IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⧖ Peer-reviewed & Refereed journal ⧖ Vol. 14, Issue 3, March 2026

DOI: 10.17148/IJIREEICE.2026.14379

NeuroVision AI: Multi-Device Eye Strain Detection Using Micro-Motion and Cognitive Behaviour

Vanitha A[1], Dr. K. Arunkumar[2], Keerthana S[3], Karthika V[4]

Department of Computer Science, Rathinam College of Arts and Science[1]

School of Computer Science, Rathinam college of Arts and Science[2]

B.Sc AIML, Department of Computer Science, Rathinam College of Arts and Science[3,4]

Abstract: Digital devices such as laptops, smartphones, and tablets have become essential tools for communication, nd professional work. As people increasingly depend on these devices, the amount of time spent looking at screens has grown significantly. Long hours of screen exposure can cause a condition commonly known as digital eye strain. Symptoms of digital eye strain include tired eyes, dryness, blurred vision, headaches, and reduced ability to focus. Many individuals experience these symptoms after extended periods of screen usage, but they often ignore them until the discomfort becomes severe.

Traditional solutions that attempt to reduce eye strain mainly rely on simple screen-time reminders or break notifications. These systems usually prompt users to rest their eyes after a fixed amount of time. However, these reminders do not evaluate the actual condition of the user's eyes. Eye fatigue depends on several factors, such as blinking behaviour, gaze stability, posture, and the intensity of interaction with digital devices. Therefore, time-based reminders alone are not sufficient to detect or prevent eye strain effectively.

This research proposes an AI-based eye strain detection system that monitors eye behaviour in real time using a standard webcam. The system analyses several indicators, including blink rate, gaze movement, ocular micro-motions, head posture, and user interaction patterns such as typing and scrolling activity. These indicators are combined to calculate an eye strain score that represents the fatigue level of the user.

When the strain score crosses a predefined threshold, the system alerts the user and suggests taking a short break or adjusting posture. The proposed system also supports multi-user identification and multi-device environments, making it suitable for shared computers and modern workspaces. Because the system relies only on webcam input and computer vision techniques, it does not require specialised hardware. This makes the solution affordable, scalable, and suitable for everyday use in homes, offices, and educational institutions.

Keywords: Digital Eye Strain, Ocular Micro-Motion,Cognitive Load, Multi-Device Monitoring, Computer Vision.

I. INTRODUCTION

Digital technology has become deeply integrated into everyday life. In modern society, computers, laptops, smartphones, and tablets are used for almost every activity,including communication, education, entertainment, and professional work. The increasing availability of high-speed internet and digital tools has made it easier for people to work and study remotely. As a result, individuals now spend a significant portion of their day interacting with screens. While digital devices provide many benefits, extended screen exposure can lead to several health-related concerns, particularly those related to eye comfort and visual fatigue.

One of the most common issues associated with prolonged screen usage is digital eye strain, sometimes referred to as computer vision syndrome. Digital eye strain occurs when the eyes become tired or irritated after long periods of focusing on digital displays. Unlike printed text, digital screens often require the eyes to continuously adjust focus due to factors such as screen brightness, glare, and small text size. This continuous adjustment places extra pressure on the eye muscles, which can lead to fatigue over time.

People who experience digital eye strain often report symptoms such as blurred vision, dry eyes, headaches, difficulty focusing, and a feeling of heaviness around the eyes. These symptoms may appear mild at first, but can gradually become more noticeable when screen usage continues for several hours without breaks. In many cases, individuals ignore these symptoms because they assume the discomfort will disappear after resting. However, frequent exposure to digital screens without proper breaks can reduce visual comfort and may affect productivity and concentration.

DOI: 10.17148/IJIREEICE.2026.14379

Another important factor contributing to eye strain is reduced blinking frequency. Under normal conditions, humans blink approximately 15 to 20 times per minute. Blinking helps maintain moisture on the surface of the eye and prevents dryness. However, studies have shown that when people focus on digital screens, their blink rate often decreases significantly. In some cases, users blink only half as often as they normally would. This reduced blinking leads to dryness and irritation, which are common symptoms of digital eye strain.

In addition to blinking behaviour, other factors such as gaze stability, screen distance, and posture also influence eye fatigue. For example, sitting too close to the screen forces the eyes to

focus more intensely, which increases strain on the eye muscles. Similarly, maintaining poor posture while using digital devices can create additional tension in the neck and shoulders, which may indirectly affect visual comfort.

