

Implementation Of Face Distance, Usage Duration, And Smart Break Monitoring System Using Python-Based Haar Cascade on Digital Device Usage

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Abstract— The prolonged use of digital devices with improper viewing distance can lead to eye strain and visual discomfort. This study aims to develop a real-time monitoring system for digital device usage based on digital image processing. The system is implemented using the Python programming language and the OpenCV library, with the Haar Cascade Classifier method used to detect the user's face through a webcam. Distance estimation is performed using single-camera distance estimation based on facial anthropometric data and the width of the detected face in the image and is stabilized using smoothing techniques. In addition, the system utilizes user age input to determine the recommended viewing distance range, calculates device usage duration, and evaluates the level of usage risk based on distance, age, and usage time. The system provides warnings in the form of visual alerts, beep sounds, break reminder audio, and a Smart Break feature that requires the user to rest for 20 seconds after a certain usage duration is reached. The implementation results show that the system is capable of detecting faces in real time, estimating distance with stable performance, and providing adaptive and responsive usage notifications. Therefore, the proposed system can be used as a simple and effective eye health monitoring tool without requiring additional hardware.

Keywords— *Digital image processing; Face detection, Haar Cascade; OpenCV; Distance estimation; Smart Break; Device usage monitoring*



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I. INTRODUCTION

The era of digital modernization brings significant changes where electronic equipment such as laptops transforms into mandatory tools for human activities. The

majority of individuals spend hours staring at screens without paying attention to duration limits that are safe for their bodies. This continuous visual exposure to monitor radiation is highly prone to triggering visual sensory system disorders. The most common complaints felt by workers include stinging eyes, blurred vision, to dizziness in the head. Non-ideal sitting positions and leaning too close to the screen are believed to be the dominant triggers of this eye strain syndrome [1]. Unfortunately, discipline in maintaining an ergonomic posture is often forgotten due to the absence of an instant warning mechanism when someone is fully concentrating. Based on this urgency, the creation of a smart innovation is absolutely necessary to detect the user's position directly to minimize future adverse effects [2].

As an answer to these medical challenges, digital image processing engineering presents a practical monitoring alternative. Through the branch of computer vision, software is now able to translate and analyze the visual components captured by the lens. The use of a built-in camera on a laptop device is more than enough to be turned into a sophisticated monitoring tool without having to buy additional instruments [3]. This smart scheme operates by immediately isolating human visual patterns the moment the user starts looking at the monitor. The ease of designing this recognition mechanism is also supported by the existence of a very complete open programming library, namely OpenCV. The platform offers a variety of ready-to-use mathematical functions to accelerate the transition from raw video formats to quantitative numbers. The harmonious blend of machine vision discipline and programming code has often been applied with satisfactory results in various object-tracking software [4].

In the design of visual depth measurement applications, the search stage for human facial features becomes the most crucial phase requiring high accuracy. The Haar

Cascade classification technique emerges as one of the most reliable algorithmic solutions frequently utilized to track facial positions [5]. This computational procedure functions optimally by scanning basic attributes of a person's face to separate it from surrounding background objects. The highest selling point of using this method lies in its rapid analytical capabilities even when supported only by mid-range hardware specifications. Its non-memory-burdening processing nature makes this technique highly suitable for software requiring instant response times. Many previous experiments have investigated this approach and validated its positive track record in finding human facial coordinates [6]. The successfully and accurately marked facial coordinate points will later be processed using calculation formulas to estimate the user's distance to the monitor.

Several previous studies have implemented face detection techniques for attendance systems, face recognition, and object monitoring using Haar Cascade and other computer vision methods. However, most of these studies focus only on face detection or recognition tasks and do not integrate user distance monitoring, usage duration tracking, risk assessment, and mandatory break management into a single system. In addition, many existing eye health monitoring applications require additional hardware sensors or focus solely on posture monitoring without considering screen usage duration and age-based ergonomic recommendations. Therefore, there is still a need for a lightweight and real-time monitoring system that can simultaneously evaluate viewing distance, usage duration, and user rest behavior using only a standard webcam.

The novelty of this research lies in the integration of three monitoring components, namely face-to-screen distance estimation, device usage duration monitoring, and an adaptive Smart Break mechanism within a single computer vision-based system. Unlike previous studies that mainly focus on face detection, this system combines age-based ergonomic distance recommendations, risk level classification, pause timer functionality, and mandatory break validation using real-time face detection. The proposed system is designed to operate using only a webcam without requiring additional hardware, making it practical and cost-effective for daily digital device usage monitoring.

