Computer-Vision-Based Web Service for Human Mental Fatigue Analysis Using Physiological Characteristics

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***Abstract*—Mental fatigue caused by prolonged computer-based activities can reduce attention, impair decision-making, and increase the likelihood of human error. Although numerous computer vision approaches have been proposed for fatigue detection, many remain research prototypes and lack practical deployment. This paper presents a web-based service for automated contactless mental fatigue assessment using facial videos acquired from a standard RGB camera. The proposed platform implements a complete processing pipeline, including video acquisition, facial landmark detection, behavioral feature extraction, contactless physiological estimation, feature aggregation, and fatigue analysis. Two complementary analysis modes are provided: a detailed mode based on physiological and behavioral features and a lightweight mode relying only on RGB signal statistics for rapid fatigue screening. The fatigue assessment module was developed using two complementary datasets collected during prolonged cognitive workload experiments. Among the evaluated machine learning models, a class-weighted CatBoost classifier demonstrated the best performance, achieving an accuracy of 91% and an F1-score of 88%.The developed web service demonstrates how computer vision and machine learning can be integrated into an accessible web-based service for practical mental fatigue assessment without requiring wearable sensors or specialized hardware.**

I. Introduction

The rapid digitalization of modern workplaces has fundamentally changed how many professionals perform their daily tasks. Occupations such as software engineering, air traffic control, healthcare, transportation, industrial supervision, and security monitoring increasingly require prolonged computer use, continuous information processing, and sustained attention. These professions rely heavily on cognitive resources, which gradually become depleted during extended work, leading to mental fatigue [1], [2]. Because fatigue develops gradually, people often fail to recognize it before it begins to affect performance. As fatigue accumulates, reaction time slows, attention decreases, decision-making deteriorates, and the likelihood of human error increases, potentially causing reduced productivity, economic losses, and safety-critical incidents [3], [4].

Since mental fatigue cannot be observed directly, its objective assessment has become an important research topic. Traditional approaches rely on physiological measurements such as EEG, ECG, EMG, and PPG, together with behavioral observations and subjective questionnaires [5]–[8]. While physiological measurements provide reliable and objective information, they require specialized sensors, physical contact, and controlled acquisition conditions, limiting their use outside laboratory environments. Subjective assessments are easier to administer but cannot provide continuous or objective monitoring.

Recent advances in computer vision and artificial intelligence have enabled contactless fatigue monitoring using conventional RGB cameras [9]. Improvements in facial landmark detection, remote photoplethysmography (rPPG), and deep learning allow physiological parameters to be estimated directly from facial videos without wearable devices. Modern vision-based methods extract multiple fatigue-related indicators, including eye movements, blink frequency, yawning, head pose, facial appearance changes, and cardiovascular characteristics estimated from subtle skin color variations [10]–[12]. Recent studies further demonstrate the benefits of combining behavioral and physiological information for more robust fatigue estimation [13].

Despite these advances, most studies focus on feature extraction or improving classification accuracy using offline datasets, while relatively few describe complete software systems suitable for practical use. In reality, fatigue monitoring requires an integrated pipeline that includes video acquisition, preprocessing, facial landmark detection, physiological signal estimation, feature extraction, fatigue prediction, and result visualization [14], [15]. The lack of accessible end-to-end software remains one of the main barriers to wider adoption.

Accessibility is another challenge. Existing solutions often depend on specialized software, dedicated hardware, or complex installation procedures. However, recent developments in web technologies make it possible to deploy advanced computer vision algorithms through browser-based applications, allowing users to perform fatigue assessment using only a webcam or a prerecorded facial video. This significantly improves the accessibility of fatigue monitoring for healthcare, education, and industrial applications.

Motivated by these challenges, this paper presents a computer vision-based web service for automated mental fatigue analysis from facial videos. Unlike traditional research prototypes that focus mainly on prediction models, the proposed system provides a complete browser-accessible processing

pipeline. Users can upload prerecorded videos or record new ones directly from a webcam. The system automatically extracts physiological and behavioral characteristics, including estimates of blood pressure, oxygen saturation, eye movement dynamics, blink-related measures, yawning characteristics, head pose, and statistical RGB features. These features are analyzed by machine learning models to estimate fatigue level, with the results presented through an interactive web interface.

The proposed service integrates all processing stages into a lightweight web application, providing a contactless and hardware-independent solution that runs on conventional devices equipped with standard RGB cameras. It demonstrates how recent advances in computer vision and physiological estimation can be translated into an accessible tool for both research and practical fatigue monitoring.

The scientific novelty of this work lies in the development of a dual-mode contactless mental fatigue assessment framework that integrates heterogeneous physiological and behavioral characteristics extracted exclusively from standard RGB facial video within a unified web-based processing pipeline. In contrast to approaches focused on individual fatigue indicators or offline classification, the proposed framework combines eye behavior, head and mouth dynamics, facial RGB statistics, and contactless physiological estimates within a detailed assessment mode, while providing a complementary lightweight mode based solely on RGB signal statistics. This design enables the same browser-based system to support two different accuracy–computational-efficiency trade-offs without requiring wearable sensors or specialized acquisition hardware.

The main technical and practical contributions of this work can be summarized as follows::

- We develop an end-to-end web-service that performs automated mental fatigue analysis directly from facial videos using only a conventional RGB camera.
- We integrate physiological estimation and behavioral analysis within a unified computer vision pipeline capable of extracting multiple complementary indicators related to cognitive fatigue.
- We implement a browser-accessible platform that supports both prerecorded video upload and real-time webcam acquisition without requiring specialized hardware or software installation.
- We demonstrate a practical software architecture that bridges recent advances in computer vision-based fatigue assessment with real-world deployment scenarios, providing an accessible tool for researchers and practitioners.

The remainder of this paper is organized as follows. Section II reviews existing vision-based techniques for mental fatigue assessment, and digital healthcare services. Section III presents the proposed web-based fatigue assessment service, describing its architecture, processing pipeline, fatigue assessment methodology, and implementation details. Section IV describes the datasets, experimental setup, fatigue classification models, and the performance evaluation of the developed web service. Finally, Sections V and VI discuss the obtained results, summarize the main contributions of this work, and outline directions for future research.

II. Literature Review

This section reviews previous research relevant to the development of the proposed web service. The discussion first considers vision-based approaches to mental fatigue assessment, including methods based on facial behavior, eye and mouth characteristics, head movements, and contactless physiological information extracted from video. It then examines existing digital healthcare services for fatigue monitoring and management, with particular attention to how fatigue-related information is collected, analyzed, and presented to users

A. Vision-Based Mental Fatigue Assessment

The practical limitations of wearable and contact-based sensors have encouraged the development of fatigue assessment methods that rely on ordinary image and video data. Vision-based systems are particularly attractive because they can observe a person without attaching equipment to the body or interrupting an ongoing activity. A camera positioned near a workstation, vehicle dashboard, or industrial control panel can continuously capture facial and postural changes associated with declining alertness.

A substantial part of the existing literature concentrates on visible behavioral manifestations of fatigue. Eye closure is among the most commonly used indicators because it can be measured continuously and tends to become more frequent or prolonged as alertness decreases. Mouth opening and yawning provide additional evidence, while gradual changes in head posture may indicate nodding or loss of postural control. These signals are often quantified using measures such as the Percentage of Eyelid Closure over the Pupil over Time (PERCLOS), eye aspect ratio, mouth aspect ratio, mouth-opening frequency, and head-pose angles. Combining several indicators is generally more reliable than applying a decision rule to a single facial feature, since blinking, looking downward, speaking, or briefly opening the mouth may occur even when the subject is not fatigued.