Although awareness of digital eye strain has increased in recent years, many people still struggle to manage their screen habits effectively. A commonly recommended solution is the 20-20-20 rule, which suggests that users should take a break every 20 minutes and look at something 20 feet away for 20 seconds. While this guideline is helpful, it relies on users remembering to follow the rule consistently. In practice, many individuals become so focused on their work that they forget to take breaks. To address this problem, several software applications have been developed to remind users to take breaks after a fixed amount of time. These applications typically monitor screen usage and display notifications encouraging the user to rest their eyes. However, these reminders are based only on elapsed time and do not consider the actual condition of the user's eyes. Two individuals may spend the same amount of time looking at a screen but experience very different levels of fatigue depending on their blinking behaviour, posture, and interaction patterns.

Because of these limitations, there is a growing need for intelligent systems that can monitor eye behaviour in real time. Instead of relying solely on time-based reminders, such systems should analyse multiple indicators of fatigue to determine when the user's eyes are becoming strained. Advances in computer vision and machine learning have made it possible to analyse facial features and eye movements using standard webcams. By detecting facial landmarks and tracking the eye region, a system can measure blinking behaviour, gaze movement, and other visual indicators of fatigue.

This research proposes an AI-based eye strain detection system that monitors eye behaviour and user interaction patterns using a standard webcam. The system analyses several indicators, including blink rate, gaze stability, head posture, and behavioural patterns such as typing and scrolling activity. These indicators are combined to generate a strain score that represents the current fatigue level of the user. When the strain score exceeds a safe threshold, the system alerts the user and recommends taking a break or adjusting posture.

One of the main advantages of the proposed system is that it does not require specialised hardware such as infrared eye trackers. Instead, it uses widely available webcams and computer vision algorithms to analyse eye behaviour. This makes the system affordable and accessible to a wide range of users, including students, office workers, and individuals working from home.

Another important feature of the proposed system is its ability to support multi-user environments. In many situations, computers are shared among multiple users, such as in libraries or computer laboratories. The system includes a user identification component that allows it to recognise

different individuals and track their eye strain levels separately. Additionally, the system is designed to function across multiple devices, making it suitable for environments where users frequently switch between laptops and desktops.

Overall, the goal of this research is to develop a practical and reliable system for monitoring digital eye strain. By analysing real-time eye behaviour and interaction patterns, the system aims to provide users with meaningful feedback that encourages healthier screen usage habits. This approach can help reduce the negative effects of prolonged screen exposure and contribute to improved digital well-being.

II. PROBLEM STATEMENT

With the rapid growth of digital technology, people spend a large portion of their day using devices such as laptops, smartphones, and tablets. Continuous screen usage for studying, working, or entertainment often leads to digital eye strain. Many users experience symptoms such as tired eyes, blurred vision, dryness, headaches, and difficulty focusing after prolonged screen exposure. Despite the increasing awareness of this issue, most users fail to recognise the early signs of eye strain and continue working until discomfort becomes severe.

Existing solutions mainly depend on simple screen-time reminders that notify users to take breaks after a fixed period.

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 3, March 2026
DOI: 10.17148/IJIREEICE.2026.14379

However, these systems do not analyse the actual condition of the user's eyes. Eye strain is influenced by several factors, such as blinking behaviour, gaze stability, posture, and the intensity of user interaction with the device. Ignoring these factors limits the effectiveness of current systems.

Therefore, there is a need for an intelligent system that can continuously monitor eye behaviour and user activity in real time. Such a system should detect early signs of eye fatigue and provide timely alerts to users. The proposed research aims to develop a webcam-based eye strain detection system that combines ocular features, behavioural patterns, and posture analysis to provide more accurate and practical monitoring of digital eye strain.

Furthermore, many current monitoring systems assume that only one user interacts with a device at a time. In real-world environments such as libraries, computer laboratories, and shared office spaces, multiple individuals may use the same computer. Traditional monitoring systems cannot distinguish between different users, which limits their usefulness in shared environments.

III. Literature Review

Researchers have been studying eye fatigue and digital eye strain for several years. Early studies mainly focused on understanding how prolonged screen exposure affects human vision. One of the earliest findings was that blink rate decreases significantly when individuals focus on digital screens. Reduced

blinking can lead to dryness and irritation because the eyes are not lubricated as frequently.

Several researchers explored methods to measure eye fatigue by analysing blink patterns. In these studies, cameras were used to monitor eye closure and blinking frequency. By measuring how often the eyelids close, researchers could estimate fatigue levels. Although blink detection provided useful insights, relying only on blink rate was not always sufficient to determine eye strain accurately.

Other studies investigated gaze tracking techniques. Gaze tracking involves monitoring where a person is looking on the screen and how their eyes move between objects. Researchers observed that when people become fatigued, their gaze movements become less stable and slower. This information can be used to identify visual fatigue. However, many gaze-tracking systems require specialised hardware such as infrared cameras or dedicated eye-tracking devices. These devices are expensive and difficult to deploy in everyday environments.