Referring to the vast opportunities for utilizing the above innovation, this study is concentrated on building an integrated monitoring program for distance and screen staring time. This application carries a precision measurement method from a single camera lens that bases its calculations on human facial anthropometric dimensional metrics. The standard width of an adult human face is applied as a basic benchmark to mathematically estimate a person's physical position from the device. In addition to monitoring the viewing radius, this system is also equipped with the ability to record the

total time spent by users in front of their devices. The software will instantly react by issuing notifications in the form of sound warnings and screen displays when the subject is detected violating safe limits. To perfect the health aspect, a smart break function is integrated into the program to temporarily halt user activity for twenty seconds. Armed with this comprehensive prevention scheme, the application is projected to build a safer work routine and optimally reduce potential vision damage.

II. LITERATURE REVIEW

A. *Computer Vision Syndrome (CVS) and Digital Ergonomics*

Interacting with a device screen continuously without rest breaks can significantly trigger a decline in eye health functions. This medical condition in the form of visual sensory fatigue due to excessive monitor staring duration is often termed Computer Vision Syndrome [7]. Some physical complaints frequently experienced by sufferers include stinging eyes, double vision, to recurring headaches. Bad habits in the form of non-compliance in maintaining viewing distance and excessively long working durations are the main contributors to this problem [8]. Addressing this threat, the implementation of ergonomic body layouts while operating computers becomes a necessity to prevent visual complaints. The utilization of software designed to remind users to take breaks is an innovative mitigation step today. Setting proportional sitting positions coupled with regular time breaks is believed to be able to protect users' vision from long-term damage.

B. *Digital Image Processing and Computer Vision*

Image processing is a branch of science focused on manipulating image data to extract meaningful information within it [9]. This discipline encompasses various methods of visual quality improvement up to the automatic identification of an object's characteristics using digital computation. In its development, this technique merges closely with the field of machine intelligence, popularly known as computer vision [10]. Machine vision was developed with the main goal of providing electronic devices with the ability to see and interpret their surrounding environment. This algorithm works by breaking down a set of video frames into a pixel matrix to directly study its visual patterns. The application of this concept is very broad, ranging from automatic security tools, industrial robot control, to body posture health monitoring. In this system's design, the combination of these two disciplines is functioning to translate the user's facial layout in front of the device.

C. *Face Detection*

Face detection is one of the most essential implementations in the realm of current machine vision technology development. This computational mechanism is built with the main goal of finding the existence of a face

and its exact location within an image [11]. There is a fundamental difference between this object location tracking scheme and facial recognition systems. The detection stage only cares about finding the facial area without needing to extract the personal identity of the subject being observed. The output of this location identification process is generally presented in the format of a two-dimensional bounding box. This facial localization acts as the very first step before the machine performs further manipulation or measurement of visual components. Regarding distance monitoring applications, it is the change in size of this facial marker box that is later converted into an estimation of the user's physical range.

D. Haar Cascade Classifier Method

The Haar Cascade Classifier is known as a visual pattern detection algorithm whose performance is highly robust and time-tested. The basic logic of this method relies on machine learning techniques that recognize simple visual feature variations of the facial surface [13]. The system works intensively by comparing pixel brightness levels in specific areas using features that resemble the Haar concept. To speed up its mathematical processes, this algorithm adopts a special image representation technique often called an integral image. The subsequent process involves strict feature sorting using the AdaBoost method so that unimportant visual elements can be quickly discarded [14]. The cascade structure concept allows object evaluation to be done in stages, making the computational memory burden very light and efficient. It is the combination of these advantages that makes this method highly ideal when applied to real-time high-performance automatic detection applications.

Although modern face detection approaches such as MediaPipe Face Detection, SSD, YOLO, and deep learning-based CNN models generally provide higher detection accuracy [13], they require greater computational resources and more complex implementation. This research employs the Haar Cascade Classifier because the proposed system is intended to run on standard consumer laptops without requiring dedicated GPU hardware. Haar Cascade offers a good balance between detection speed, implementation simplicity, and computational efficiency, making it suitable for real-time monitoring applications where fast response time is prioritized over facial recognition accuracy.

