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Computer vision syndrome prevention: detection of expression and eye distance with monitor screens

Aufaclav Zatu Kusuma Frisky, Elang Arkanaufa Azrien, Raden Sumiharto, Sri Hartati
Department of Computer Science and Electronics, Faculty of Science and Mathematics, Universitas Gadjah Mada, Yogyakarta, Indonesia

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ABSTRACT

Computer vision syndrome (CVS) is a vision-related complaint caused by computer usage. CVS can be analyzed through facial expressions detected by a camera. Expression detection is categorized into two groups: safe and dangerous. The safe category comprises happy, neutral, disgusted, sad, angry, and surprised, while the dangerous category includes sad and fearful emotions. This division is based on the similarity of CVS symptoms to facial emotion characteristics. Additionally, an additional feature is implemented to detect the distance between the screen and the user's eyes using the FaceMeshModule to prevent the user's eyes from getting too close to the screen. Both detections will provide warning notifications when a dangerous category expression is detected ≥70% every minute, and when the distance between the screen and the eyes is ≤40 cm. Notifications in this program use the Tkinter library as a graphical user interface (GUI) message box. In this research, facial expressions are detected using the CascadeClassifier for face detection and the extreme inception (Xception) as the facial expression classifier. The results of expression detection achieved an accuracy of 94%, an F1-score of 94%, precision of 95%, and recall of 94%.

Corresponding Author:

Aufaclav Zatu Kusuma Frisky
Department of Computer Science and Electronics, Faculty of Science and Mathematics
Universitas Gadjah Mada
Sleman, Special Region of Yogyakarta, Indonesia
Email: aufaclav@ugm.ac.id

1. INTRODUCTION

Computer vision syndrome (CVS) refers to a collection of visual and musculoskeletal symptoms that arise from prolonged exposure to digital screens, such as computers, mobile phones, and tablets [1]. With increasing digital reliance in daily life, CVS has become a significant public health concern, affecting vision, comfort, and productivity [2]. The American Optometric Association recommends maintaining a 40–76 cm viewing distance to minimize eye strain [3].

A method for detecting CVS utilizes facial recognition directly linked to the laptop. Facial expressions are known to convey up to 55% of communicative information, compared to 45% from spoken and audible cues [4]. The system identifies and processes facial features, which are then filtered and classified based on pre-trained data to recognize emotional states [5]. Additionally, the distance between the eyes and the screen can be accurately measured using only a camera.

Several studies have investigated advanced methods to mitigate CVS, particularly through eye-blink detection and facial expression recognition (FER). Lapa *et al.* [6] proposed a real-time CVS detection approach using eye-blinking as a primary indicator, but its reliability was affected by factors such as age, gender, and lighting conditions. In contrast, Medeiros *et al.* [7] introduced a machine learning-based method to identify eye blinks in individuals with CVS. Their study emphasized that, although eye-blink detection is a useful feature, it is insufficient in isolation for precise CVS evaluation. They recommended integrating eye-blink detection with additional facial parameters, such as FER, to achieve a more comprehensive and accurate assessment. Building on this, Mutanu *et al*. [8] developed a self-adjusting FER-based system to detect eye strain and reduce visual discomfort, but their 77% classification accuracy highlighted the need for better feature representation and training diversity. These studies suggest that while individual features offer some insight, an integrated approach combining multiple facial cues is more promising for robust and reliable CVS detection.

In addition to these studies, this research is inspired by advancements in driver fatigue detection that highlight the need to combine multiple facial features. Sun *et al*. [9] proposed a multi-stream convolutional neural network integrating both global and local facial features to enhance fatigue detection performance, particularly under low-quality inputs, though their model still lacked temporal context. Balasundaram *et al*. [10] emphasized incorporating facial gestures such as yawning to improve reliability. Similarly, Zhao *et al*. [11] demonstrated that fusing eye and mouth features improves accuracy significantly; however, their approach can still be enhanced optimizing real-time performance for deployment in safety-critical systems.

