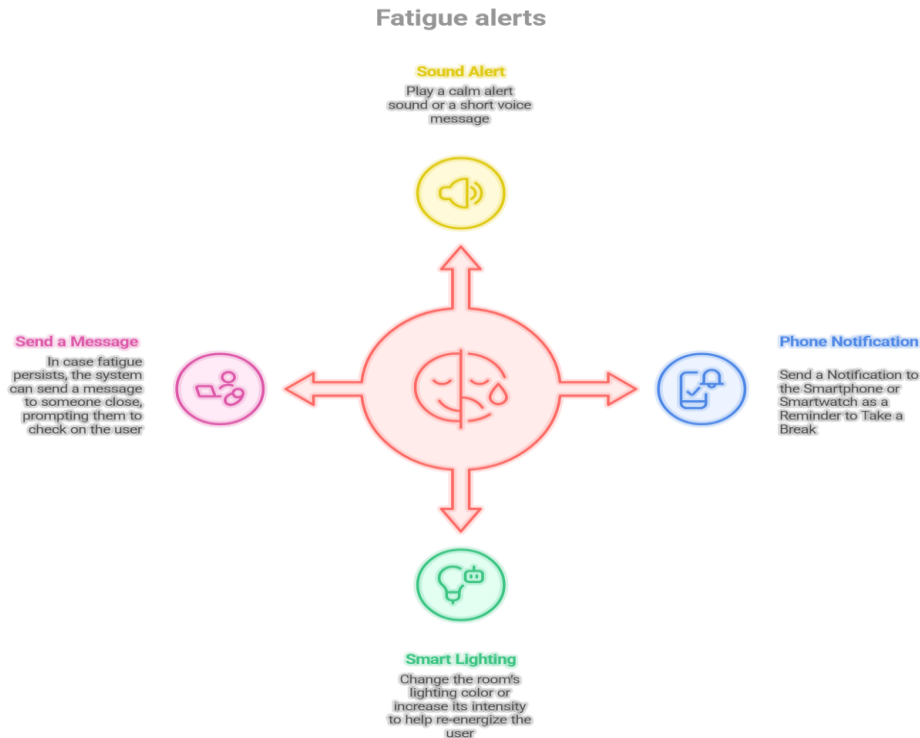
#### 4. Artificial Intelligence

AI is a special field within computer science where its purpose is to create systems that are able to imitate human performance for, among other things, attention, learning, analysis, pattern recognition, and decision-making. Deep learning algorithms are being used. It has been determined that models could be developed to study patterns of mental fatigue due to behavioral or visual data more accurately than in classical ways [22] [20]. It has recently been shown that fatigue detection can be used as an integrated approach. Mechanisms and transformers have helped in identifying fatigue over time, making AI one approach to monitoring the status of users continuously [23] [18]. Recent empirical study of its applications using AI, on the other hand, has made great progress in the direction of the use of data-driven models on fine-grained behavioral indicators of human mental fatigue detection. [18] applied supervised learning (SVM and Random Forest) algorithms. High performance in the evaluated physiological features on ECG, EDA, RESP signals of accuracy in laboratory conditions. In addition, CNN and other machine

learning models were used in other works. CNN-LSTM is promising for facial expressions and body posture analysis. The effectiveness of deep learning for both spatial and temporal patterns for fatigue is demonstrated in [21] and [22]. [20] proposed an approach based on multimodal Transformer models that is able to capture all three of these, improved interpretability and real-time responsiveness. Moreover, lightweight artificial intelligence was proposed in [24]. Edge devices (Edge AI) of MobileNet based intelligent models with decrease to latency and enhance privacy, moving from cloud-based processing to real-time, local analysis.

#### 5. Internet of Things (IoT)

Internet of Things (IoT) – one of the most significant innovations of the current decade. The term describes a network of connected smart devices, capable of collecting and processing data, and interacting automatically with the local environment and users. It has recently helped generate AI-based fatigue detection systems that use intelligent devices to gather behavioral and environmental data in real-time without human intervention. By bringing this new integration together, the system is now able to respond to the situation immediately and take direct action, like a notification to the user, play an audible sound, and change lights, therefore alleviate cognitive impairment and thus improve overall performance [11]. Research also shows that local data processing could be achieved by integrating edge AI technologies with IoT networks, maintaining privacy for live detection [24] [25] [12]. The Internet of Things (IoT) is increasingly central to real-time mental fatigue detection systems in intelligent environments. [11], which used AI-based fatigue monitoring with IoT architectures to further integrate collecting data from webcams and wearable sensors and adaptive responses, such as user alerts or screen dimming (see Figure 3 ). [12] demonstrated that multimodal IoT networks combining facial and ocular signals enhance contextual awareness in workplace environments. [26] discussed the potential of federated learning and edge-based deployment for privacy-preserving fatigue detection systems, reducing data transmission requirements. Similarly, [24] demonstrated the feasibility of real-time fatigue detection on embedded platforms such as the NVIDIA Jetson Nano, achieving over 90% accuracy with low power consumption. Collectively, these studies highlight the evolution of IoT from passive sensing systems to intelligent cognitive monitoring environments that preserve privacy and operate efficiently in real time.



**Figure 3.** IoT-enabled fatigue-alert mechanisms.

This figure illustrates how the fatigue-detection system interacts with Internet-of-Things (IoT) devices to provide adaptive alerts. The module can activate a sound alert, send a notification to the user's smartphone or smartwatch, adjust smart-lighting devices to increase alertness, or send a message to a close contact when prolonged fatigue is detected.