E. Single-Camera Distance Estimation and Facial Anthropometry

Estimating the physical range between a human and a monitor can be developed by utilizing only one standard digital camera sensor. The single-camera distance estimation concept operates based on the inverse ratio between the object's pixel size on the screen and its actual depth. The conversion process from pixel units to real measurement units requires a consistent biological reference value as a benchmark [12]. In anthropometric studies, the average distance between the left and right cheekbones of an

adult human is known to be a constant value of around 13.7 centimeters. It is this biological dimension that is then combined with the camera lens focal length value through structured mathematical calculations. By comparing the variations in the width of the detected facial box, the system can calculate how far backward or forward the user's physical position is. This touchless measurement approach is considered far more economical because it eliminates the need for additional distance transmitter hardware.

F. OpenCV (Open Source Computer Vision)

Library OpenCV is an open programming function collection most highly favored by developers in the computer vision field. This software library is specifically formulated to facilitate high-performance image processing and video analysis needs [15]. Inside it are various mature algorithmic modules ready for use, ranging from object recognition to spatial analysis. In this software architecture, the CascadeClassifier function is utilized to execute the pre-trained XML model of the Haar algorithm. Additionally, this tool also provides a video stream capture feature allowing direct camera frame reading. Its dynamic nature makes OpenCV very easy to combine with various other data analysis libraries within a programming environment. Its capability to process image arrays quickly makes it an irreplaceable standard in optical sensor-based monitoring research.

G. Python Programming Language

Python is recognized as a high-level programming language offering a concise and highly intuitive code writing style. Its main advantage lies in the availability of an exceptionally complete external library ecosystem for scientific and technological purposes [16]. The completeness of these software facilities accelerates developer workflows in building and testing a smart system prototype. Through Python, complex distance calculation logic can be combined with visual image processing modules very efficiently. In this ergonomic warning system, Python plays a crucial role as the main brain governing the rules of the Smart Break feature. Pause time parameters and eye hazard level evaluations are fully controlled through code branching instructions in this language. The use of this development tool promises a robust application structure while providing ease if future upgrades are desired.

III. RESEARCH METHOD

A. Research Type

The research method utilized in this study is the software engineering method with a prototyping-based experimental approach. This method is used to design, develop, and test a computer vision-based eye health monitoring system in stages until an optimal system is obtained. The system development process starts from the requirements identification stage, system design, implementation using the Python programming language and OpenCV library, to

the system testing stage under various usage conditions. The developed system utilizes the Haar Cascade Classifier method to detect faces in real-time via webcam, and user distance estimation relative to the camera is carried out using the single-camera distance estimation method. This method utilizes facial anthropometric data as a real object reference measurement. The average human bizygomatic width is set at 13.7 cm based on previous facial anthropometry research. The user's distance to the camera is calculated using the equation (1):

$$D = \frac{W \times F}{P} \quad (1)$$

This equation represents the general form of single-camera distance estimation utilizing real object size, camera focal length, and object size on the image. Where D is the user's distance to the camera (cm), W is the actual face width (13.7 cm), F is the camera focal length, and P is the detected face width on the image in pixels. To enhance measurement stability, the system applies smoothing techniques using the average of several previous measurement results so that small user position changes do not cause significant distance value fluctuations.

B. System Process Flow

Fig. 1 is the system process flowchart. The developed system operates through several stages as follows:

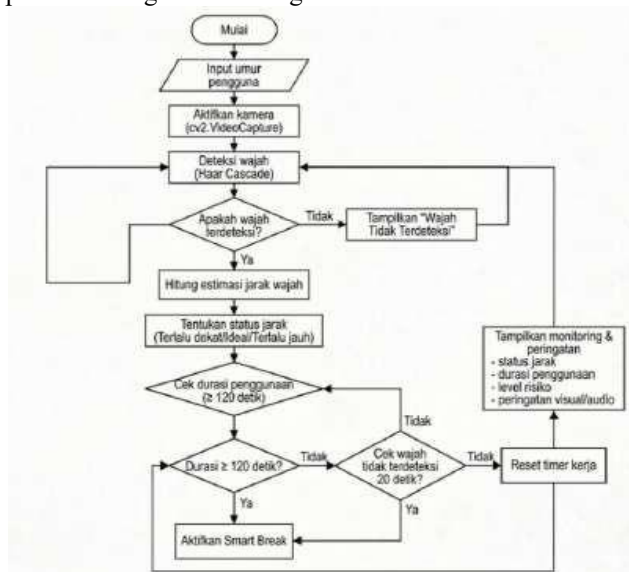


Fig. 1. Research methodology flowchart

- The user inputs age as an initial parameter used to determine the ideal distance range during digital device usage
- The system activates the camera (webcam) to capture real-time user facial images using the cv2.VideoCapture module
- Each acquired image frame is converted into grayscale form to improve the efficiency and speed of the