An example of this strategy was presented in [16], where a real-time driver-fatigue monitoring system was constructed from two consecutive stages. A lightweight detection network first identified whether the eyes and mouth were open or closed in each video frame. These observations were then processed by an EYE–MOUTH fatigue evaluation module that calculated PERCLOS and the Frequency of Open Mouth. Instead of treating either measure as sufficient by itself, the authors applied a multi-feature fusion rule to produce the final fatigue decision. At the same time, the method illustrates a common characteristic of many vision-based fatigue systems: the final assessment depends strongly on the reliable localization of relatively small facial regions.

Traditional computer vision and classical machine learning remain relevant, particularly when computational simplicity and fast inference are required. In [17], facial landmarks around the eyes, nose, and mouth were detected us-

ing histogram-of-oriented-gradient features [18] and a linear support vector machine. Eye aspect ratio, mouth opening ratio, and nose length ratio were then calculated to represent blinking, yawning, and head inclination. Following an initial adaptive-thresholding stage, several classifiers were evaluated for distinguishing alert and drowsy states. This study shows that effective fatigue monitoring does not always require a large end-to-end neural architecture; carefully selected geometric descriptors may remain competitive while requiring fewer computational resources.

Recent work has also investigated temporal deep-learning architectures that process sequences of facial images rather than evaluating each frame independently. Makhmudov *et al.* [19] proposed a real-time system that combines the recognition of eye state and yawning behavior using convolutional models. The approach emphasizes continuous fatigue analysis from video and demonstrates how temporally accumulated eye and mouth observations can be converted into an operational warning decision. Such methods are more suitable for practical monitoring than isolated image classifiers because fatigue is not represented by a single facial configuration; it develops over time and must therefore be inferred from the duration, recurrence, and co-occurrence of several visual events.

Overall, the reviewed studies demonstrate that computer vision provides an effective foundation for contactless fatigue assessment by combining behavioral analysis with physiological signal estimation. However, most existing approaches focus primarily on driver drowsiness and visible signs such as eye closure, yawning, or head nodding, which may not adequately reflect the gradual development of mental fatigue during cognitively demanding tasks. In addition, their performance can be affected by illumination changes, facial occlusions, and variations in recording conditions, while many models are evaluated only under controlled experimental settings. These limitations highlight the need for more comprehensive and practical solutions that integrate multiple visual and physiological cues within a unified framework. This motivation underlies the proposed browser-based web service, which combines video acquisition, feature extraction, physiological estimation, fatigue assessment, and result visualization into a single end-to-end computer vision pipeline.

B. Digital Healthcare Services for Fatigue Monitoring

Fatigue is difficult to evaluate during an occasional clinical appointment because its intensity often changes throughout the day. It may be influenced by sleep, medication, physical activity, emotional state, cognitive demands, and the surrounding environment. A patient may therefore report an average level of fatigue that does not fully describe when the symptom occurs or which activities make it worse. This problem has led to growing interest in digital healthcare services that collect fatigue-related information repeatedly in everyday settings. Most of these services use smartphone applications, wearable devices, or a combination of the two. Their main purpose is not simply to replace a paper questionnaire with an electronic form, but to observe changes over time and provide a more detailed picture of the patient's daily condition.

A common approach is ecological momentary assessment, in which users answer short questions several times during the day. Because the assessment is completed close to the time when the symptom is experienced, it is less dependent on long-term memory than a questionnaire completed once a week or during a hospital visit. The PROfeel system proposed by Nap-van der Vlist *et al.* [20] is one example of this approach. It was developed for adolescents with chronic medical conditions who experienced persistent fatigue. Participants used a smartphone to report fatigue and possible related factors during daily life. The collected data were then analyzed at the individual level and discussed with the participant in order to formulate personalized advice. The study showed that the method was feasible and that users considered the feedback useful. An important feature of PROfeel is that it does not assume that the same factors explain fatigue in every patient. Instead, it attempts to identify the combinations of activities and circumstances that are relevant to a particular individual.

A similar idea was used in the Energy InSight application described by Bootsma *et al.* [21]. The system was developed for patients with chronic cancer-related fatigue and was evaluated as part of psycho-oncological care. During a three-week period, participants reported fatigue, mood, activity, coping responses, and contextual information five times per day. The system then produced descriptive and network-based feedback that was discussed during therapy sessions. Patients reported that the application helped them notice relations between fatigue and other aspects of daily life that had not previously been clear. Therapists also found the information helpful for understanding the individual case, although interpreting the network feedback was not always straightforward. Since the study included only a small number of participants, its findings should be viewed as evidence of feasibility rather than proof of clinical effectiveness. Nevertheless, it illustrates how a fatigue-monitoring service can contribute to treatment planning instead of producing only a numerical score.

Smartphone services have also been examined in multiple sclerosis, where fatigue is one of the most common and disabling symptoms. Palotai *et al.* [22] developed an application for the real-time recording of fatigue and related symptoms in people with multiple sclerosis. Participants entered information several times during the day, allowing the researchers to study circadian symptom patterns and differences between fatigue phenotypes. The application was designed around the idea that fatigue is not stable and may follow different daily trajectories in different patients. The reported compliance suggested that repeated assessment was acceptable to many users, although adherence varied among participants. This is an important practical limitation of self-report services. The value of the resulting data depends on whether users continue answering the prompts, and people may be less likely to respond at the very times when their fatigue is most severe.

Block *et al.* [23] reviewed the role of remote monitoring in the evaluation of fatigue and fatigability in multiple sclerosis.

They emphasized the distinction between subjective fatigue and objective fatigability. Fatigue refers to the person's perceived lack of physical or mental energy, whereas fatigability describes a measurable decline in performance during an activity. Wearable devices may record step count, movement, physical activity, sleep, or changes in task performance, but these variables should not automatically be interpreted as direct measures of fatigue. A person may be inactive because of fatigue, but inactivity may also result from disability, work conditions, or a deliberate rest period. The authors therefore argued that remote assessment is most useful when subjective reports and objective performance measures are considered together.

More recent research has moved from descriptive monitoring toward digital phenotyping and machine learning. In this setting, patterns of smartphone use, mobility, activity, sleep, or wearable measurements are analyzed to estimate short-term changes in symptoms. Such methods may be useful because fatigue is affected by several interacting factors rather than by one physiological signal. They may also allow monitoring to continue with less direct input from the user. However, the interpretation of digital biomarkers remains difficult. A change in movement or sleep may be associated with fatigue, but it may also be explained by disease severity, medication, depression, pain, or changes in routine.

The study protocol proposed by Adam *et al.* [24] reflects this broader view of fatigue. The project was designed to investigate fatigue in individuals with myeloma, long COVID, heart failure, and in participants without problematic fatigue. It combines real-time self-reports with data from digital devices and qualitative interviews. Its purpose is not only to distinguish fatigued and non-fatigued individuals, but also to examine how fatigue develops over time and whether the relevant patterns differ between medical conditions. This design is valuable because a model trained on one patient population may not represent fatigue in another. It also recognizes that within-person variation may be as important as differences between participants.

Overall, the reviewed healthcare services demonstrate the value of digital technologies for fatigue monitoring by combining self-reported symptoms with data collected from mobile devices and wearable sensors. However, most existing solutions rely on repeated user input or continuous sensor use, while computer-vision approaches are rarely integrated into practical healthcare platforms. Although vision-based fatigue detection has shown promising results, many studies remain limited to algorithm evaluation without providing a complete user-oriented system. The proposed web service addresses this gap by integrating browser-based video acquisition, automated computer-vision analysis, and machine learning into a single platform that enables contactless fatigue assessment without requiring dedicated wearable devices.