This study proposes a CVS prevention system that integrates FER with eye-to-screen distance measurement. The system alerts users when their eye distance falls under 40 cm and classifies expressions as either "safe" or "dangerous", if a "dangerous" expression appears with over 70% certainty within a minute, the system issues a warning. This approach leverages a regularized extreme inception (Xception) model with extra training data and a step decay learning rate to enhance recognition accuracy.

2. METHODOLOGY

This study developed a system to detect weariness in laptop users by analyzing facial expressions and eye-to-screen distance to mitigate CVS. The system employs the Xception architecture [9], trained on FER2013, CK+, and extended and augmented Google FER datasets, to classify emotions into seven categories. Facial detection is performed using the Viola-Jones method with the CascadeClassifier algorithm [10]. Fear and sadness are classified as "dangerous (*bahaya*)", while other expressions are "safe (*aman*)", with a warning triggered if "dangerous" expressions exceed 70% [12]. The system continuously monitors user behavior, processing facial expression data in real-time to provide immediate alerts and encourage safe posture [13]. Additionally, it measures the eye-to-screen distance using focal length calculations, issuing warnings when the distance is 40 cm or less. Figure 1 illustrates the system's workflow.

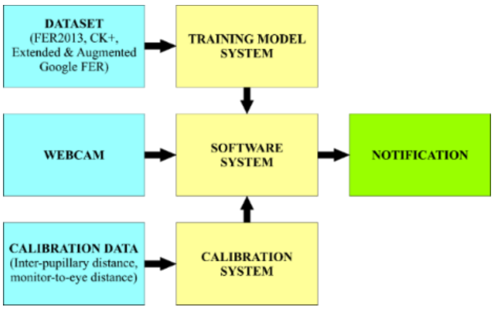


Figure 1. Block diagram system

2.1. Dataset description

Ekman [14] identifies happiness, anger, disgust, fear, sadness, and surprise as the fundamental human emotions. The study utilized multiple datasets of face emotions for training, including FER2013 (training data) [15], CK+ [16], and extended and augmented Google FER [17]. The FER2013 dataset consisted of 35,887 grayscale photographs categorized into seven emotional categories. Additionally, the CK and extended, and augmented Google FER datasets were included in the training data, resulting in a total of 67,881 images. The FER2013 (public test) dataset is utilized for validation purposes, whereas the FER2013 (private test) dataset is employed for testing. The dimensions of each image in the collection are 48 by 48 pixels.

2.2. Categorize expression

According to the dataset, seven emotional types would be reclassified into two groups: safe and dangerous. The safe group comprised emotions such as angry, disgust, happy, neutral, and surprise while the dangerous group consisted solely of sad and fear. The category is derived from the parallels observed between the symptoms of CVS and facial emotional traits. CVS symptoms encompass blurring of vision, burning, double vision, eye pain, watering eys, and multiple symtomps [1]. Conversely, the display of sad and fear is characterized by a lack of focus and a fixed gaze [14]. Hence, the classification of sad and fear as a category of "dangerous" is based on their resemblance to the symptoms of CVS.

2.3. Training model system

The training model employed in this system is based on regularized Xception for FER with extra training data and step decay learning rate [18]. This model utilizes a regularized Xception architecture, data augmentation, and a step decay learning rate to enhance its accuracy. Using the FER2023, CK+, and extended and augmented Google FER datasets, the model achieved an accuracy of 94.34%, surpassing the results of previous studies, as shown in Table 1.

At the beginning of the training process, the program ingests datasets that include training, validation, and test data. The data undergoes preprocessing, which includes normalization and data augmentation. The processed data is then used in the training phase with the regularized Xception architecture, employing the step decay approach that adjusts the learning rate at specific epochs. Upon completion of the training procedure, the finalized model will be evaluated to assess its performance. The system architecture is illustrated in Figure 2.