detection process

- The system performs face detection using the Haar Cascade Classifier method to obtain the facial area in the form of a bounding box with coordinate parameters (x, y) and size (w, h). The face width value (w) is subsequently used as a parameter in the user's distance estimation process toward the camera
- Based on the obtained distance value, the system determines the user's distance status into three categories: too close, ideal distance, and too far
- Next, a check is performed to see if the user's duration has reached or exceeded 120 seconds.
- If the duration has not reached 120 seconds, the system will directly display monitoring information including distance status, usage duration, risk level, and visual or audio warnings
- If the usage duration has reached or exceeded 120 seconds, the system will activate the Smart Break feature as a reminder for the user to rest
- While the Smart Break is active, the system will monitor whether the user's face remains undetected for a minimum of 20 seconds as an indicator that the user has truly moved away from the screen
- If this condition is met, the system will reset the work timer and stop the rest mode
- If it is not met, the system will continue to display rest reminders until the specified duration is reached.

C. Monitoring System Logic Design

The monitoring system is designed with rule-based logic utilizing face detection results as the main parameter. The user's distance status is determined based on the size area and width of the facial bounding box obtained from webcam detection results. Additionally, the system categorizes users based on age input to determine the recommended usage distance range. Subsequently, the system calculates a risk score based on a combination of several parameters, namely user distance, device usage duration, age group, and the user's resting condition. The system is also equipped with a pause timer mechanism, which is the temporary suspension of work duration calculation when the user's face is undetected under normal conditions. This feature aims to ensure that the calculated work duration truly represents the user's active time in front of the device. When the work duration exceeds the specified limit, the system will enter Smart Break Mode. In this mode, users are required to step away from the camera for 20 seconds. If the user is detected again before the rest time is fulfilled, the rest process is halted and the system will continue requesting the user to rest.

IV. RESULT AND DISCUSSION

A. System Implementation Results

The following are the results of the system implementation:

1) Normal face detection and ideal distance

The initial system display shows the success of the Haar

Cascade algorithm in detecting the user's face in real-time (Fig. 2). In this condition, the system calculates the face distance to be within the ideal range (according to the user's age input), marked by green text labeling indicating that the user's sitting posture is ergonomic and safe for eye health.



Fig. 2. Ideal distance face detection results

2) Detection of face distance being too close

Fig. 3 shows the algorithm's response to the user's position being outside the safe limit. The system detects that the face distance (43.9 cm) is categorized as "TOO CLOSE", triggering red text labeling and a red bounding box. This condition is accompanied by a Level Risk: HIGH indicator, providing a visual warning so the user promptly corrects their sitting position to maintain eye health.



Fig. 3. Display when face is too close

3) Detection of face distance being too far

Fig. 4 shows a condition where the user is at a distance exceeding the ideal limit, specifically 70.6 cm. The system provides a response in the form of the text label "TOO FAR" with a yellow bounding box. Although this position is not as directly dangerous to the eyes as a close distance, the system still issues a warning because being too far can cause eye strain when attempting to view screen content, thereby establishing the Level Risk: MEDIUM.

4) Display of User Age Categories

Fig. 5 shows the user age category based on the age data entered at the beginning of system use. Age information is

used as a parameter to determine the recommended ideal distance range during digital device usage. With this age categorization, the system can provide distance recommendations that are more suited to the user's characteristics, making the monitoring process more adaptive.



Fig. 4. Display when face is too far



Fig. 5. Display of age detection and category

5) Work duration description

Fig. 6 shows the real-time device usage time monitoring feature. The text "Work Duration" logs the time spent by the user (18-time units), which is then accumulated with the distance factor to yield a "Level Risk: LOW". This information serves as an early warning system, so users are aware of potential eye fatigue due to increasing work duration.



Fig. 6. Work duration display

6) Active rest mode description

Fig. 7 demonstrates the condition when the system activates the Smart Break feature after the usage duration reaches the specified threshold (123). At the same time, the user's face distance is detected as too close (47.0 cm), so the system issues a high-risk level warning and displays the instruction "REST YOUR EYES!" as an effort to mitigate eye fatigue risk caused by prolonged device use.