III. Proposed Web Service

This section presents the design and implementation of the proposed web-based mental fatigue assessment service. It begins with the main design objectives and the overall client–server architecture, followed by a description of the video processing pipeline and the extraction of physiological and behavioral characteristics from facial recordings. The section then explains how the extracted features are aggregated and used for fatigue assessment, and concludes with the main implementation details of the developed web service.

A. Design Objectives

The primary objective of the proposed system is to provide an accessible and practical platform for contactless mental fatigue assessment that can be used outside specialized research laboratories. While numerous studies have demonstrated promising fatigue detection algorithms, their implementation often remains limited to offline experiments or standalone software intended primarily for research purposes. As a result, reproducing these methods or integrating them into routine healthcare and occupational monitoring workflows may require considerable technical expertise. The system presented in this work was therefore designed with deployment and usability considered from the beginning rather than as an afterthought.

A key design objective was accessibility. The platform is intended to operate through a standard web browser, allowing users to access the service without installing dedicated desktop software or configuring complex execution environments. Since modern computers and mobile devices are commonly equipped with RGB cameras, restricting the hardware requirements to a conventional camera considerably lowers the barrier for practical use. The browser-based interface also enables the same system to be accessed from different operating systems while maintaining a consistent user experience.

Another important consideration was modularity. Instead of implementing fatigue estimation as a single monolithic deep neural network, the proposed framework separates the processing pipeline into several independent modules responsible for video acquisition, preprocessing, facial analysis, physiological estimation, feature extraction, fatigue prediction, and result visualization. Such an architecture simplifies maintenance and future development because individual components can be replaced or improved without redesigning the entire system. For example, an updated physiological estimation model or a new fatigue classifier can be integrated while preserving the remaining processing pipeline.

Computational efficiency also played an important role during system development. Real-world deployment requires considerably more than achieving high prediction accuracy. Processing time, memory consumption, hardware availability, and model portability directly affect the usability of a web service. For this reason, the platform combines lightweight computer vision techniques with machine learning models that provide reliable fatigue estimation while avoiding unnecessary computational complexity. This design enables the system to execute on conventional computing hardware without requiring specialized GPUs on the client side, as the computationally intensive processing is performed on the server.

Finally, the system was designed to support multiple usage scenarios. Users may analyze previously recorded facial videos or acquire new recordings directly through a webcam using the same interface. The complete processing workflow from video submission and feature extraction to fatigue estimation and result visualization is performed automatically, minimizing user intervention. Such an approach makes the platform suitable not only for research studies but also for educational demonstrations, preliminary health screening, and future integration into broader telemedicine and occupational health solutions.

B. Overall System Architecture

The proposed web service which is accessible through http://hvpro.ru/ follows a modular client–server architecture designed to provide automated mental fatigue assessment from facial videos while maintaining accessibility, scalability, and ease of deployment. Rather than implementing fatigue estimation as a single end-to-end application, the system separates the complete workflow into several independent processing stages, each responsible for a specific task. This design improves maintainability and allows individual modules to be updated or replaced without affecting the remainder of the platform. As illustrated in Figure. 1, the complete workflow consists of six principal stages: video acquisition, data transmission, video preprocessing, feature extraction, fatigue assessment, and result visualization.

The interaction begins at the browser interface, which serves as the entry point to the system. To support different practical scenarios, the platform allows users to either upload a previously recorded facial video or capture a new recording directly through the device's webcam. Supporting both acquisition modes increases the flexibility of the platform. Previously recorded videos may be used for retrospective analysis or research experiments, whereas webcam recording enables immediate fatigue assessment without requiring additional software. Since the interface operates entirely within a standard web browser, the service remains independent of the user's operating system and requires no dedicated desktop installation.

Once a video has been selected or recorded, it is securely transferred to the backend server, where all computationally demanding processing is performed. This architectural decision was made deliberately. Although recent advances in web-based machine learning have demonstrated that neural networks can be executed directly on client devices, the computational requirements of the proposed fatigue assessment pipeline extend beyond a single prediction model. The analysis includes video decoding, facial localization, feature extraction, physiological estimation, temporal signal analysis, and machine learning inference. Performing these operations on the server ensures a consistent execution environment, avoids large performance differences between client devices, and simplifies future model updates without requiring changes on the user's side.

The backend is organized as a sequence of independent processing modules connected through a unified workflow. The

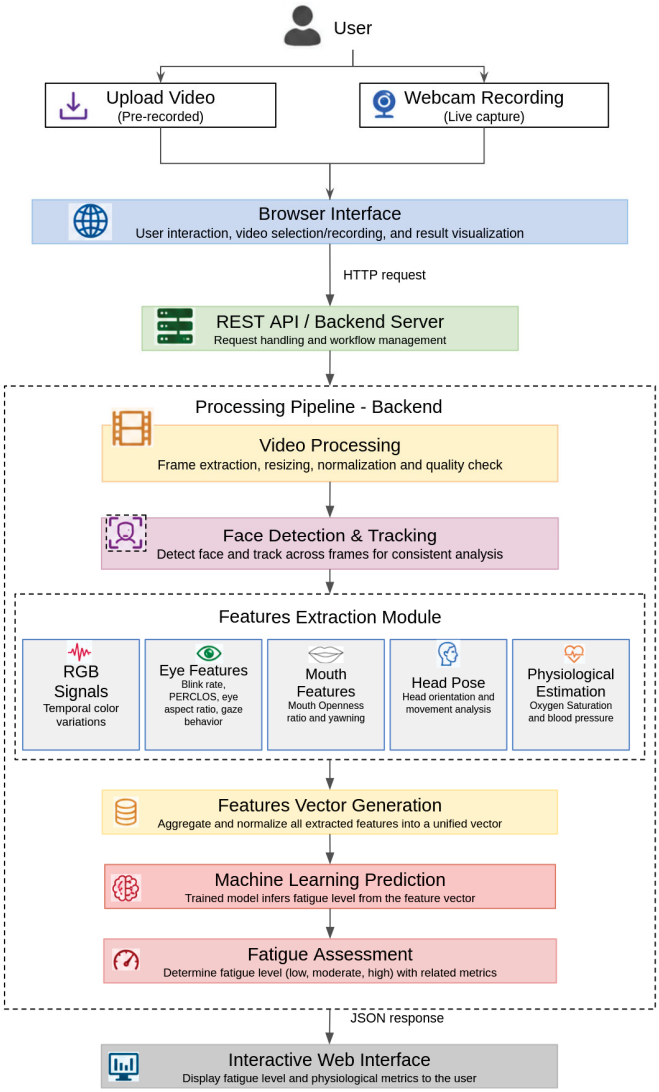


Fig. 1. Overall architecture of the proposed web service. The system follows a modular client–server design for contactless mental fatigue assessment.

first module performs video preprocessing, where the uploaded recording is validated and prepared for subsequent analysis. Video frames are extracted and standardized to provide a consistent input representation for the remaining stages of the pipeline.

Following preprocessing, the system identifies and tracks the facial region throughout the recording. Instead of processing the complete image, subsequent analysis focuses exclusively on the detected face, reducing computational cost while improving robustness against background variations. This localized representation forms the basis for all subsequent physiological and behavioral analysis. Facial tracking also ensures temporal consistency between consecutive frames, which is essential for extracting dynamic characteristics associated

with mental fatigue.