Table 1. The comparison of accuracy for each model

References	Method	Accuracy (%)
Jaymon *et al.* [19]	Simple CNN model	54
Gunawan *et al.* [20]	ConvNet model	57.4
Jaymon *et al.* [19]	Inception model	61.42
Jaymon *et al.* [19]	Xception model	65.2
Vignesh *et al.* [21]	Segmentation VGG-19	75.97
Zhang *et al.* [22]	CNN+image edge computing (FER2013+LFW Dataset)	88.56
Debnath *et al.* [23]	Fussion features (CNN+LBP+ORB)+ConvNet	91.01
Azrien *et al.* [18]	Regularized Xception for FER with extra training data and step decay learning rate	94.34

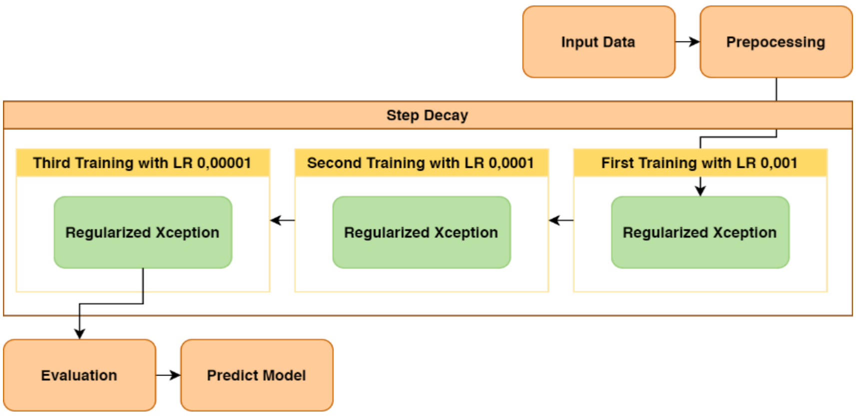


Figure 2. The stages of the system for training method

2.4. Software system

The software system simultaneously performs facial expression identification and screen-to-eye distance measurement. Expression detection uses CascadeClassifier with a 60-second timer, classifying emotions as "safe" or "dangerous." If "dangerous" expressions reach 70%, a warning appears, and the user can press 'ok' to continue. Distance measurement utilizes the calibrated focal length value, calculated using (1) [24], where 'd' represents the detected screen-to-eye distance. The equation requires actual pupil distance (W), focal length (f), and real-time eye distance (w) detected via FaceMeshModule. A warning triggers if the distance is ≤40 cm, requiring user confirmation to proceed.

$$d=(W.f)/w \tag{1}$$

2.5. Calibration system

The calibration system determines the focal length, which is then used to compute the distance between the screen and the eye. This process employs the FaceMeshModule from MediaPipe to obtain precise eye coordinates. MediaPipe face mesh is a real-time system that maps 468 3D facial landmarks [25].

The system calculates the focal length using (2), where f represents the focal length, w is the inter-pupillary distance (IPD) detected by the camera, D is the distance from the monitor to the eye, and W is the actual IPD.

$$f = (w.D)/W \quad (2)$$

The calibration process begins by setting reference values: the actual pupil distance (W) and the measured screen-to-eye distance (D). The system then detects the IPD (w) using FaceMeshModule. With these three parameters, the focal length is computed for accurate distance estimation.

2.6. Notification

In this study, we utilize the Tkinter module. Tkinter is a Python package that facilitates the creation of programs with a graphical user interface (GUI). The GUI allows users to interact with the application through visual elements such as icon images. This module offers a range of GUI functionalities, including a notification capability [26].

3. RESULTS AND DISCUSSION

The program was evaluated under two distinct lighting conditions, 40 lux and 2,130 lux, to assess its performance in low-light and high-light environments. Differences in illumination can substantially affect the accuracy of feature extraction, as insufficient lighting may obscure facial details. Otherwise, excessive brightness can introduce overexposure [27].