7) When face is undetected

Fig. 8 shows the system's response when the Haar Cascade algorithm fails to identify facial features within the camera frame. This condition occurs because the user's face is turned away from the sensor or out of the detection range area. The system automatically provides feedback in the form of red text "Face Not Detected", signaling that the distance and work duration monitoring processes are temporarily paused until the face is identified again.



Fig. 7. Display of command to rest



Fig. 8. Display when face is not detected

8) 20-second rest countdown

Fig. 9 display outlines the Smart Break process implemented in the system. In the research implementation, the rest duration is set for 20 seconds to facilitate the testing process and feature demonstration without having to wait too long. Conceptually, this mechanism refers to the 20-20-20 ergonomic principle which advises users to look away from the screen periodically to reduce eye fatigue. The work duration and rest duration values in the system can be customized according to user needs.

9) FPS and risk bar

Fig. 10 display exhibits the FPS (Frames Per Second) indicator representing the system's image processing speed per second. The number "FPS: 9" indicates that the face detection and distance calculation algorithms are running very smoothly (fluidly). This performance ensures that eye

health monitoring can be conducted in real-time without significant latency (lag) constraints.



Fig. 9. Display during rest countdown



Fig. 10. FPS and risk bar display

B. System Testing Results

TABLE 1 is the system testing results. This testing was conducted to determine the application's performance across various usage conditions. Testing was done through several scenarios to ensure that every primary and secondary feature could operate according to the designed system logic.

TABLE 1. SYSTEM TESTING RESULTS

No	Test scenario	Input condition	System output	Result
1	Normal face detection	Face in front camera	Face Bounding box appears	Successful
2	Distance too close	Face moves closer to camera	Status "too close", red color	Successful
3	Ideal distance	Face at normal position	Status "ideal distance", green color	Successful
4	Distance too far	Face moves away from camera	Status "too far", yellow color	Successful

No	Test scenario	Input conffition	System ouput	Result
5	Duration monitorin g	Face remains in front of camera	Timer runs	Successful
6	Pause timer	Face disappears from camera	Work timer paused	Successful
7	Smart Break active	Work duration >120 seconds	Text "REST YOUR EYES!" appears	Successful
8	Rest is successful	Face is undetected for 20 seconds	Work timer is reset	Successful
9	Audio warning	Medium/high risk	Beep sound/audi o played	Successful
10	Visual warning	High risk	Red overlay displayed	Successful

Based on the testing results, all main and additional features in the system were able to run well. The system was not only capable of performing real-time face detection and distance estimation, but also successfully executed duration monitoring logic, pause timer, risk evaluation, and Smart Break according to the designed usage scenarios.

TABLE 2 is the testing result for distance estimation to evaluate the accuracy of the proposed distance estimation method, additional experiments were conducted at various distances ranging from 40 cm to 100 cm. The obtained measurement results were then evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) metrics.

TABLE 2. TESTING RESULTS FOR DISTANCE ESTIMATION USING FACIAL ANTHROPOMETRY

Actual Distance (cm)	Estimated Distance (cm)	Error (cm)
40	42	2
50	53	3
60	58	2
70	72	2
80	77	3
90	87	3
100	104	4

$$MAE = \frac{\sum(Actual - Estimated)}{n} \quad (2)$$

$$MAPE = \frac{1}{n} \sum \left| \frac{Actual - Estimated}{Actual} \right| * 100\% \quad (3)$$

$$RMSE = \sqrt{\frac{\sum(Actual - Estimated)^2}{n}} \quad (4)$$

Based on the accuracy evaluation results presented in TABLE 3, the proposed distance estimation system achieved an MAE value of 2.71 cm, indicating that the average measurement error remained relatively low. The obtained MAPE value of 4.04% shows that the percentage deviation between the estimated distance and the actual distance was small. Furthermore, the RMSE value of 2.80 cm indicates that large measurement deviations rarely occurred during testing. These results demonstrate that the anthropometric-based distance estimation approach is sufficiently accurate and reliable for real-time eye health and ergonomic monitoring applications using a standard webcam.

TABLE 3. ACCURACY EVALUATION RESULTS USING MAE, MAPE, AND RMSE

Metric	Result
MAE	2.71 cm
MAPE	4.04 %
RMSE	2.80cm

C. Discussion

The accuracy evaluation results further support the effectiveness of the proposed distance estimation method. The low MAE, MAPE, and RMSE values indicate that the system can estimate user distance with acceptable precision for monitoring purposes. Although the proposed method is relatively simple compared to deep learning-based approaches, it provides satisfactory performance while maintaining low computational requirements and real-time responsiveness.