## 6. Motivation and Significance

Mental and cognitive fatigue have a noticeable impact on users' attention, concentration, and performance during prolonged use of digital devices [1] [2]. Continuous monitoring using traditional physiological methods such as EEG and ECG is often intrusive, inconvenient, and impractical for extended digital usage [8] [18].

Computer vision methods for nonverbal behavior analysis allow a sound and predictable, simple means for fatigue detection with conventional webcams without disturbing the user [1]. This has led to the formulation of intelligent and interactive systems that can dynamically respond to users' cognitive states to minimize errors and support productivity [11] [12]. Research objectives in detection of mental and cognitive fatigue have grown from measuring physiological signals to intelligently and non-invasively analyzing behavior. [18] sought to obtain a valid scientific evaluation of fatigue through physiological signals (EEG and ECG) to reduce human bias in typical

techniques. [8] aimed to improve driver safety by combining supervised learning algorithms with physiological signals to detect drowsiness in real-time. [1] focused on the connection between cognitive load and physiological indicators to show the importance of mental endurance and sustained attention during prolonged tasks. [27] and [19] developed non-contact detection.

is an improved user-friendly facial expression/eye movement system for analysis based on webcams as a more user-friendly alternative to intrusive wearable devices. Hybrid CNN-LSTM architectures were developed [22] that combine spatial and temporal features to model continuous variations in mental states. In addition, two multimodal Transformer-based models were introduced [12] and [20] to enhance accuracy, interpretability, and adaptability to real-world environments. It is important to enhance privacy and real-time performance through the development of lightweight artificial intelligence models that can be executed on edge devices with high accuracy, thereby reducing the need for data transmission and minimizing response time, as confirmed by recent studies such as [26] and [24].

## 7. Review Methodology

This review takes a structured methodological stance by aiming to establish reliability in examining AI-based methods for mental and cognitive fatigue detection. The framework is based on established research and analytical methodologies [18] [8] [1] and encompasses a

comparative analysis of results, systematic searches across databases, and feature extraction based on modern practices in machine learning dataset development[28].

### 7.1. Search Strategy

A systematic search strategy was applied to the Scopus, Web of Science, IEEE Xplore, and ScienceDirect databases to identify relevant studies. The following keywords and logical links were used: ("mental fatigue" OR "cognitive fatigue") AND ("artificial intelligence" OR "machine learning") AND ("webcam" OR "nonverbal behavior" OR "face analysis").

### 7.2. Inclusion and Exclusion Criteria

**Inclusion:** Peer-reviewed studies (2012–2025) that included AI-based methods for detecting mental fatigue using webcam or visual cues.

**Exclusion:** Studies that were not peer-reviewed or unpublished, as well as those written in non-English languages, were excluded. In addition, research that did not present clear experimental validation or quantitative results, or that focused solely on non-AI-based fatigue detection methods, was omitted.

### 7.3. Data Extraction

For each selected study, the following data was recorded:

Author's name, year of publication, type of input data, algorithm or intelligent model used, database used, evaluation criteria, and main results.

### 7.4. Dataset

In AI research, one definition of database is a set of samples, images or structured signals employed in training and evaluating intelligent models. These datasets are of various types: type (e.g., ophthalmic, facial, physiological, and multimodal), the source (public or private), and purpose (training, testing, or comparison). Quality and diversity of data are the most determinants of data set and diversity and data quality, shaping a model's ability to learn useful patterns, make it more generalizable to meaningful patterns and have reliable results across different real world conditions [28]. The data sets applied in detecting mental and cognitive fatigue may be classified into two main types [19] [21] [18]:

1. A public dataset, such as NTHU-DDD, UTA-RLDD and YawDD, is publicly available and is frequently used to cross-check performance of models from many studies.
2. Private or laboratory datasets are obtained from the field or experiment within an institution, described on the basis of well-quality correct data. But these datasets are

frequently constrained, as they lack a broad diversity of participants, sample size and environmental conditions to generalize to real-life context.

Using the public NTHU-DDD database, simulated driving sequences with driver fatigue and drowsiness states were employed [21]. At 37 frames per second, their multi-level hybrid CNN–LSTM model was ~90% accurate. Since the lab data was created and was carried out under controlled conditions, the generalizability of these results to actual driving conditions is limited. As an example, [22] devised a separate dataset for the temporal drivers performance study solely as part of their hybrid model YOLOv3-LSTM. This model had good robust real-time performance with good stability to light and head position differences. But the data are constrained to the same public accessibility and diversity. HNUFD Multimedia Database was proposed in [12] to perform fatigue detection in a model using Residual Spin Converter and Feature Parameter Images in the Fatigue driving recognition and Residual Swin Transformer (FPIRST) with accuracy attained to ~96.5%. The model runs pretty well, but the problem is that it needs a lot of computation. Lightweight EMFastDet based on visual attention and anchor-free learning mechanism on eye–mouth features was proposed [26] for the fatigue detection system. The response of the model was shown accurate with fast response time and its computational resources reduced well. In [24], LiteFat, a lightweight spatio-temporal graph learning framework that converts characteristic facial features, was adopted. Features into the form of graph structures for the real-time fatigue detection task. The model was competitive in performance yet it can be said to have the lower computational complexity and inferencing time, making it appropriate for the edge AI domain.