With the development of computer vision technology, researchers began using standard webcams to analyse eye behaviour. Facial landmark detection algorithms can identify important points around the eyes and estimate eye openness and blinking patterns. One commonly used technique is the Eye Aspect Ratio (EAR), which measures the relationship between vertical and horizontal distances of eyelid landmarks. When the eyes close during a blink, the EAR value decreases significantly.

Despite these advancements, many existing webcam-based systems focus only on visual features of the eye and ignore other important factors that contribute to eye strain. For example, posture, screen distance, and interaction intensity can significantly influence visual fatigue. Users who sit too close to the screen or maintain poor posture often experience higher levels of strain.

Another limitation in many previous systems is the assumption that only one user interacts with the device. In real-world situations, computers are often shared among multiple users. Therefore, an effective eye strain monitoring system should be able to distinguish between different individuals.

The proposed research addresses these limitations by integrating multiple indicators of eye strain, including ocular features, behavioural patterns, and posture estimation. By combining these factors, the system provides a more comprehensive and accurate assessment of eye fatigue.

IV. Related Work

Several studies have explored methods for detecting eye fatigue and visual strain. Early research mainly focused on blink rate measurement, since blinking frequency tends to decrease when users concentrate on screens. Other studies examined pupil dilation and gaze fixation as indicators of mental workload and fatigue.

Advanced systems used infrared cameras or specialised eye-tracking hardware to measure detailed eye movements. Although these methods achieved high precision, they required expensive equipment and controlled environments. Such systems are not practical for everyday users working on laptops or personal computers.

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 3, March 2026
DOI: 10.17148/IJIREEICE.2026.14379

More recent approaches use standard webcams with computer vision techniques. These systems detect facial landmarks and analyse eye behaviour from video frames. However, many existing webcam-based models only examine visual features and ignore other important factors such as posture, interaction intensity, and multi-device usage.

Another limitation in existing research is the assumption of a single-user environment. In real-world situations, devices may be shared among multiple users, and individuals may switch between devices throughout the day. Most earlier systems do not handle these scenarios effectively.

Our proposed system improves upon previous work by combining:

- Ocular micro-motions
- Blink rate
- Gaze stability
- Behavioural signals (typing, scrolling, mouse movement)
- Posture and screen distance
- Multi-user identification

This multi-feature approach increases reliability and makes the system suitable for real-world deployment.

V. PROPOSED MODEL

The proposed model is designed to detect eye strain by combining visual and behavioural features obtained from webcam input. The system processes video frames captured by the webcam and extracts relevant information related to eye behaviour, posture, and user interaction.

The dataset used for training and testing the system was collected using real-time webcam recordings under normal working conditions. Instead of using a controlled laboratory environment, the recordings were captured while users performed typical digital activities such as reading documents, typing reports, browsing the internet, and attending online meetings.

Each recording session involved only one user to ensure clear detection of facial landmarks and eye features. Video recordings were divided into frames, and face detection algorithms were applied to identify the facial region. From the detected face, the eye region was extracted for further analysis.

The collected frames were manually reviewed and labelled

into two categories: normal eye condition and strained eye condition. The labelling process was based on visual indicators such as blinking frequency, eye openness, gaze stability, and user feedback after long periods of screen usage.

To improve the quality of the dataset, frames with poor lighting, blurred images, or partially visible faces were removed. Data augmentation techniques were applied to increase dataset diversity. These included slight rotation of images, brightness adjustment, scaling, and contrast variation. These modifications helped the model learn to handle different lighting conditions and camera qualities.

The final dataset represented realistic user behaviour rather than artificial experimental conditions. This ensures that the trained model performs effectively in real-world scenarios.

The proposed system is entirely software-based and operates using a standard webcam. The architecture is divided into several functional modules that work together to estimate eye strain in real time.

A. Webcam Capture Module

This module continuously records facial video while the user interacts with the device. Frames are processed at fixed intervals to ensure smooth monitoring.

B. Face and Eye Detection Module

Using facial landmark detection techniques, the system identifies key facial points. The eye region is extracted for further analysis. This ensures accurate measurement of eye-related features.

DOI: 10.17148/IJIREEICE.2026.14379

C. Ocular Feature Extraction

This module calculates important eye-related metrics such as: • Blink frequency • Eye openness ratio • Gaze movement consistency • Micro-movements of the pupil These features help identify subtle fatigue patterns.

D. Behavioural Monitoring

To estimate cognitive load, the system tracks: • Typing speed
• Frequency of scrolling • Mouse activity intensity Increased interaction without breaks often indicates higher mental strain, which contributes to eye fatigue.

E. Posture and Distance Estimation

Head angle and eye-to-screen distance are estimated using facial geometry. Poor posture or close screen distance increases strain risk.