After face localization, the system enters the feature extraction stage. Rather than relying on a single observable indicator, the proposed framework combines multiple complementary sources of information describing both physiological and behavioral changes. Independent modules estimate facial motion characteristics, mouth and eye-related measurements, head movement, temporal RGB signal variations, and contactless physiological parameters derived from facial video. The extracted information is subsequently aggregated into a unified feature representation describing the observed recording. Such a multi-source strategy improves robustness because mental fatigue rarely manifests through only one visual characteristic. Instead, it develops gradually and influences several physiological and behavioral processes simultaneously.

The generated feature vector is then forwarded to the fatigue assessment module. This component applies the trained machine learning model to estimate the user's fatigue level based on the integrated physiological and behavioral information extracted during the previous stages. Separating feature extraction from fatigue prediction provides two practical advantages. First, improvements to individual feature extraction algorithms do not require redesigning the prediction model. Second, alternative fatigue estimation models may be evaluated using the same extracted feature set, facilitating future research and comparative experiments.

The final stage of the architecture is responsible for presenting the analysis results to the user. After prediction has been completed, the backend returns the estimated fatigue level together with the corresponding physiological and behavioral measurements through the web interface. Rather than displaying only a single classification result, the platform provides an integrated overview of the extracted information, enabling users to interpret the prediction in the context of the measured characteristics. This design improves transparency and supports future extension of the system toward more comprehensive health-monitoring applications.

Overall, the proposed architecture was designed according to three main engineering principles: modularity, computational efficiency, and deployment flexibility. The modular organization enables independent development and replacement of processing components, the server-side execution ensures stable performance across heterogeneous client devices, and the browser-based interface provides an accessible environment requiring only a conventional RGB camera. These characteristics allow the proposed service to bridge the gap between laboratory-oriented fatigue detection algorithms and a practical software system suitable for real-world deployment.

C. Video Processing Pipeline

The proposed web service processes each submitted recording through a sequential analysis pipeline that transforms a raw facial video into a structured representation suitable for fatigue assessment. Rather than performing end-to-end prediction directly from video frames, the system extracts a set of physiological and behavioral descriptors before applying the final machine learning classifier. This modular design improves interpretability and allows individual processing components to be updated independently as shown in Figure 2.

After a video is received by the server, it is decoded and processed frame by frame. In the current implementation, every frame is analyzed to preserve the complete temporal information contained in the recording. Facial landmarks are detected using the MediaPipe Face Mesh framework, which estimates a dense set of facial landmarks for each visible face. These landmarks provide the geometric information required for estimating eye behavior, mouth movements, head orientation, and facial motion throughout the recording.

To facilitate temporal analysis, the extracted frame-level measurements are grouped into one-minute segments. Each segment is processed independently, producing a collection of statistical descriptors that summarize the observed physiological and behavioral characteristics during that time interval. This strategy reduces the influence of short-term fluctuations while preserving the temporal evolution of fatigue-related indicators over longer recordings.

For every one-minute interval, the system additionally estimates contactless physiological characteristics directly from facial video. Blood pressure estimation is performed using two dedicated ONNX models that independently predict systolic and diastolic pressure values [25], whereas oxygen saturation is estimated using a separate deep learning model [26]. These physiological estimates are combined with the behavioral measurements extracted from the same time interval to construct a comprehensive feature vector describing the recorded minute.

After all video segments have been processed, the minute-level feature vectors are aggregated to produce a single representation of the entire recording. The selected features are averaged across all analyzed minutes before being forwarded to the fatigue assessment module. This aggregation strategy provides a compact description of the complete video while reducing the influence of variations that may occur during individual frames or short recording intervals.

D. Physiological and Behavioral Feature Extraction

The proposed system estimates fatigue using multiple groups of complementary features extracted from facial video. Instead of relying on a single visual indicator, the framework combines behavioral observations with contactless physiological measurements, providing a more comprehensive description of the user's condition.

The first group consists of eye-related features derived from the detected facial landmarks. Eye Aspect Ratio (EAR) is calculated separately for the left and right eyes and serves as the basis for estimating blink characteristics. Using the temporal evolution of EAR, the system computes several blink-related descriptors, including blink frequency, blink duration, Percentage of Eye Closure (PERCLOS), total blink count, blink ratio, and eye asymmetry. These measurements are widely recognized as sensitive indicators of reduced alertness and increasing fatigue.

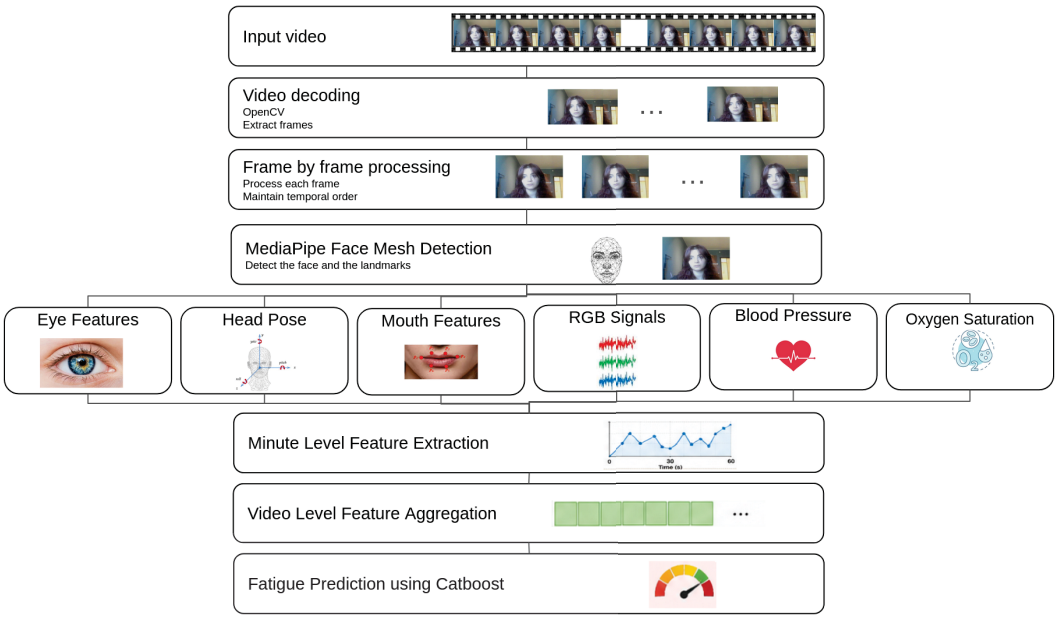


Fig. 2. Video processing pipeline of the proposed web service

The second feature group characterizes head movement during the recording. Head orientation is estimated through pitch, yaw, and roll angles derived from facial landmark geometry. In addition to orientation, the system analyzes head translation and motion dynamics by calculating displacement, velocity, acceleration, and jerk in three-dimensional space. Statistical measures, including mean, standard deviation, minimum, maximum, and range, are computed for these variables together with descriptors such as head movement energy, stillness ratio, and the number of large movement events.

Facial color information is analyzed through remote photoplethysmographic (rPPG) measurements. For every detected facial region, pixel intensity values from the red, green, and blue channels are collected and summarized using statistical descriptors, including the mean, standard deviation, minimum, maximum, quartiles, and median. These color-based measurements provide information associated with subtle physiological changes observable from facial video.

The proposed framework further incorporates contactless physiological estimation by predicting systolic blood pressure, diastolic blood pressure, and peripheral oxygen saturation directly from the recorded video. Blood pressure estimation is performed using dedicated ONNX regression models, while oxygen saturation is obtained through a separate deep learning model. These physiological parameters complement the visual descriptors and provide additional information that may reflect changes associated with mental fatigue.