### 7.5. Feature Extraction

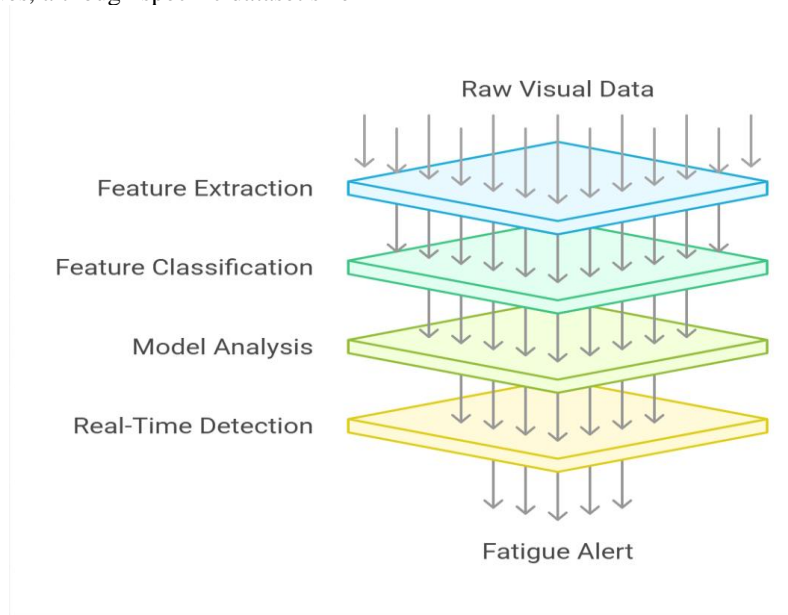
Feature extraction is one of the most important stages in cognitive fatigue detection systems. It converts raw visual data (such as videos and images captured from webcams) into numerical variables that represent the user's cognitive state[29]. The extracted features are generally classified as ocular (pupil dilation and blink rate), postural (head and torso orientation), facial (micro-facial expressions), and kinetic (behavior and posture changes). These features feed into intelligent models that analyze the user's mental state in real time [10][22][30](see **Figure 4**).

Facial and physiological characteristics According to a report by [10], facial and physiological features were obtained with the smartphone camera and the biosensors i.e. ECG, PPG. Visual eye cues and physiological signals were combined using a fuzzy-Bayesian data-fusion method to classify the driver's fatigue rate in real-time. System generated an Alert/Fatigued classification. [22] constructed a new private

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dataset and showed we can use a hybrid YOLOv3–LSTM model to predict postural/facial patterns for real-time driver fatigue detection under varying illumination and head-pose conditions. [26] presented an anchor-free real-time lightweight fatigue-detection model and visual attention mechanisms with better accuracy and reduced latency. The multimodal fusion of spatial and temporal visual cues, although specific dataset size

and accuracy metrics were not reported. Research indicates that the efficacy of a system for recognizing fatigue depends on the particular type. Not only model type, but also extracted features, of them, their type, and how they are represented in the model. The addition of temporal, spatial, and multimodal features improves detection of mental fatigue in real-world environments [31] [23].



**Figure 4.** Feature Extraction Pipeline

This figure shows the multi-stage processing of raw visual input, including feature extraction, feature classification, model analysis, and real-time fatigue detection.

## 7.6. Model Development

Model building is the process of designing, building, and evaluating intelligent models to facilitate making correct decisions and to spot patterns. This gradual process comprises the selection of algorithm, data selection, feature extraction, model training, and evaluation [15] [16]. Artificial intelligence algorithms are computational methods that mimic human cognition (such as decision-making, learning, and problem-solving mechanisms) [13] [15]. Deep learning and machine learning are the two main types of algorithms, and the decision between them is based on either the size of the data or the complexity of the task. Machine learning algorithms are based on analyzing structured data to determine patterns and predict outcomes of unseen activities. To use support vector machine (SVM) as an example, and random forest algorithms have been applied successfully for mental and cognitive fatigue

detection via face and eye features [18] [15]. Deep learning algorithms consist of multi-layer neural networks mimicking the operation of the human brain to extract features from raw data automatically. Prominent examples include convolutional neural networks (CNNs) that help with image processing, recurrent networks (LSTMs) used for processing time-based signals, and transformers for combining time and space context [22][20][26].

Since then, systems with capacity for monitoring real-time user status have been established, paving the way for efficient adaptive AI analyzing mental fatigue [16]. In early days of development, previous investigations such as [8] and [1] employed classical classification methods like SVM and Random Forest, which handled physiological data (EEG and ECG) for fatigue detection. However, such algorithms were unable to capture complex spatial characteristics. Subsequent research like [10] and [21] utilized multimodal fusion and CNNs to study facial and physiological cues, leading to effective visual recognition of subtle changes and complex expressions. At a more sophisticated step, previous work [22] [31] demonstrated the value of a convolutional processing model, using a combination of CNN's spatial capacity and

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LSTMs' ability to learn on a temporal scale to build hybrid CNN-LSTMs that could actively monitor fatigue over timescales. Recent models leverage attention and transformer mechanisms to perform this effectively, combining diverse modes—eye, face, and pose—into unified architectures, as in the study done by [12] and [20], which showed noteworthy improvements in accuracy.

Recent studies are centered around the realization of lightweight (MobileNet, LiteFat) models for real time implementation on edge devices, which are not only cheaper from a computational point of view (less effort to simulate high efficiency) but also lead to the cost efficient and economical implementation, with above 90% accuracy [26] [24] [23]. Such sequential development has brought about the transition away from heavy models towards smart, real time, efficient, privacy-preserving intelligent, autonomous models.

### **7.7. AI-Based Fatigue Detection Applications**

Among AI-based fatigue detection systems have been educational, industrial, and healthcare industries. Smart models were utilized in various occupations and age categories, providing maximum levels of response and precision in real-time. For instance, in one case [10] constructed a smartphone-based driver fatigue monitoring system, visual and physiological signals merged (eye images and ECG/PPG data) through a fuzzy-Bayesian data-fusion approach for real time alertness assessment. This model was implemented over the vehicle drivers in street using smartphone cameras and wearable sensors during simulated driving. In another study, [1] observed the mental state based on EEG and ECG signals, fatigue in participants with stressful cognitive tasks and found

that cognitive decline strongly correlates with physiological measures, which indicates superior reliability to behavioral models (see **Figure 5**). The experiments were performed on healthy adult subjects under cognitive load in laboratory conditions.