F. Multi-User Identification

Face recognition ensures that data is correctly associated with individual users when devices are shared.*Prediction Module*

All extracted features are combined to calculate a final eye strain score.

G. Alert Module

If the strain score exceeds a predefined safe threshold, the system provides alerts suggesting short breaks or posture correction.

VI. DATASET PREPARATION

The dataset used in this project was collected using normal webcam recordings under real-life working conditions. Instead of using artificial laboratory settings, users were recorded while performing typical screen-based tasks such as typing documents, browsing the internet, attending virtual meetings, or reading digital content.

Each recording session involved only one user at a time to maintain clear feature extraction. Video frames were extracted and cropped to isolate the eye region. The collected samples were labelled into two categories:

- Normal – Eyes show stable blinking and consistent gaze.
- Strained – Visible signs such as reduced blinking, unstable gaze, or prolonged fixation.

Frames affected by motion blur, poor lighting, or partial face visibility were removed to maintain data quality.

To improve robustness, data augmentation techniques were applied, including slight brightness adjustments, minor rotations, and scaling variations. This ensured that the system could perform reliably under different lighting conditions and camera qualities.

The final dataset represented realistic user behaviour rather than controlled experimental conditions, making it suitable for real-world applications.

VII. PROPOSED METHODOLOGY

The proposed methodology for the eye strain detection system focuses on monitoring eye behaviour and user interaction patterns in real time using a standard webcam. The system is designed to detect early signs of digital eye strain by analysing multiple indicators such as blink rate, gaze stability, posture, and user activity. By combining these factors, the system can estimate the level of eye fatigue and provide timely alerts to the user.

The first step in the methodology is video capture. A webcam continuously captures video frames while the user interacts with the computer. These frames serve as the input for further processing. Each frame is analysed using computer vision techniques to detect the presence of a human face. Once the

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 3, March 2026
DOI: 10.17148/IJIREEICE.2026.14379

face is detected, the system applies facial landmark detection to identify key points around the eyes, nose, and mouth. Facial landmarks are important because they help locate the exact position of the eyes within the frame.

After identifying the facial landmarks, the system isolates the eye region for detailed analysis. This step ensures that the system focuses only on relevant visual information related to eye behaviour. From the extracted eye region, several important features are calculated. One of the primary features is blink detection. Blinking is identified by measuring the distance between eyelids using facial landmark coordinates. When theas offices, classrooms, and home workspaces. Mathematical Representation:
Blink rate is calculated as:

$$Blink\ Rate = \frac{Total\ \ Blinks}{Time\ \ Duration}$$

Behavioural load is calculated as: eyelids close and reopen, the system records a blink event. The number of blink events over a period of time is used to calculate the blink rate. A reduced blink rate may indicate increased visual concentration and potential eye fatigue.

Another important feature is gaze stability. The system tracks subtle movements of the eyes across consecutive frames to determine how stable the user's gaze is. When users become fatigued, their eye movements may become slower or less stable. By analysing these movement patterns, the system can detect signs of visual fatigue.

In addition to visual eye features, the methodology also considers behavioural indicators. The system monitors user interactions such as typing activity, mouse movement, and scrolling behaviour. Continuous interaction with the computer without breaks often indicates increased cognitive workload, which can contribute to eye strain. These behavioural signals provide additional context that helps the system understand the user's activity level.

The system also estimates posture and screen distance using facial geometry. By analysing the position and angle of the face relative to the webcam, the system can determine whether the user is sitting too close to the screen or tilting their head forward. Poor posture can increase the effort required to focus on the screen, which contributes to eye fatigue.

All extracted features—including blink rate, gaze stability, behavioural activity, and posture—are combined in a feature integration stage. In this stage, the system calculates an overall eye strain score that represents the user's fatigue level. The score is compared with a predefined threshold to determine whether the user is experiencing eye strain.

If the strain score exceeds the safe threshold, the system activates the alert mechanism. The alert may appear as a notification suggesting that the user take a short break, adjust posture, or rest their eyes. By providing timely feedback, the system encourages healthier screen usage habits and helps reduce the risk of digital eye strain.

Overall, this methodology provides a comprehensive approach to monitoring eye fatigue by integrating visual, behavioural, and posture-related indicators. The use of a standard webcam and computer vision algorithms makes the system practical and accessible for everyday environments such $Behavioural\ Load = Typing+Scrolling+Mouse\ Activity$

The final eye strain score is computed using:

$$EyeStrainScore = w1 + w2 + w3$$

w1=Eye Features w2=Behavioural w3=posture

If the score exceeds a predefined threshold, the system generates alerts recommending a break.