Finally, mouth dynamics are analyzed to capture yawning-related behavior. The system computes the Mouth Aspect Ratio (MAR), lip separation distance, mouth width, yawn frequency, yawn duration, and mouth opening ratio. Together with the eye, head, rPPG, and physiological features, these descriptors form the complete feature representation used for fatigue assessment. After feature extraction, minute-level measurements are statistically aggregated and subsequently combined into a single feature vector representing the entire recording before classification.

E. Fatigue Assessment

Once the physiological and behavioral features have been extracted, the system estimates the user's fatigue level using a supervised machine learning model. Rather than performing prediction directly from individual video frames, the proposed framework operates on the aggregated representation of the entire recording. This design reflects the gradual nature of mental fatigue, which develops over time and is better characterized by persistent physiological and behavioral patterns than by isolated visual observations.

As described in the previous subsection, feature extraction is performed independently for each one-minute segment of the recording. For every feature, the corresponding values obtained from all analyzed segments are averaged to generate a single feature vector representing the complete video. This aggregation strategy reduces the influence of short-term fluctuations caused by natural blinking, temporary head movements, facial expressions, or small illumination changes, while preserving the overall characteristics of the recording.

The resulting feature vector is then supplied to a CatBoost classifier trained to distinguish between different fatigue states. The classifier analyzes the combined physiological and behavioral information and produces the final fatigue prediction for the analyzed recording. Since the prediction is based on an integrated set of complementary descriptors rather than on a single indicator, the assessment is less sensitive to variability in individual features and provides a more stable estimation of the user's condition.

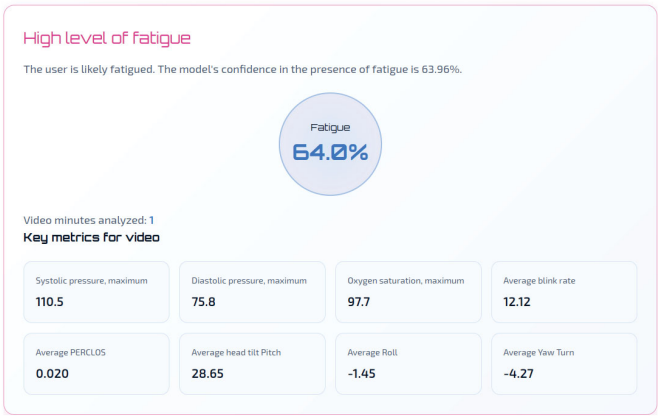


Fig. 3. Example of the fatigue assessment report generated by the Detailed Analysis mode

After the prediction has been completed, the estimated fatigue level is returned to the web application together with the extracted physiological parameters. The results are presented automatically through the user interface, allowing the complete analysis—from video submission to fatigue assessment—to be performed without requiring any manual processing or parameter adjustment by the user.

An example of the report generated by the Detailed Analysis mode is shown in Fig. 3.

F. Implementation Details

The proposed web-service was implemented using a modular software architecture in Python, where each processing stage is encapsulated within an independent component. This organization separates user interaction, video processing, feature extraction, physiological estimation, and fatigue prediction into distinct modules, simplifying maintenance and allowing individual components to be updated without affecting the overall system. Such a design also facilitates future integration of alternative feature extraction algorithms or machine learning models while preserving the existing processing pipeline.

The backend is implemented using the Flask framework, which provides a lightweight REST-based interface for handling user requests and coordinating the complete analysis workflow. Once a video is submitted through the browser interface, the server automatically performs video decoding, feature extraction, physiological estimation, fatigue assessment, and result generation before returning the prediction to the client. This centralized execution ensures that all recordings are processed under identical software and hardware conditions, eliminating variations that may arise from differences in client devices.

Computer vision operations are implemented using OpenCV together with the MediaPipe Face Mesh framework. OpenCV is responsible for video processing and frame manipulation, while MediaPipe provides dense facial landmark localization for every analyzed frame. These landmarks serve as the basis for estimating eye behavior, mouth dynamics, head movements, and facial geometry throughout the recording. The modular integration of these libraries enables reliable facial analysis while maintaining computational efficiency.

TABLE I. SOFTWARE ENVIRONMENT USED FOR IMPLEMENTING THE PROPOSED WEB SERVICE

Component	Version	Purpose
Python	3.8	Programming language
Flask	3.0.3	Backend web framework
Flask-CORS	5.0.0	Cross-origin communication
OpenCV	4.6.0.66	Video processing
MediaPipe	0.10.9	Facial landmark detection
NumPy	1.23.2	Numerical computations
Pandas	2.0.3	Data manipulation
SciPy	1.9.0	Signal processing
ONNX Runtime	1.19.2	Physiological model inference
Pillow	9.5.0	Image processing
CatBoost	1.2.8	Detailed fatigue classifier
XGBoost	0.90	SpO_2 regression
Scikit-learn	1.3.2	Lightweight classifiers (KNN)

Contactless physiological estimation is performed using pretrained ONNX models executed through the ONNX Runtime inference engine. Separate regression models are employed for systolic and diastolic blood pressure estimation, while an additional model is used to estimate peripheral oxygen saturation. Using ONNX Runtime provides a platform-independent inference environment and enables efficient execution of the trained models without introducing dependencies on the original training framework.

The extracted physiological and behavioral features are subsequently processed by a CatBoost classifier that generates the final fatigue prediction. The predicted fatigue level, together with the estimated physiological parameters, is returned to the browser interface and presented to the user through an interactive report. By integrating all processing stages within a single web service, the proposed platform provides a complete workflow ranging from video acquisition to automatic fatigue assessment while requiring only a standard web browser and an RGB camera from the user's perspective. The main stages of user interaction with the developed service are illustrated in Fig. 4.

Table I summarizes the software environment used to implement the proposed web service, including the main frameworks and libraries employed for computer vision, machine learning, and web deployment.

IV. EXPERIMENTAL EVALUATION

This section presents the experimental evaluation of the proposed fatigue assessment system. It first describes the datasets used in the study and the experimental setup. The performance of the investigated fatigue classification models is then examined, with particular attention to the selected CatBoost model and the lightweight RGB-based approach. Finally, the computational performance of the developed web service is evaluated by analyzing the execution time of its main processing stages.