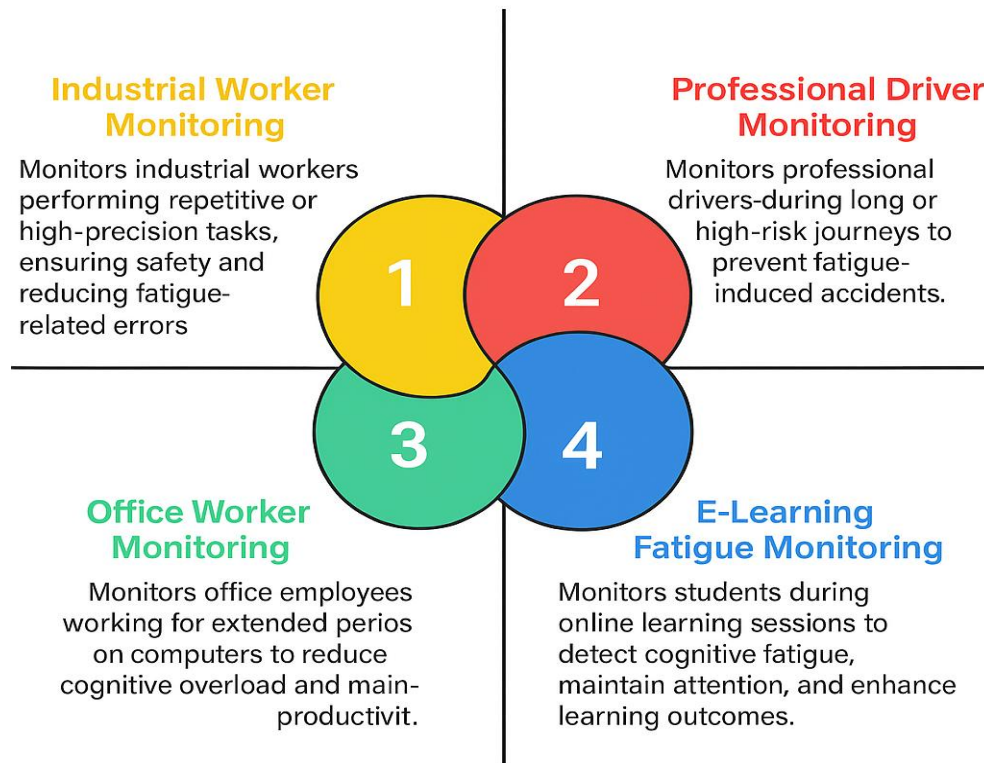
Drivers were monitored in real-time using the public NTHU-DDD dataset [21]. Their CNN-LSTM model analyzed facial micro-expressions and ocular behavior to detect moments of drowsiness and lapses in attention. This study targeted university students and volunteer drivers recorded through in-vehicle cameras.

In industrial applications, [8] applied SVM and Random Forest algorithms in driver-monitoring systems to assess fatigue levels through eye and facial cues, achieving accuracy exceeding 90 % in real-world driving conditions. Their work mainly addressed professional and long-distance drivers.

A multimodal fatigue detection system combining superficial electromyography (sEMG) and internal measurement unit (IMU) signals using a hybrid CNN-LSTM-Attention model has been proposed [11]. The system achieved about 88 % accuracy in distinguishing fatigued from non-fatigued states during controlled physical-activity experiments. This model was designed for industrial workers performing repetitive physical tasks.

Recent research has also employed edge-AI frameworks, such as [24], in digital work and office environments. These lightweight models operate locally without cloud connections, ensuring faster response and improved privacy protection. The

LiteFat model was tested on office employees and general computer users for real-time webcam-based fatigue detection.



**Figure 5.** Applications of Fatigue Detection Across Different Sectors

The figure presents four key application areas for fatigue-detection systems: industrial workers, professional drivers, office employees, and e-learning environments. Each sector benefits from monitoring mental and cognitive fatigue to enhance safety, productivity, and user well-being.

### 8. Thematic Classification of Literature

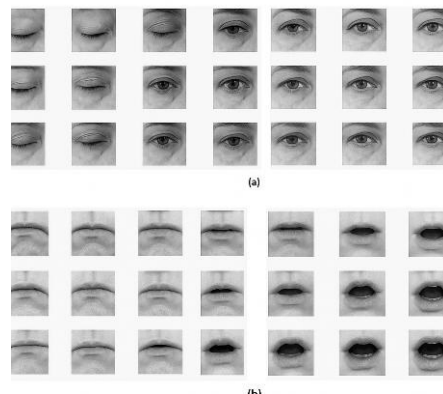
The literature on mental and cognitive fatigue detection found in this review can be segmented in thematic direction depending on input type and analysis methodology. These findings comprise facial expression-based detection, eye and mouth movement analysis, head posture estimation, and multimodal integration combining several visual inputs. This categorization gives an organized overview of the development of computer vision approaches to the enhancement of robustness, real-time effectiveness, and non-intrusive capability for fatigue recognition systems [12].