VIII. Implementation

The implementation of the proposed eye strain detection system focuses on creating a real-time monitoring solution that can run on a standard computer using a webcam. The system is designed to detect eye fatigue by analysing visual and behavioural indicators while the user interacts with digital devices. The implementation process involves selecting appropriate software tools, preparing the development environment, building the computer

ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 3, March 2026
DOI: 10.17148/IJIREEICE.2026.14379

vision pipeline, and testing the system under real working conditions.

The system was implemented using the Python programming language, which is widely used for computer vision and artificial intelligence applications. Python provides many libraries that simplify image processing, machine learning, and real-time video analysis. One of the main libraries used in this project is OpenCV, which is an open-source computer vision library that allows the system to capture video frames from the webcam and process them efficiently. OpenCV provides several built-in functions for face detection, image manipulation, and frame processing, making it suitable for real-time applications.

Another important library used in the implementation is MediaPipe, which provides advanced facial landmark detection capabilities. MediaPipe can identify multiple key points on the human face, including points around the eyes. These landmarks help the system locate the eye region accurately and analyse eye movements. Using the coordinates of these landmarks, the system can calculate distances between eyelids and determine when a blink occurs. The combination of OpenCV and MediaPipe allows the system to perform accurate eye detection and tracking using a standard webcam.

To implement the system, the first step was setting up the development environment. The necessary libraries, such as Python, OpenCV, MediaPipe, and other supporting packages, were installed. A webcam connected to the computer was used as the input device for capturing real-time video. Once the environment was ready, the system was designed to continuously capture frames from the webcam while the user works on the computer.

The captured frames are then processed one by one. The system first detects the user's face in each frame. After detecting the face, facial landmark detection is applied to identify key points around the eyes. These landmarks allow the system to isolate the eye region for further analysis. Once the eye region is detected, the system calculates features such as eye openness and blink frequency. Blink detection is implemented by measuring the distance between upper and lower eyelid landmarks. When this distance decreases below a certain threshold, the system identifies that the eye is closed, indicating a blink event. By counting the number of blinks over a specific time interval, the system calculates the blink rate. A significant decrease in blink rate can indicate visual fatigue.

In addition to eye feature extraction, the system also monitors basic behavioural activity. Keyboard activity, mouse movement, and scrolling patterns are observed to estimate how actively the user is interacting with the computer. Continuous interaction without breaks increases cognitive workload and contributes to eye strain.

Another part of the implementation focuses on posture detection. Using facial landmark positions, the system estimates the orientation of the user's head relative to the camera. If the user leans too close to the screen or maintains an uncomfortable viewing angle, the system recognises this as a potential risk factor for eye fatigue.

After extracting all necessary features, the system calculates an eye strain score based on blink rate, gaze stability, posture, and interaction activity. If this score exceeds a predefined threshold, the system generates a notification suggesting that the user take a short break or adjust their posture.

To ensure that the system operates smoothly, several tests were conducted under different lighting conditions and user environments. These tests helped confirm that the system could accurately detect facial landmarks and eye movements using a standard webcam.

Overall, the implementation demonstrates that an effective eye strain monitoring system can be developed using commonly available hardware and open-source software tools. This makes the solution practical and accessible for everyday users who wish to monitor and improve their digital eye health. DATASET IMPLEMENTATION

In this project, the dataset is generated using real-time webcam input instead of relying only on pre-existing datasets. The purpose of using a real-time dataset is to capture the natural behavior of users while they interact with digital devices. This allows the system to analyze realistic eye movements, blinking patterns, posture, and user interaction during normal computer usage.

The dataset collection begins when the system activates the webcam. The webcam continuously captures video frames of the user while they are working on the computer. Each captured frame acts as a data sample containing information about the user's face and eye region. These frames are processed in real time using computer vision techniques to detect facial landmarks and extract eye-related features.

Once the face is detected, the system identifies important facial landmarks around the eyes. These landmarks help the system locate the exact position of the eyes within the frame. From the eye region, the system calculates features such as eye openness, blink detection, and gaze movement. Blink detection is performed by measuring the distance between the upper and lower eyelids. When this distance becomes very small, the system records a blink event.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⨳ Peer-reviewed & Refereed journal ⨳ Vol. 14, Issue 3, March 2026
DOI: 10.17148/IJIREEICE.2026.14379

The system also tracks the blink rate, which represents the number of blinks per minute. Normally, people blink around 15–20 times per minute. However, when users concentrate on screens for long periods, the blink rate often decreases. A reduced blink rate is considered an important indicator of eye strain.

In addition to eye features, the system collects behavioral data such as keyboard typing activity, mouse movement, and scrolling behavior. These interactions indicate how actively the user is working on the computer. Continuous interaction without breaks can increase cognitive load and contribute to eye fatigue.