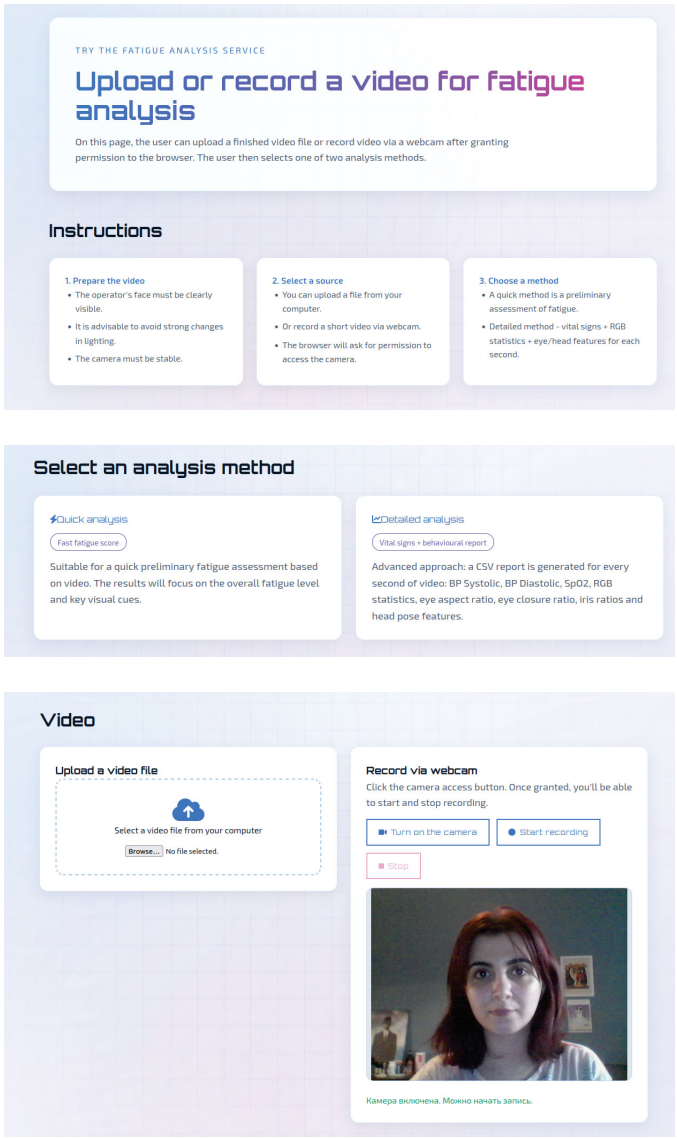


Fig. 4. User workflow of the developed web service: (a) main page and recording instructions, (b) selection between Quick Analysis and Detailed Analysis, and (c) video upload or webcam recording interface.

A. Datasets

The proposed web service was evaluated using two complementary datasets. The first was the publicly available OperatorEYEVP dataset [27], which contains synchronized eye-tracking, physiological signals, facial videos, and subjective fatigue assessments collected from ten participants during repeated cognitive workload sessions. The dataset provides a controlled benchmark for studying fatigue under realistic operator conditions.

To further increase the diversity of participants and recording conditions, a second dataset was collected specifically for this study. It consists of recordings from 14 participants acquired during approximately three-hour experimental sessions involving prolonged cognitively demanding tasks. Similar to the OperatorEYEVP dataset, objective minute-level fatigue labels were generated using the previously developed eye movement–based machine learning model rather than relying solely on subjective questionnaires.

Together, the two datasets provide a broader representation of fatigue progression under prolonged computer-based activities while preserving objective fatigue annotations for training and evaluation of the proposed fatigue assessment model.

B. Experimental Setup

The fatigue assessment model integrated into the proposed web service was developed using the two datasets described in the previous subsection. For each facial video, physiological and behavioral features were extracted following the processing pipeline presented in Section III. The extracted descriptors included eye movement, head movement, mouth activity, RGB-based statistics, and contactless physiological estimates, including blood pressure and oxygen saturation. Minute-level features were aggregated to obtain a single feature vector representing each video before classification.

Several machine learning and deep learning models were evaluated during model development, including LightGBM, CatBoost, TabNet, TabTransformer, and FT-Transformer. To reduce the effect of class imbalance, different balancing strategies, including SMOTE, ADASYN, and class weighting, were investigated.

Model performance was evaluated using Accuracy, Precision, Recall, and F1-score. The model demonstrating the best overall performance and generalization capability was integrated into the proposed web service and used for all subsequent experiments.

C. Fatigue Classification Model

To identify the most suitable classifier for the proposed web service, several machine learning and deep learning models were evaluated, including LightGBM, CatBoost, TabNet, FT-Transformer, and TabTransformer (See Figure 5. All models were trained using the same feature set and evaluated under identical conditions. Since the fatigue classes were not evenly distributed, three imbalance-handling strategies were also investigated: SMOTE, ADASYN, and class-weighted learning. Based on these experiments, CatBoost demonstrated the most consistent performance and was therefore selected as the fatigue assessment model integrated into the web service. Before training the final classifier, the extracted features were organized into five groups: eye behavior, head movement, mouth activity, RGB-based statistics, and physiological parameters. Feature importance analysis was then performed within each group to identify the most informative descriptors, which were combined to form the final feature set used for model training. This procedure reduced feature redundancy while preserving complementary information from the different modalities.

Table II presents the performance of the CatBoost classifier using the investigated imbalance-handling strategies. The 95% confidence intervals were estimated using percentile bootstrapping with 2,000 resamples of the held-out test set. The results show that all approaches achieved comparable performance;

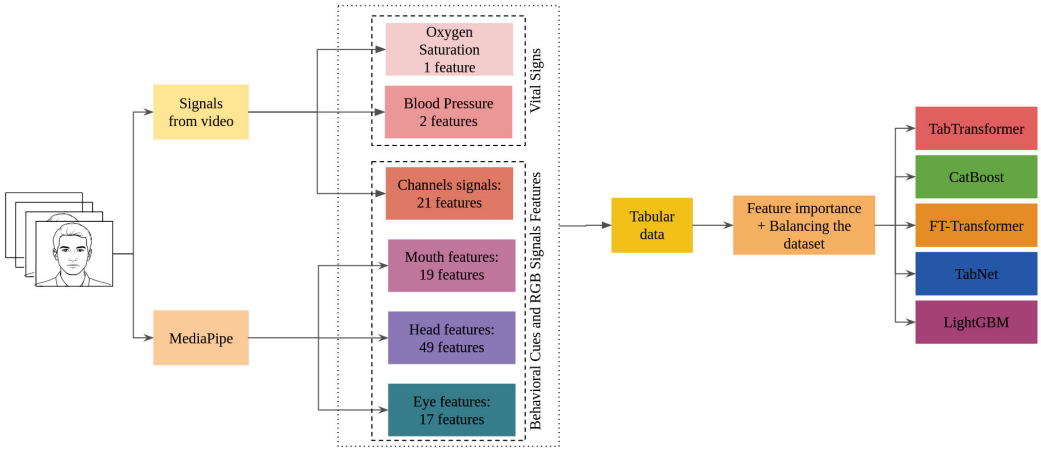


Fig. 5. The general scheme of a contactless mental fatigue assessment system based on video data

however, the class-weighted model obtained the highest overall accuracy (91%) and F1-score (88%). Since this approach provided a good balance between overall performance and minority-class recognition, it was selected for deployment in the proposed web service.

In addition to the comprehensive fatigue assessment model, the proposed web service provides a lightweight analysis mode intended for situations where rapid processing is preferred over the extraction of a large number of physiological and behavioral descriptors. Unlike the detailed analysis, which combines contactless physiological estimation with eye, mouth, head movement, and RGB-based features, the lightweight model relies exclusively on statistical characteristics extracted from the facial RGB signals.

The RGB signals are obtained by averaging the pixel intensities within the detected facial region for each video frame. After temporal filtering, statistical descriptors, including the mean, standard deviation, minimum, maximum, median, quartiles, and additional distribution-based measures, are calculated for each color channel. These features form a compact representation of the recorded video and are supplied directly to the fatigue classifier.

The lightweight model, which corresponds to the Quick Analysis option available through the web interface, was developed in our previous work [28] and integrated into the proposed platform as an alternative fatigue assessment method. Although its prediction accuracy is lower than that of the full feature-based model, it requires considerably fewer computational steps because no physiological estimation, or high-dimensional behavioral feature extraction is performed. This substantially reduces the processing time while preserving acceptable prediction performance for preliminary fatigue screening.

The performance of several machine learning models trained using only RGB statistical features is summarized in Table III. Among the evaluated approaches, KNeighborsClassifier achieved the highest classification accuracy (81%), while MLPClassifier and CatBoost also demonstrated competitive performance.