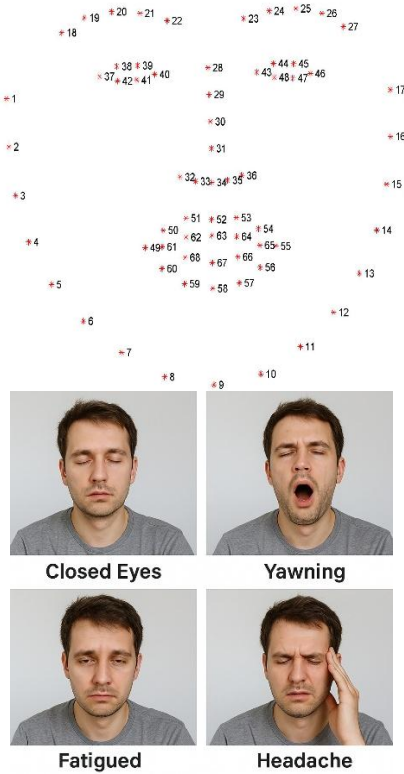
#### 8.1. Facial Expression-Based Detection

Facial expression analysis is one of the most important factors in nonverbal fatigue detection, as eye closure, yawning, and subtle facial muscle relaxation are key indicators of cognitive fatigue [27][1](see **Figure 6**).

Deep learning models, such as convolutional neural networks (CNNs), residual networks

(ResNets), and vision transformers (ViTs), have also been employed in recent studies to detect fine-grained facial variations linked to fatigue [8]. Publicly available databases such as FEEDTUM, NTHU-DDD, and UTA-RLDD have been widely used to train and test models at different illuminations and expressions. But the small number of participants and low demographic diversity for most datasets limit the extent to which these models generalize to real-world users [23]. So, researchers are currently implementing multimodal fusion approaches, combining facial, ocular, and behavioral cues to improve model stability and accuracy in naturalistic environments [11] [12][40].





**Figure 6.** Facial Expression–Based Indicators Used in Fatigue Detection

This figure illustrates key visual cues used in fatigue detection systems, including eye appearance variations, mouth openness states related to yawning, and standardized facial landmark points.

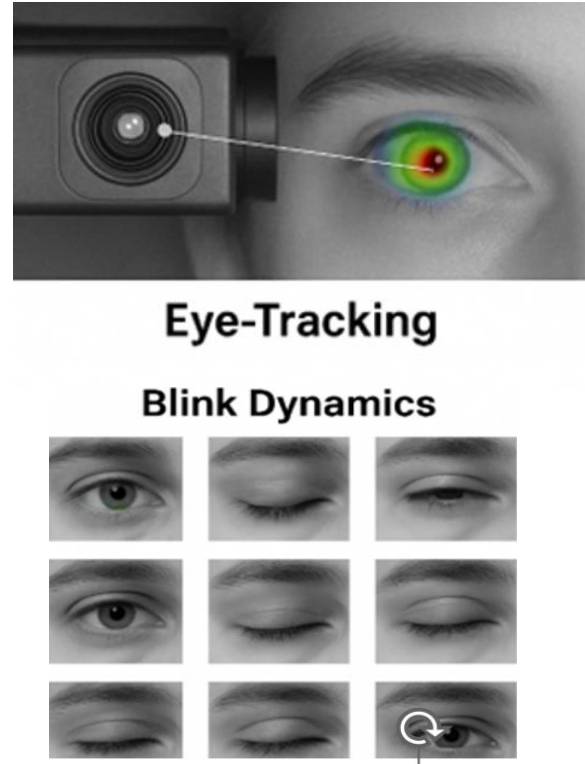
### 8.2. Eye-Tracking and Blink Dynamics

Eye properties such as blink rate, pupil dilation, and gaze deviation are important markers for detecting cognitive and mental fatigue (see **Figure 7**), as these are directly correlated to reduced attention and cognition during prolonged computer use. Convolutional neural networks (CNNs) and hybrid CNN-LSTM architectures are the recent techniques for detecting changes over time [23][31].

Studies have also demonstrated that integrating eye features with other data—such as facial expressions or nonverbal behavioral cues—helps enhance the efficiency and reliability of models under changing lighting scenarios or shooting angles [11]. However, most datasets are still limited in size and diversity [23]. Body posture and head movement are effective indicators of mental and behavioral fatigue, which are associated with head hunching and slouching; the degree of fatigue increases during prolonged cognitive tasks. Modern computer vision tools like OpenPose, MediaPipe, and skeleton tracking methods enable the detection and real-time processing of motion cues using intelligent technologies [23]. Other research has shown that behavioral patterns such as frequent slumping or lowering of the head are key nonverbal indicators of cognitive and mental fatigue,

especially when combined with other visual cues such as eye movement or facial expressions [23][31]

However, varying lighting and camera angles remain a major challenge affecting the accuracy of models in realistic environments.



**Figure 7.** Eye-Tracking and Blink Dynamics Visualization

This figure presents two essential visual cues used in fatigue detection systems. The left panel demonstrates eye-tracking behavior through gaze movement patterns, while the right panel illustrates blink dynamics by comparing open-eye and closed-eye states.

### 8.3. Body Pose and Motion Analysis for Fatigue Detection

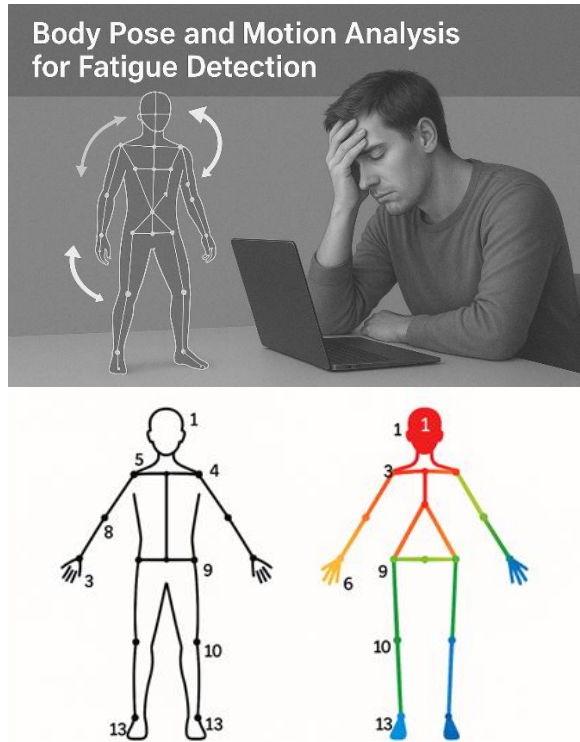
Body posture and head movement analysis are effective indicators of cognitive and behavioral fatigue, as changes in head tilt and sway are associated with fatigue levels during prolonged cognitive tasks.