3.1. Result for first condition

The first test was conducted under 40 lux light intensity to evaluate expression classification and screen-to-eye distance detection. Parameters included monitor luminance (50% or 100%) and screen distance (50 cm or 76 cm). The system successfully identified “safe” expressions when they remained under 70% within one minute and issued a notification for “dangerous” expressions when they reached 70% or more. For screen-to-eye distance, the system correctly triggered alerts when the distance was ≤40 cm and refrained from notifying when it exceeded 40 cm. The results remained consistent across all conditions. Table 2 presents the outcomes for expression detection and distance measurement.

3.2. Results for second condition

The second test, conducted under 2,130 lux lighting, evaluated expression classification and screen-to-eye distance detection using the same monitor luminance (50% or 100%) and screen proximity (50 cm to 76 cm). The system successfully issued notifications when “dangerous” expressions reached 70% within one minute. For screen-to-eye distance, alerts were correctly triggered at ≤40 cm and suppressed beyond 40 cm. The system performed consistently across all conditions. Table 3 presents the results for expression recognition and distance measurement.

3.3. Discussion

The results show that both the facial recognition system and the eye-to-screen distance detection system performed successfully under all tested conditions, including variations in ambient lighting, screen brightness, and viewing distance. These findings suggest that the system is robust and adaptable to different environmental settings. Previous studies indicate that extreme lighting conditions can affect facial recognition performance due to contrast reduction and glare [28]. However, our system maintained stable accuracy across both dim and bright environments. Similarly, screen brightness variations, which are often associated with changes in visual adaptation and contrast sensitivity [29], did not impact recognition performance, further demonstrating the system's reliability. Viewing distance, another important factor in image clarity [30], also did not affect recognition accuracy, as the system successfully recognized faces at both 50 cm and 76 cm distances.

Although this study focused on environmental factors, one of the major challenges in facial recognition and eye-to-screen distance measurement is the presence of additional variables such as the use of glasses, contact lenses, or refractive errors. Prior research suggests that glasses and occlusions caused by eyewear can affect detection accuracy [31]. This factor was not explicitly examined in this study, as the evaluation was limited to variations in lighting conditions. However, future research could explore its impact further to assess whether the system’s robustness extends beyond the tested parameters.

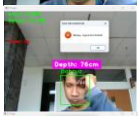
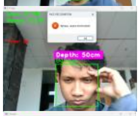
Previous studies have shown that lighting conditions can significantly impact eye detection accuracy [32]. However, despite these potential challenges, the eye-to-screen distance detection system in this study performed reliably under all tested conditions. This consistency suggests that advancements in recognition algorithms have improved adaptability, mitigating the adverse effects of lighting, screen brightness, and viewing distance observed in earlier research.

Overall, the findings confirm that the tested system remains effective across varying conditions, supporting its practical application in diverse settings. Future studies could further explore the impact of additional factors, such as eyewear and refractive conditions, to refine its performance in broader user scenarios. Additionally, considering prolonged screen exposure, established guidelines such as the 20-20-20 rule have been recommended to reduce visual strain and improve eye health [31]. Studies suggest that following these guidelines can help alleviate digital eye strain symptoms and maintain visual comfort during extended screen use. Integrating these preventive measures into future research could provide a more comprehensive evaluation of user well-being in prolonged usage scenarios.

Table 2. Recognize test for first condition

Recognize test	LI	ED	Program	Result
Safe	50%	50 cm		Success
Safe	50%	76 cm		Success
Safe	100%	50 cm		Success
Safe	100%	76 cm		Success
Dangerous	50%	50 cm		Success
Dangerous	50%	76 cm		Success
Dangerous	100%	50 cm		Success
Dangerous	100%	76 cm		Success
Screen-to-eye Distance	50%	40 cm		Success
Screen-to-eye Distance	50%	60 cm		Success
Screen-to-eye Distance	100%	40 cm		Success
Screen-to-eye Distance	100%	60 cm		Success