Consequently, the proposed web service supports two complementary fatigue assessment modes. The Detailed Analysis mode combines physiological estimation with behavioral feature extraction to provide the most comprehensive evaluation of the recorded video. The Quick Analysis mode relies exclusively on RGB statistical features, allowing substantially faster processing while maintaining useful performance for preliminary fatigue screening. This dual-mode design enables users to select the analysis strategy that best matches their requirements and available computational resources.

D. Web Service Performance

To evaluate the computational efficiency of the proposed web service, the execution time of each processing stage was measured during the analysis of a representative video recording. The results are summarized in Table IV. The complete fatigue assessment required 15.87 s for a video of one minute, with the majority of the execution time spent on minute-level feature aggregation and physiological estimation (69.84%), followed by per-frame feature extraction (26.61%). In contrast, the final CatBoost prediction required only 0.01 s, demonstrating that the computational cost of the system is dominated by feature extraction rather than classification. These results indicate that further optimization efforts should primarily focus on the preprocessing and physiological estimation stages.

The lightweight analysis mode significantly reduces the computational requirements by relying exclusively on statistical RGB features and omitting physiological estimation together with high-dimensional behavioral feature extraction. As a result, the feature extraction stage requires only 5.52 s, making the lightweight mode well suited for rapid preliminary fatigue assessment while preserving the simplicity of browser-based deployment.

TABLE II. PERFORMANCE OF CATBOOST WITH DIFFERENT CLASS IMBALANCE HANDLING STRATEGIES. VALUES IN BRACKETS INDICATE 95% CONFIDENCE INTERVALS.

Method	Accuracy (95% CI)	Precision (95% CI)	Recall (95% CI)	F1-score (95% CI)
Baseline	0.9132 [0.8984, 0.9273]	0.9011 [0.8766, 0.9260]	0.8640 [0.8352, 0.8908]	0.8822 [0.8623, 0.9022]
SMOTE	0.9078 [0.8930, 0.9219]	0.8663 [0.8378, 0.8943]	0.8927 [0.8657, 0.9176]	0.8793 [0.8582, 0.8989]
ADASYN	0.9044 [0.8890, 0.9193]	0.8626 [0.8333, 0.8899]	0.8873 [0.8597, 0.9143]	0.8748 [0.8531, 0.8951]
Class Weights	**0.9125** [0.8977, 0.9266]	**0.8865** [0.8591, 0.9121]	**0.8801** [0.8522, 0.9062]	**0.8833** [0.8623, 0.9031]

TABLE III. PERFORMANCE OF MACHINE LEARNING MODELS USING RGB STATISTICAL FEATURES. VALUES IN BRACKETS INDICATE 95% CONFIDENCE INTERVALS.

Model	Accuracy (95% CI)	Precision (95% CI)	Recall (95% CI)	F1-score (95% CI)
CatBoostClassifier	0.7833 [0.7631, 0.8035]	0.7861 [0.7696, 0.8027]	0.7863 [0.7692, 0.8039]	0.7860 [0.7665, 0.8045]
MLPClassifier	0.8072 [0.7860, 0.8275]	0.7969 [0.7789, 0.8143]	0.7952 [0.7740, 0.8122]	0.7960 [0.7793, 0.8150]
KNeighborsClassifier	**0.8113** [0.7907, 0.8312]	**0.8037** [0.7828, 0.8236]	**0.7994** [0.7779, 0.8198]	**0.8015** [0.7807, 0.8216]

V. DISCUSSION

The obtained results demonstrate that computer vision can be effectively integrated into a practical web service for contactless mental fatigue assessment. Unlike many existing studies that primarily evaluate classification models in offline settings, the proposed system combines all stages of the analysis within a single browser-accessible platform. Users are not required to install dedicated software or wear specialized sensors, making the system more suitable for practical deployment in everyday environments.

An important characteristic of the proposed platform is the availability of two complementary analysis modes. The detailed mode combines physiological estimation with behavioral analysis, allowing fatigue to be assessed using a broad set of visual and physiological indicators. Although this approach requires a more computationally intensive processing pipeline, it provides a richer description of the user's condition and achieved the highest classification performance. In contrast, the lightweight RGB-based mode offers a significantly simpler alternative that relies only on statistical characteristics extracted from facial color signals. While this model uses a reduced feature set, it enables rapid fatigue screening and extends the applicability of the service to scenarios where fast processing is preferred. The modular architecture also contributes to the flexibility of the proposed system. Individual processing components, including physiological estimation models and fatigue classifiers, can be updated independently without redesigning the complete application. This makes the platform suitable for future integration of improved computer vision algorithms, alternative physiological estimators, or newly developed machine learning models.

Despite these advantages, several limitations should be acknowledged. The proposed system was evaluated using datasets collected under controlled recording conditions, and its performance may be affected by substantial illumination changes, facial occlusions, or large head movements. Furthermore, although contactless physiological estimation provides valuable complementary information, it does not replace clinical measurements obtained using medical devices. Consequently, the proposed web service should be considered as a decision-support and screening tool rather than a diagnostic system. Future work will focus on improving the robustness of physiological estimation under unconstrained recording conditions, extending the evaluation to larger and more diverse populations, and optimizing the processing pipeline for real-time analysis. Additional physiological indicators and personalized fatigue models may further improve the applicability of the proposed platform in healthcare and occupational monitoring.

TABLE IV. EXECUTION TIME OF THE MAIN PROCESSING STAGES OF THE PROPOSED WEB SERVICE (FOR ONE MINUTE VIDEO).

Processing Stage	Time (s)	Runtime (%)
Video upload	0.019	0.12
Video initialization	0.015	0.09
Video decoding	0.388	2.44
Per-frame feature extraction	4.223	26.61
Minute-level feature aggregation	11.081	69.84
DataFrame construction	0.004	0.02
CatBoost classification	0.010	0.07
Application overhead	0.127	0.80
Total	**15.867**	**100**

VI. CONCLUSION

This paper presented a computer-vision-based web service for automated contactless mental fatigue assessment using facial videos captured with a conventional RGB camera. The proposed platform integrates video acquisition, facial landmark detection, physiological estimation, behavioral feature extraction, fatigue classification, and result visualization into a unified browser-accessible application. By combining these components within a modular client–server architecture, the system provides an end-to-end solution that can be used without wearable sensors or specialized hardware.

Two complementary fatigue assessment modes were implemented within the platform. The detailed mode combines behavioral and physiological features and employs a CatBoost classifier that achieved an accuracy of 91% and an F1-score of 88%, while the lightweight mode provides rapid preliminary assessment using only statistical RGB signal features. This dual-mode design allows users to balance prediction accuracy

and computational efficiency according to their application requirements.

The developed web service demonstrates that recent advances in computer vision, physiological signal estimation, and machine learning can be translated into an accessible software platform suitable for practical fatigue monitoring. The proposed approach may support applications in occupational health, telemedicine, education, and human-computer interaction by enabling convenient and contactless assessment of mental fatigue using standard camera-equipped devices.

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REFERENCES

[1] G. Zhang, K. K. Yau, X. Zhang, and Y. Li, "Traffic accidents involving fatigue driving and their extent of casualties," *Accident Analysis Prevention*, vol. 87, pp. 34–42, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0001457515301159

[2] D. Dawson, A. K. Searle, and J. L. Paterson, "Look before you (s)leep: Evaluating the use of fatigue detection technologies within a fatigue risk management system for the road transport industry," *Sleep Medicine Reviews*, vol. 18, no. 2, pp. 141–152, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1087079213000300

[3] D. Xie, X. Wang, and C. Yin, "Research on the influence of operator fatigue factors on port service capability based on discrete system simulation," *SHS Web of Conferences*, vol. 181, p. 6, 2024.