Modern computer vision tools such as OpenPose, MediaPipe, and Skeleton Tracking methods enable the detection and real-time processing of motion cues using intelligent technologies [23] (see **Figure 8**).

Other research has shown that behavioral patterns such as frequent slouching or head tilt are key nonverbal indicators of cognitive and mental fatigue, especially when combined with other visual

cues such as eye movement or facial expressions [23][31].

But lighting and different camera angles are still significant hurdles that affect the accuracy of models in real-world environments.



**Figure 8.** Comparative Body Pose Representations for Motion Analysis

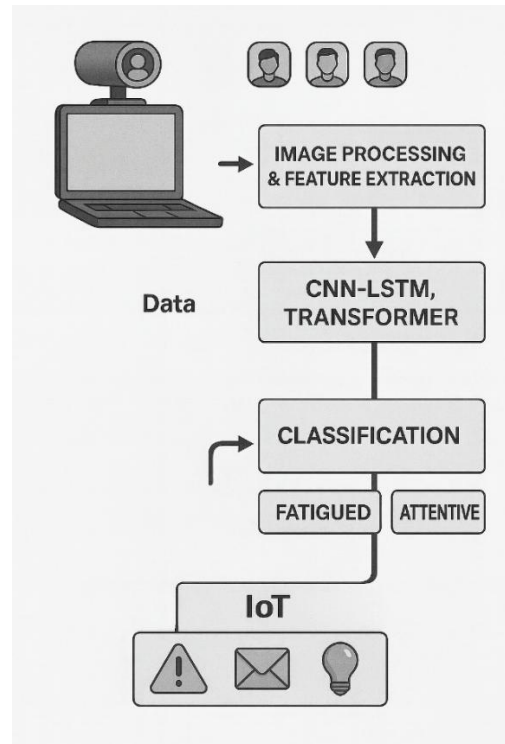
This figure illustrates two common skeletal models used in body-pose and motion analysis. The left model shows a simplified stick-figure representation with numbered keypoints, while the right model provides a color-coded pose structure highlighting joint connectivity.

#### 8.4. Hybrid Multimodal Detection Frameworks

Multimodal detection systems are rapidly developing due to their ability to blend facial, eye, and pose data with other signals (e.g., voice or keystrokes) to strengthen the models' ability to accurately interpret fatigue. Recent works such as [32] have demonstrated that fusion significantly increases detection accuracy. [31] also highlighted the importance of using attention-based deep learning models and transformers for better understanding the relationships among different signals and improving the ability to predict user states. However, [23]note that difficulties in multimedia systems are still widespread, including efficiency and privacy protection owing to large data volumes and complex integration processes (see **Figure 9**).

Real-time implementation of real-time edge AI systems. There has been increasing development of

actual systems to detect cognitive fatigue in real time on digital devices. This is intended to lessen dependency on cloud computing and to realize instant response without exposing the privacy of users [23]. These systems use lightweight AI models such as MobileNet and TinyCNN. Several studies [32] have demonstrated the ability to run on resource-constrained systems (e.g., the NVIDIA Jetson Nano at speeds up to 20 frames per second) when using memory-conserving model optimization or quantization techniques that reduce memory consumption and speed inference while ensuring classification accuracy above 90%. On-device analysis without cloud connection is another approach that [31] emphasized being adopted. It helps improve user security and privacy by preventing facial imagery and visual data from being sent to remote servers. Other research [26] has shown that combining these lightweight models with transformer algorithms and attention mechanisms helps achieve a better balance between accuracy and computational efficiency.



**Figure 9.** Hybrid Multimodal Detection Framework for Non-Verbal Fatigue Analysis

This figure illustrates the full processing pipeline of the proposed hybrid multimodal fatigue detection framework. Webcam visual inputs undergo image processing and feature extraction before being analyzed using CNN-LSTM and Transformer-based models. The system then classifies the user as attentive or fatigued, and the final output triggers IoT-based actions such as alerts, messages, or smart-lighting adjustments.

### 9. Comparative Analysis

A systematic comparison among previous research shows that in recent years there has been a paradigm shift in the detection methods for mental and cognitive fatigue, moving away from physiology-based techniques towards non-invasive computer vision and non-verbal behavior analysis techniques.