Table 3. Recognize test for second condition

Recognize test	LI	ED	Program	Result
Safe	50%	50 cm		Success
Safe	50%	76 cm		Success
Safe	100%	50 cm		Success
Safe	100%	76 cm		Success
Dangerous	50%	50 cm		Success
Dangerous	50%	76 cm		Success
Dangerous	100%	50 cm		Success
Dangerous	100%	76 cm		Success
Screen-to-eye Distance	50%	40 cm		Success
Screen-to-eye Distance	50%	60 cm		Success
Screen-to-eye Distance	100%	40 cm		Success
Screen-to-eye Distance	100%	60 cm		Success

4. CONCLUSION

The proposed system effectively classifies facial expressions as either "safe" or "dangerous" and issues warnings when a "dangerous" expression appears with 70% certainty. Additionally, the eye-to-screen distance detection alerts users when their viewing distance falls under 40 cm, accounting for variations in lighting conditions. While this approach enhances CVS prevention, further research is required to refine symptom timing detection, integrate fatigue-related facial expressions, and explore potential correlations with ocular disorders. Implementing preventive measures such as the 20-20-20 rule remains beneficial. Future studies could improve system adaptability by leveraging diverse deep learning frameworks to enhance accuracy and usability across different environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Aufaclav Zatu Kusuma Frisky	✓			✓	✓	✓	✓	✓		✓		✓	✓	✓
Elang Arkanaufa Azrien	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Raden Sumiharto						✓				✓			✓	✓
Sri Hartati	✓									✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets used in this study are publicly accessible. The FER2013 dataset can be obtained from Kaggle at https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data. The CK+ can be accessed at https://doi.org/10.1109/CVPRW.2010.5543262. Additionally, the extended and augmented Google FER dataset is available on Kaggle at https://www.kaggle.com/datasets/prajwalsood/google-fer-image-format/data.

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BIOGRAPHIES OF AUTHORS

Aufaclav Zatu Kusuma Frisky received the bachelor degree in Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences from Universitas Gadjah Mada, Indonesia in 2012 and M.Sc. degree in Department of Computer Science and Information Engineering from National Central University, Taiwan in 2015. He graduated as a Doctoral Student at Computer Vision Lab, Institute of Visual Computing and Human-Centered Technology, TU Wien, Austria, in 2023. His research interests include computer vision, machine vision, single image reconstruction, and its applications in cultural heritage preservation. He can be contacted at email: aufaclav@ugm.ac.id.

Elang Arkanaufa Azrien graduated with a Bachelor of Science degree in Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences from Universitas Gadjah Mada, Indonesia, in 2024. Currently, he is one of the researchers in the Electronics and Instrumentation Studies Program at Universitas Gadjah Mada. His main research focuses on machine learning and computer vision. With knowledge in both fields, he engages in research aimed at gaining in-depth understanding and developing practical solutions. He can be contacted at email: elang.arkanaufa.azrien@gmail.com or elang.arkanaufa.azrien@mail.ugm.ac.id.

Raden Sumiharto received his bachelor's degree in Physics from Universitas Gadjah Mada, Indonesia, in 2002 and his master's degree in Computer Science from Universitas Gadjah Mada, Indonesia, in 2007. He is currently a lecturer at the Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada. His research interests include nano satellite, UAV, parallel processing, sensor networks, and grid systems. He can be contacted at email: r_sumiharto@ugm.ac.id.

Sri Hartati currently holds the position of lecturer in the Department of Computer Science and Electronics at the Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada (UGM). She earned her master's degree in Computer Science from the University of New Brunswick, Canada, during the period of September 1988 to October 1990. With a profound academic background, she has been actively contributing to the fields of computer science, computer reasoning, and artificial intelligence. Her dedication is reflected in her extensive publication record, boasting 114 articles in reputable journals and conferences. She can be contacted at email: shartati@ugm.ac.id.