[4] W. P. Rogers, J. Marques, E. Talebi, and F. A. Drews, "Iot-enabled wearable fatigue-tracking system for mine operators," *Minerals*, vol. 13, no. 2, 2023. [Online]. Available: https://www.mdpi.com/2075-163X/13/2/287

[5] X. Hu and G. Lodewijks, "Detecting fatigue in car drivers and aircraft pilots by using non-invasive measures: The value of differentiation of sleepiness and mental fatigue," *Journal of Safety Research*, vol. 72, pp. 173–187, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0022437519306735

[6] S. Huang, J. Li, P. Zhang, and W. Zhang, "Detection of mental fatigue state with wearable ecg devices," *International Journal of Medical Informatics*, vol. 119, pp. 39–46, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1386505618305677

[7] Y.-X. Chen, C.-K. Tseng, J.-T. Kuo, C.-J. Wang, S.-H. Chao, L.-J. Kau, Y.-S. Hwang, and C.-L. Lin, "Fatigue estimation using peak features from ppg signals," *Mathematics*, vol. 11, no. 16, 2023. [Online]. Available: https://www.mdpi.com/2227-7390/11/16/3580

[8] V. Romaniuk and A. Kashevnik, "Intelligent eye gaze localization method based on eeg analysis using wearable headband," , vol. 23, no. 2, p. 521–541, Mar. 2024. [Online]. Available: http://dx.doi.org/10.15622/ia.23.2.8

[9] W. Othman, B. Hamoud, N. Shilov, and A. Kashevnik, "Human operator mental fatigue assessment based on video: Ml-driven approach and its application to hfavd dataset," *Applied Sciences*, vol. 14, no. 22, 2024. [Online]. Available: https://www.mdpi.com/2076-3417/14/22/10510

[10] A. Revanur, A. Dasari, C. S. Tucker, and L. A. Jeni, "Instantaneous physiological estimation using video transformers," 2022.

[11] M. Jain, S. Deb, and A. V. Subramanyam, "Face video based touchless blood pressure and heart rate estimation," in *2016 IEEE 18th International Workshop on Multimedia Signal Processing (MMSP)*, 2016, pp. 1–5.

[12] N. Sujata Gupta, K. R. Ramya, and R. Karnati, "A review work: Human action recognition in video surveillance using deep learning techniques," , vol. 23, no. 2, p. 436–466, Mar. 2024. [Online]. Available: http://dx.doi.org/10.15622/ia.23.2.5

[13] A. Liu, F. Chiossi, F. Henninger, L. B. Andersen, T. Wistuba, S. Greven, F. Kreuter, and F. Draxler, "Physiological and behavioral modeling of stress and cognitive load in web-based question answering," 2026. [Online]. Available: https://arxiv.org/abs/2601.17890

[14] C. Dong, T. Li, K. Xu, Z. Wang, F. Maldonado, K. Sandler, B. Landman, and Y. Huo, "Characterizing browser-based medical imaging ai with serverless edge computing: towards addressing clinical data security constraints," vol. 12469, 04 2023, p. 5.

[15] T.-H. Lin, H.-Y. Chung, M.-J. Jian, C.-K. Chang, C.-L. Perng, G.-S. Liao, J.-C. Yu, M.-S. Dai, C.-P. Yu, and H.-S. Shang, "An advanced machine learning model for a web-based artificial intelligence–based clinical decision support system application: Model development and validation study," *Journal of Medical Internet Research*, vol. 26, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1438887124005442

[16] Z. Cui, H.-M. Sun, R.-N. Yin, L. Gao, H.-B. Sun, and R.-S. Jia, "Real-time detection method of driver fatigue state based on deep learning of face video," *Multimedia Tools Appl.*, vol. 80, no. 17, p. 25495–25515, jul 2021. [Online]. Available: https://doi.org/10.1007/s11042-021-10930-z

[17] S. Dey, S. A. Chowdhury, S. Sultana, M. A. Hossain, M. Dey, and S. K. Das, "Real time driver fatigue detection based on facial behaviour along with machine learning approaches," in *2019 IEEE International Conference on Signal Processing, Information, Communication Systems (SPICSCON)*, 2019, pp. 135–140.

[18] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, vol. 1, 2005, pp. 886–893 vol. 1.

[19] F. Makhmudov, D. Turimov, M. Xamidov, F. Nazarov, and Y.-I. Cho, "Real-time fatigue detection algorithms using machine learning for yawning and eye state," *Sensors*, vol. 24, no. 23, 2024. [Online]. Available: https://www.mdpi.com/1424-8220/24/23/7810

[20] M. M. Nap-van der Vlist, J. Houtveen, G. W. Dalmeijer, M. A. Grootenhuis, C. K. van der Ent, M. van Grotel, J. F. Swart, J. M. van Montfrans, E. M. van de Putte, and S. L. Nijhof, "Internet and smartphone-based ecological momentary assessment and personalized advice (profeel) in adolescents with chronic conditions: A feasibility study," *Internet Interventions*, vol. 25, p. 100395, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221478292100035X

[21] T. I. Bootsma, M. P. Schellekens, R. A. van Woezik, J. Slatman, and M. L. van der Lee, "Using smartphone-based ecological momentary assessment and personalized feedback for patients with chronic cancer-related fatigue: A proof-of-concept study," *Internet Interventions*, vol. 30, p. 100568, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214782922000756

[22] M. Palotai, M. Wallack, G. Kujbus, A. Dalnoki, and C. Guttmann, "Usability of a mobile app for real-time assessment of fatigue and related symptoms in patients with multiple sclerosis: Observational study," *JMIR Mhealth Uhealth*, vol. 9, no. 4, p. e19564, Apr 2021.

[23] V. J. Block, R. Bove, and B. Nourbakhsh, "The role of remote monitoring in evaluating fatigue in multiple sclerosis: A review," *Frontiers in Neurology*, vol. Volume 13 - 2022, 2022. [Online]. Available: https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2022.878313

[24] R. Adam, Y. Lotankar, C. Sas, D. Powell, V. Martinez, S. Green, J. M. Cooper, K. Bradbury, J. Sive, and D. L. Hill, "Understanding patterns of fatigue in health and disease: protocol for an ecological momentary assessment study using digital technologies," *BMJ Open*, vol. 14, no. 5, p. e081416, may 2024. [Online]. Available: https://bmjopen.bmj.com/content/14/5/e081416.abstract

[25] B. Hamoud, A. Kashevnik, W. Othman, and N. Shilov, "Neural network model combination for video-based blood pressure estimation: New approach and evaluation," *Sensors*, vol. 23, no. 4, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/4/1753

[26] B. Hamoud, W. Othman, N. Shilov, and A. Kashevnik, "Contactless oxygen saturation detection based on face analysis: An approach and case study," in *2023 33rd Conference of Open Innovations Association (FRUCT)*, 2023, pp. 54–62.

[27] S. Kovalenko, A. Mamonov, V. Kuznetsov, A. Bulygin, I. Shoshina, I. Brak, and A. Kashevnik, "Operatoreyevp: Operator dataset for fatigue detection based on eye movements, heart rate data, and video information," *Sensors*, vol. 23, no. 13, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/13/6197

[28] B. Hamoud, W. Othman, N. Shilov, and A. Kashevnik, "Lightweight ml-based method for mental fatigue assessment using human facial video," in *2025 38th Conference of Open Innovations Association (FRUCT)*, 2025, pp. 97–104.