High accuracy of the traditional methods of EEG and ECG were achieved in the laboratory. Nevertheless, they have limited real-world applicability as they relied mostly on human contact and are not practical for prolonged use [18][8]. Systems later relying on webcams would analyze facial expressions, blink rate, head posture etc. making monitoring a continuous and unobtrusive affair [10][21]. For visual features, convolutional neural networks (CNNs) have been the dominant method of extraction but hybrid models (CNN–LSTM), attention models (Transformer architectures) are also better at integrating spatial and temporal dynamics [22][31][26] had shown that spectral and entropy integrated EEG features together with deep models such as CNN–GRU are able to accurately identify mental fatigue, but its accuracy level in generalizing to real world conditions was limited due to participant numbers and controlled settings. [18] further verified that physiological signals, particularly ECG, can outperform self-report measures. Using supervised

learning algorithms including SVM and Random Forest and the experimental design helped their model achieve high classification accuracy, though under controlled environment, it still struggled to be applicable to real environments due to contextual variability and small sample size. Multimodal applications integrating facial, ocular, vocal and postural cues have been demonstrated superior performance in fatigue detection, despite ongoing challenges in privacy and computational complexity [12]. Although numerous studies have utilized public datasets like FEEDTUM, NTHU-DDD, and UTA-RLDD, constrained environmental and demographic diversity still play a role in generalizability of the results [11][1][37][39]. More recent studies using lightweight models and real-time edge processing, for example MobileNet and LiteFat have shown that computational efficiency can be combined with privacy protection [24][38]. Together, these findings demonstrate a growing inclination towards lightweight, multimodal and privacy-preserving AI systems that are able to operate in real-time for accurate mental-fatigue detection.

Table1 is a methodological comparison of the most important experimental studies in the area of mental-fatigue and non-verbal behavior detection for 2012–2025 employing AI and computer-vision techniques.

**Table1:** Comparative Summary of Core Studies on Fatigue Detection

No.	Year	Authors	Input Modality	Model Used	Dataset	Accuracy (%)	Feature Extraction Algorithm	Key Limitations	Key Strength
1	2012	Lee, B. G., & Chung, W. Y.	Eye, ECG, PPG, Temp, Accelerometer, Speed	Fuzzy Bayesian Framework	Custom (Real Driving)	94	Statistical + Frame Diff.	Contact sensors; no public dataset	Combining multiple physiological data provides greater reliability for estimating fatigue while driving.
2	2017	Van Cutsem et al.	EEG/ECG	SVM	Custom	92	EEG band + HRV	Intrusive hardware	High sensitivity to brain stress through analysis of frequency bands in EEG signals.
3	2018	Lyu et al.	Facial	CNN–LSTM	NTHU-DDD	90	Spatio-temporal features	Limited generalization to real-world	A robust model of time-visual features using CNN–LSTM to detect facial fatigue.
4	2021	Ye et al.	EEG	CNN–GRU (vs SVM/RF)	Private (Cognitive Tasks)	85.3	Spectral energy + entropy	Small dataset; lab setting	CNN–GRU demonstrates superiority over traditional learning algorithms in detecting cognitive fatigue from EEG.
5	2021	Faraji et al.	Face + Posture	CNN–LSTM	Custom	94.2	Temporal facial & head-posture features	Small dataset; controlled environment	Enhancing the accuracy of behavioral fatigue detection by combining facial expressions and head posture.

6	2023	Cos et al.	EEG + ECG	SVM, Random Forest	Private	93.8	Time-frequency & statistical features	Limited generalization to real-world scenarios	Significant improvement in accuracy through multimodal integration of EEG and ECG signals.
7	2023	Wang, Y. & Turnbull, A. & Xu, Y. & Heffner, K. & Lin	Facial gestures/video cues	Recurrent Video Transformer (RVT)	CCT Video dataset	Balanced Acc 78.0	Recurrent Video Transformer for temporal nonverbal feature integration	Focus on cognitive training; validated fatigue vs engagement in real-time video	The RVT model provided advanced capabilities for analyzing time signals using the attention of recurrent Transformers.
8	2023	Zeng, W. & Xiao	Eye blink detection from untrimmed video	Spatio-temporal end-to-end detection	MPEblink dataset	-	One-stage spatio-temporal optimization	Focus on robust real-time blink cues for fatigue and nonverbal behaviour	Eye blink detection using a highly robust, single-stage method to extract accurate fatigue indicators.
9	2023	Hosseini, M. & Bodaghi	Facial landmarks + biometric signals	Early/late fusion 1D-CNN + 2D-CNN	-	~98.38	Feature-level multimodal fusion with biometric + vision	Multimodal approach improves behavioural indicator integration for stress/fatigue	Effective integration of biometric measurements and visual data leads to very high accuracy.
10	2024	Xiao et al.	Face + Eye	Residual Swin Transformer	HNUFD	96.5	Self-attention + facial landmarks	Sensitive to glasses and lighting	Swin Transformer offers a strong hierarchical representation of the face based on an advanced attention mechanism.
11	2024	Zhou et al.	Face + Gaze + Speech	Multimodal CV	Education	93	Gaze tracking + speech features	Cultural bias	Multimodal analysis combines eye, facial, and voice observations to comprehensively assess fatigue
12	2024	Liu et al.	Visual (XAI)	HAG-XAI (FullGrad-CAM++)	BDD-100K / COCO	90	Saliency + human attention maps	Faithfulness trade-off	. Using XAI interpretive interest maps enhances understanding of the detection model and increases its reliability.
13	2024	Applied Intelligence	Facial/Ocular	MobileNet	Public	92	Lightweight CNN embeddings	Accuracy-latency trade-off	The MobileNet model is lightweight and efficient, suitable for instant and low-computational-power applications.
14	2025	Ren et al.	Facial	Spatio-Temporal Graph (LiteFat)	Custom (Driver)	94.7	Facial landmarks + temporal graph features	Limited public data; edge deployment constraints	Time-spatial graphical modeling capable of capturing very subtle movements associated with fatigue.
15	2025	Ha, M., et al.	Facial landmarks (EAR, MAR, Blink rate)	LSTM	UTA-RLDD	92.35	EAR + MAR + Blink-rate + facial landmark tracking	Limited dataset diversity; tested only in controlled webcam setup	Combining EAR, MAR, and limb rate provides clear and easy-to-interpret physiological indicators.