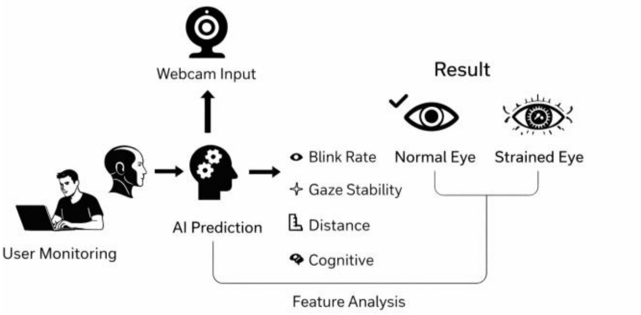

Fig. 1. process of the eye strain detection system

DOI: 10.17148/IJIREEICE.2026.14379

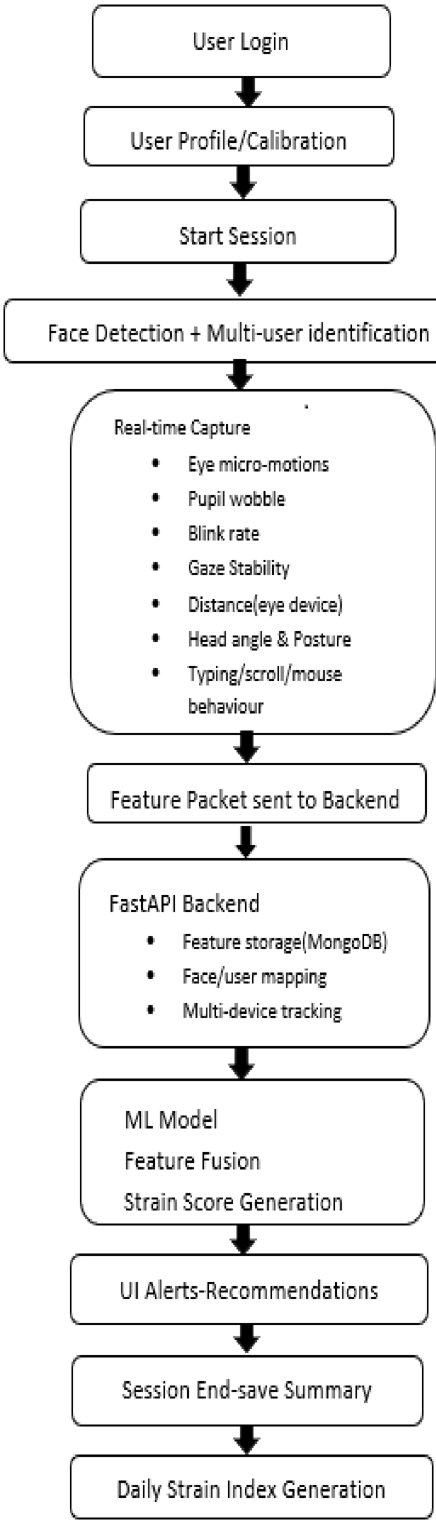

Fig. 2. Flowchart of the proposed system

The system also estimates posture and screen distance using facial landmark positions. If the user sits too close to the screen or tilts their head forward, the system records this information as a potential factor contributing to eye strain.

At the end of a session, the system generates a summary output based on the collected dataset. The output includes the total session duration, average blink rate, gaze stability, and the calculated eye strain score. This final output helps users understand their screen usage habits and encourages healthier digital behavior.

IX. RESULTS

The proposed eye strain detection system was evaluated through several testing sessions conducted under normal working conditions. Multiple users participated in the testing process while performing typical computer tasks such as reading documents, typing reports, browsing the internet, and attending online meetings. These activities were chosen because they represent common situations in which people spend long hours looking at screens.

During the testing phase, the webcam continuously captured video frames, and the system analysed facial landmarks, eye movements, and user interaction patterns. The system successfully detected the user's face and extracted the eye region in real time. Using this information, the system measured several important indicators such as blink rate, gaze stability, head posture, and interaction intensity.

One of the key observations during testing was that blink rate significantly decreased when users focused intensely on screen-based tasks. For example, when users were reading or typing for long periods without breaks, the number of blinks per minute gradually reduced. This behaviour is consistent with findings from previous research, which suggests that people tend to blink less frequently when concentrating on digital displays.

Another observation was related to gaze stability. When users became fatigued, their gaze patterns became less stable and more irregular. This indicates that prolonged visual concentration can affect eye movement control. The system successfully captured these variations and reflected them in the calculated eye strain score.

Behavioural features such as typing speed, mouse movement, and scrolling frequency also contributed to the detection results. Continuous interaction with the keyboard and mouse increased the cognitive load of the user. When this interaction continued without breaks, the eye strain score gradually increased. By combining behavioural features with visual eye features, the system produced more reliable predictions compared to systems that rely on blink rate alone.