Based on the implementation and testing results, the developed system was capable of executing its primary function, which is detecting faces and estimating user positions relative to the screen via a real-time face-to-camera distance approach. The use of the Haar Cascade method proved effective as it was able to provide fast performance with low computational demands. The distance estimation approach using facial anthropometric data, camera focal length, and face size (bounding box) showed that the larger the face size on the image, the closer the user's position to the camera. Even though this method is simple in nature, the results obtained were quite consistent for monitoring needs.

The application of smoothing techniques also had a positive impact on system stability. Without smoothing, slight user position changes could cause significant distance value fluctuations. With smoothing, the system became more stable and comfortable to use.

The duration monitoring and Smart Break System features also played vital roles in enhancing the overall system function. The system not only detected user positions but was also capable of providing control

over the device usage length. The implementation of the pause timer made the system more accurate because work duration is only counted when the user is genuinely in front of the device. In the implementation of this research, the Smart Break duration was set to 20 seconds after 120 seconds of device usage. This setting aimed to speed up the system testing and demonstration process so all functions could be observed directly without having to wait for a long time. Conceptually, this mechanism adopts the 20-20-20 ergonomic principle, where users are advised to look away from the screen every 20 minutes to reduce eye strain. Therefore, the work duration and rest duration parameters in the system can be tailored to user needs or applied health standards.

The face distance estimation feature based on bounding box width (w) successfully provided an approximation of the user's position relative to the screen and served as the primary parameter for ergonomic monitoring within the system. The estimated distance values were utilized to determine user position categories, namely too close, ideal distance, and too far. Combined with age-based recommendations and usage duration monitoring, this feature contributed significantly to the evaluation of user risk levels and the generation of adaptive warnings aimed at promoting healthier digital device usage habits.

Additionally, the implementation of visual and audio notifications made the system more interactive and responsive to non-optimal usage conditions. Users did not solely receive information via text displays but also obtained feedback in the form of sound, which could increase awareness for maintaining eye health. However, this system has several limitations, including:

- Distance estimation remains an approximation and is influenced by camera positioning.
- Face detection can be affected by lighting and facial angles.
- The system has not used more accurate deep learning-based methods.
- The system has not performed specialized camera calibration for individual users. Overall, the developed system has been able to meet the research objectives as a computer vision-based digital device usage monitoring tool that is simple, lightweight, interactive, and real-time.

V. CONCLUSION

Based on the results of the research and testing conducted, it can be concluded that the monitoring system for facial distance, usage duration, and Smart Break using the Python and OpenCV-based Haar Cascade Classifier method was successfully implemented and ran in real-time. This system was capable of stably detecting the user's face via webcam and estimating the distance between the user's face and the camera as an approximation of the user's position relative to the screen, using the single-camera

distance estimation method based on facial anthropometric data and camera focal length. Furthermore, the distance estimation evaluation demonstrated an MAE value of 2.71 cm, a MAPE value of 4.04%, and an RMSE value of 2.80 cm, indicating that the proposed approach provides acceptable accuracy for practical eye health monitoring applications.

Furthermore, the system is also equipped with an automatically running device usage duration monitoring feature and a Smart Break System feature that provides warnings for users to rest periodically. This feature helps in reducing the risk of eye strain caused by prolonged digital device use. Based on testing results, the system demonstrated fairly good performance under various usage conditions, particularly in normal lighting. The application of smoothing techniques also contributed to increasing the stability of distance estimation results so that values did not change drastically due to minor user movements.

In addition to the distance detection function, the system successfully implemented usage duration monitoring, risk level classification, pause timers when users are undetected, and the Smart Break System requiring users to rest for a certain period. The system also provided real-time visual and audio notifications to heighten user awareness concerning eye health while using digital devices. Nevertheless, the developed system still has some limitations, including distance estimation accuracy that still relies on camera position, lighting conditions, and user facial angles. Moreover, the utilized method is still based on simple approximations and has not leveraged deep learning technology, which has a higher accuracy level.

Therefore, future studies are expected to develop systems with more complex methods, such as utilizing deep learning models, and conducting more accurate camera calibration to increase distance estimation precision. With further development, this system holds the potential to become a more optimal solution in assisting users to maintain eye health when using digital devices.

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