16	2025	Hamoud, B., et al.	Eye-tracking signals + facial expression video features	TabNet + Random Forest	Private experimental dataset	82% (eye-tracking) / 78% (video)	Fixation + saccade + blink metrics + facial expression features	Dataset not public; small sample size; limited generalization	Combining eye-tracking cues with facial expressions provides a rich behavioral representation of fatigue.
17	2025	Hassan, O. F., Ibrahim	Eye ROI + eye state (open/close) + head pose	Vision Transformer (ViT) + Swin Transformer	MRL Eye + NTHU-DDD + CEW	99.15	Transformer-based feature encoding (ViT/Swin)	Requires high computation; limited real-world webcam testing	A hybrid architecture based on ViT + Swin achieves very advanced performance across multiple databases.

**Table1** shows that we can see an obvious shift in mental-fatigue detection methodologies, as research has moved away from being device-based physiological signals to studying behavioral and visual cues from the video. An increasing emphasis can be seen on hybrid systems that use deep learning to combine multimodal information. Hybrid models with complex embeddings and deep learning models have been tested on various architectures to achieve this, which have enabled their algorithms to enhance accuracy and decrease processing time. The shift from contact-based forms of physiological models to less intrusive, non-intrusive, computer-vision-based approaches is also indicated in the comparison. Based on approaches that increase practical usability and reduce user interference. However, the comparison shows most studies suffer issues regarding limited generality and real-world implementation difficulties, underscoring the need for further study to establish an approach which achieves a mix of precision and real-time operational convenience.

## 10. Discussion

Webcam-based cognitive fatigue detection was investigated by meta-analytical studies. In summary, meta-analytic systems have made considerable advancements with the use of state-of-the-art computer vision and deep learning methodologies, but still big challenges remain.

The majority of the developed models from previous research may have limited scalability because of their dependence on restricted or identical datasets of age, environment, or mental condition of subjects [18][11]. Limitations on ethical principles and privacy issues also limit the growth in data volume and diversity, mainly in real-world or cyber applications [12][26]. Some works have applied explainable artificial intelligence (XAI) concepts to understand the rationale behind model decisions and promote transparency. They have also employed federated learning, which allows models to be trained on distributed data without the need for centralized sharing [26][24]. Conversely, multimodal fusion (facial, ocular, postural) has shown a stronger relationship with subjective fatigue measures such as the Karolinska Sleepiness Scale, confirming nonverbal behavioral markers as a

substitute for tactile physiological signals [1][31]. From this, it may be suggested that the future direction in this field is the design of interactive, understandable, explainable, real-time intelligent systems that marry accuracy, efficiency, privacy, and ease of implementation. This is a critical measure to take toward a fundamental move providing safer and more efficient digital environments.

## 11. Research Gaps and Future Directions

An analytical review of the literature revealed several research gaps that limit the full development of the field of cognitive and mental fatigue detection using webcams and AI techniques, as detailed in Table 2.

Many existing studies rely on limited and non-diverse datasets, leading to poor generalizability of models in real-world settings [11][18].

The computational complexity of deep models also limits their ability to operate in real time on resource-limited devices [22][26].

In addition, privacy and ethical issues are among the most prominent challenges facing largescale visual data collection, especially in applications that directly deal with facial images or video recordings [12].

Recent studies in nonverbal behavior analysis show that capturing micro-expressions is a major challenge due to their extremely short duration and low intensity, as well as their high sensitivity to lighting and movement conditions. This directly impacts the reliability of computer vision-based systems in detecting a person's internal cognitive states [41].

To address these challenges, future research should focus on developing lightweight, explainable AI (XAI) models that can be run on edge devices using federated learning to ensure user privacy without sacrificing performance [26][24]. Interest in developing context-aware intelligent systems capable of distinguishing fatigue from emotional states or other environmental factors is also expected

to grow, increasing system reliability in culturally and operationally diverse environments [31][1][33].

**Table 2.** Identified Gaps and Proposed Future Directions

Research Area	Limitation	Future Work
<b>Dataset</b>	Poor representation of cultural and social diversity	Develop open, large, multicultural datasets
<b>Deployment in real time</b>	High inference cost and delay	Building a lightweight edge model with artificial intelligence
<b>Interpretability</b>	Deep models are opaque	Integrating XAI techniques to improve interpretation capability
<b>Design Ethics</b>	User Consent and Webcam Privacy Challenges	Train models on the device instead of the cloud
<b>Adaptation Cross-Domain</b>	The model performs poorly when used in different settings	Apply domain adaptation and transfer learning strategies

## 12. Conclusion

The present literature review provides a comprehensive overview of advances in artificial intelligence (AI) and computer vision technologies for cognitive and mental fatigue detection based on nonverbal behavior analysis using webcams. Over the past decade, this field has shifted from traditional methods based on static facial features to dynamic multi-modality systems capable of real-time analysis. Despite this progress, challenges related to privacy, interpretability (XAI), and ethics remain major obstacles to the widespread deployment of these models in real-world applications. Overcoming these challenges is a critical step toward building integrated AI systems that enhance user well-being, boost productivity, and help unlock new horizons for more conscious human-machine interaction.

Future work could focus on integrating behavioral and physiological data, expanding database diversity to improve generalization, developing self-learning and session-based adaptation algorithms to enhance long-term reliability, conducting real-time testing in unconstrained environments, exploring lightweight Transformer architectures for efficient operation on

edge devices, expanding assessment to include diverse lighting conditions, age groups, and cultural backgrounds, and implementing longer recording periods, which is essential for enhancing system realism. Incorporating privacy-preserving techniques, such as on-device processing and distributed learning, is a promising approach for providing secure and scalable webcam fatigue detection systems.

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