Posture analysis also played an important role in the results. The system observed that users sitting very close to the screen

or leaning forward experienced higher strain scores. Poor posture increases the visual effort required to focus on the screen, which contributes to eye fatigue. By monitoring head position relative to the webcam, the system was able to detect posture deviations and incorporate them into the final strain calculation.

Overall, the results demonstrate that combining multiple indicators—such as blink rate, gaze stability, posture, and behavioural activity—provides a more accurate and realistic representation of eye fatigue. The system was able to monitor eye behaviour in real time without requiring specialised hardware. This makes it suitable for everyday environments such as homes, offices, and classrooms.

X. APPLICATIONS

The proposed eye strain detection system has several practical applications in modern digital environments. As screen usage continues to increase across education, work, and entertainment, tools that help users manage eye health are becoming increasingly important.

One important application is in online learning environments. Students often attend virtual classes and complete assignments using computers for many hours each day. Prolonged screen exposure can affect concentration and learning performance. The proposed system can monitor students' eye behaviour during online classes and provide timely reminders to take breaks. This helps students maintain better focus and reduce visual fatigue.

Another important application is in office workplaces. Many professionals spend most of their working hours in front of computers. Continuous work without breaks can lead to eye strain and reduced productivity. By integrating the proposed system into office workstations, organisations can support employee well-being and encourage healthier work habits. The system can notify employees when they should rest their eyes or adjust their posture.

The system can also be useful in work-from-home environments, where employees often work without proper ergonomic setups. Since the system monitors posture and screen distance, it can help users correct unhealthy viewing habits and maintain a comfortable working position. In addition, the system can be implemented in shared computing environments such as libraries, computer laboratories, and training centres. Because the system includes a multi-user identification feature, it can recognise different users and track their eye strain levels separately. This allows accurate monitoring even when multiple people use the same device.

DOI: 10.17148/IJIREEICE.2026.14379

Another promising application is in digital wellness applications. Many software platforms are being developed to promote healthier technology use. The proposed eye strain detection system can be integrated into such applications to provide personalised feedback about screen habits. By analysing eye behaviour and user activity, the system can suggest breaks, recommend posture adjustments, and help users build healthier digital routines.

Because the system relies only on a standard webcam and software-based analysis, it does not require expensive hardware. This makes it affordable and scalable for a wide range of users.

XI. CONCLUSION

This research presented a practical eye strain detection system that uses computer vision techniques to monitor eye behaviour and user interaction patterns. The system was designed to address the growing problem of digital eye strain caused by prolonged screen usage. Instead of relying only on screen-time reminders, the proposed system analyses real-time eye behaviour to detect early signs of fatigue.

The system combines several indicators of eye strain, including blink rate, gaze stability, posture, and behavioural activity. By integrating these features into a single model, the system can estimate a strain score that reflects the current fatigue level of the user. When the strain level becomes high, the system alerts the user and recommends taking a short break or adjusting posture.

One of the major advantages of the proposed approach is that it operates using a standard webcam and does not require specialised hardware. This makes the system accessible to a large number of users and allows easy deployment in everyday environments such as homes, offices, and classrooms. The system also supports multi-user identification and multi-device environments, which makes it practical for shared computing setups.

The results of the testing phase demonstrate that combining visual eye features with behavioural and posture indicators improves the reliability of eye strain detection. The system was able to monitor user behaviour in real time and provide meaningful feedback without interrupting normal computer usage.

Overall, the proposed system contributes to the development of digital wellness technologies that promote healthier screen habits. By detecting eye fatigue early and encouraging users to take breaks, the system can help reduce the negative effects of prolonged screen exposure. Future improvements may include support for mobile devices, personalised fatigue models, and long-term eye health monitoring.

XII. FUTURE SCOPE

The proposed eye strain detection system provides a practical and effective solution for monitoring visual fatigue using a standard webcam and computer vision techniques. While the current system successfully analyzes eye behavior, posture, and user interaction patterns in real time, there are several opportunities for further improvement and expansion. These enhancements can increase the system's accuracy, usability, and applicability in a wider range of environments. One important area for future development is the integration of mobile devices. Currently, the system is designed primarily for laptops and desktop computers with webcams. However, many users spend a significant amount of time on smartphones and tablets. Extending the system to mobile platforms would REFERENCES allow users to monitor their eye health across all devices. A mobile application version of the system could use the front camera to track eye movements and provide alerts, making the solution more accessible and widely usable. Another improvement involves the use of advanced machine learning and deep learning models. The current system uses rule-based and feature-based methods to calculate the eye strain score. In future work, more advanced models such as neural networks can be trained using larger datasets to improve prediction accuracy. These models can learn complex patterns in eye behavior and provide more personalized and adaptive fatigue detection. The system can also be enhanced by implementing personalized user profiles. Different individuals have different blinking patterns, working habits, and tolerance levels for screen exposure. A personalized system can learn the normal behavior of each user over time and adjust thresholds accordingly. This would improve the accuracy of strain detection and provide more relevant recommendations. Another potential improvement is the inclusion of environmental factors such as lighting conditions, screen brightness, and room setup. Poor lighting and high screen brightness can increase eye strain, but these factors are not fully considered in the current system. By incorporating sensors or software-based brightness detection, the system can provide suggestions to adjust lighting conditions for better eye comfort. Future versions of the system can also include integration with wearable devices such as smart glasses or fitness trackers. These devices

DOI: 10.17148/IJIREEICE.2026.14379

can provide additional physiological data, such as eye movement patterns or head position, which can enhance the accuracy of fatigue detection. Combining data from multiple sources can create a more comprehensive monitoring system. Another important area of development is long-term eye health tracking. Instead of analyzing only short sessions, the system can store user data over days or weeks and generate reports showing patterns in screen usage and eye strain levels. This would help users understand their habits and make better decisions to protect their eye health. Finally, the system can be expanded to support cloud-based monitoring and remote analysis. By storing data in the cloud, users can access their eye health reports from different devices. This feature can also be useful in educational institutions or workplaces, where monitoring digital wellness is important. In conclusion, the future scope of this project includes improving accuracy, expanding device compatibility, and providing personalized and long-term solutions. With these enhancements, the system can become a comprehensive tool for promoting healthy digital habits and reducing the impact of prolonged screen usage.

REFERENCES

[1] World Health Organization, “Blindness and visual impairment.” Available: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment
[2] American Academy of Ophthalmology, “Computer Vision Syndrome.” Available: https://www.aao.org/eye-health/tips-prevention/computer-vision-syndrome
[3] National Center for Biotechnology Information, “Prolonged screen usage and eye comfort.” Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6020759/
[4] National Center for Biotechnology Information, “Cognitive load and eye fatigue.” Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7148283/
[5] ScienceDirect, “Blink rate changes during screen-based tasks.” Available: https://www.sciencedirect.com/science/article/pii/S0042698913000680
[6] IEEE, “Fatigue detection system using facial features.” Available: https://ieeexplore.ieee.org/document/8461546
[7] IEEE, “Real-time eye monitoring using computer vision.” Available: https://ieeexplore.ieee.org/document/9306322
[8] IEEE, “Eye Aspect Ratio (EAR) for blink detection.” Available: https://ieeexplore.ieee.org/document/9018842
[9] IEEE, “Gaze tracking using webcam-based methods.” Available: https://ieeexplore.ieee.org/document/8752389
[10] IEEE, “Multi-feature fatigue detection approach.” Available: https://ieeexplore.ieee.org/document/8844358
[11] IEEE, “AI-based fatigue detection models.” Available: https://ieeexplore.ieee.org/document/10007959
[12] Frontiers in Neuroscience, “Eye movement changes with mental workload.” Available: https://www.frontiersin.org/articles/10.3389/fnins.2020.00453/full
[13] ScienceDirect, “Visual fatigue using eye tracking data.” Available: https://www.sciencedirect.com/science/article/pii/S0169814114001217
[14] IEEE, “Machine learning approaches for fatigue detection.” Available: https://ieeexplore.ieee.org/document/9217054
[15] National Center for Biotechnology Information, “Impact of digital devices on eye health.” Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8471510/
[16] OpenCV, “Open Source Computer Vision Library.” Available: https://opencv.org/
[17] Google, “MediaPipe Face Mesh.” Available: https://google.github.io/mediapipe/solutions/face_mesh.html
[18] Towards Data Science, “Eye tracking with OpenCV and Python.” Available: https://towardsdatascience.com/eye-tracking-with-opencv-and-python-2e5d4d3e3b4d
[19] Mozilla Developer Network, “KeyboardEvent.” Available: https://developer.mozilla.org/en-US/docs/Web/API/KeyboardEvent
[20] Mozilla Developer Network, “MouseEvent.” Available: https://developer.mozilla.org/en-US/docs/Web/API/MouseEvent
[21] Occupational Safety and Health Administration, “Ergonomics.” Available: https://www.osha.gov/ergonomics
[22] Centers for Disease Control and Prevention, “Ergonomics.” Available: https://www.cdc.gov/niosh/topics/ergonomics/
[23] IEEE, “AI-based real-time monitoring systems.” Available: https://ieeexplore.ieee.org/document/9369656
[24] IEEE, “Eye fatigue detection during online learning.” Available: https://ieeexplore.ieee.org/document/9448044
[25] IEEE, “Webcam-based eye strain detection methods.” Available: https://ieeexplore.ieee.org/document/8941166