Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 218 (2023) 1270–1279

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering

IntelEye: An Intelligent Tool for the Detection of Stressful State based on Eye Gaze Data While Watching Video

Jyotsna C.[a,*], Amudha J.[a], Amritanshu Ram[b], Giandomenico Nollo[c]

[a]Dept. of Computer Science and Engineering, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India
[b]HCG Cancer Center, Bangalore, India
[c]Department of Industrial Engineering, University of Trento, Trento, Italy

Abstract

Technology to monitor mental health is gaining popularity as it helps to improve the cognitive and behavioral performance of an individual. Considering the growing need to monitor mental health, there is subsequent research in continuous and real-time monitoring technologies that can increase the quality of life by reducing the cost of health care. Eye tracking technology has played a significant role in monitoring a person's mental health. An intelligent system can apply several computational procedures to extract meaningful information from the massive physiological data obtained from eye tracking. The proposed model IntelEye is a tool to detect the stressful states of an individual while watching calm and stressful videos. The eye gaze measures based on pupil diameter, fixation, and blink were used for detecting stressful conditions. The data was collected from hospital employees, and the K Nearest Neighbor algorithm could successfully recognize the stressful states and the corresponding gaze location during stressful situations. IntelEye is not only identifying the stressful states but also has the novelty of identifying the scene and gaze location, making them stressful while watching the video.

Keywords: Eye Tracking; Mental Health; Real Time Monitoring; K-Nearest Neighbour; Eye Gaze Measures; Welch Two Sample t-test

1. Introduction

The personality and behavior of a healthy person have significant differences from a diseased person. The sudden changes in the conduct or character can be specific to any mental or physical health problems. Current studies show a significant increase in people suffering from depression and anxiety. There is a need to understand the impact of mental health problems on an individual's everyday life. There should be an effective mechanism to detect and treat

* Corresponding author. Tel.: +919986366510
E-mail address: c_jyotsna@blr.amrita.edu

10.1016/j.procs.2023.01.105

mental health problems to improve the quality of life of people suffering from mental health. Existing interventions and research shows some promising result but are limited in their accessibility and usage [1].

The changes in the behavior and thinking of a person may not always be because of mental health problems. It can also be related to some medications. The identification of the disease at the right time can make a better impact on the person suffering from the issues. There is limited access to healthcare facilities for people living in villages than in cities. Remote patient monitoring is an effective mechanism to monitor people's mental health and wellbeing in rural places [2].

The changes in the physiological measures of a person help to understand their behavioral changes [3]. Many wearable devices and sensors help to monitor an individual's physiological measures [4]. The recent advancements in physiological sensors and wearables enabled people to monitor their daily lives and allowed health professionals to monitor their patients remotely. It also helped the researchers to collect real-time data without interrupting human behavior. Eye tracking technology has gained a remarkable role in monitoring a person's mental health based on ocular measures. It is an unobtrusive device that helps to track a person's gaze while watching any stimulus on the computer [5].

Eye tracking measures obtained from individuals provide deeper insight into their traits, and cognitive processing [6]. Since eye tracking can tap into the unconscious processing of the mind, that makes continuous and involuntary data collection [7]. It explores the possibility of health monitoring in smart environments and adaptive workplaces [8]. Since the eye and mind are interconnected, the eyes can reflect the mental processing of an individual while watching any image or video. Eye tracking technology helps to understand where we look at, how long, which content in the image has influenced the thought process, which element attracted the immediate attention, the order in which the elements are noticed, the elements that are being ignored or overlooked, and the elements that could draw above-average attention [9].

Our proposed model IntelEye predicts the stressful state of a person based on their eye gaze measures while watching a calm and stressful video. Statistical analysis is performed to understand the significant difference in eye tracking measures while watching both videos.

The paper is organized as follows. Section II explains various studies on eye tracking techniques to monitor a person's mental health. Section III presents the working of the proposed model IntelEye in detecting stressful states while watching videos. Section IV explains the significant difference in eye tracking measures observed during calm and stressful videos based on the obtained results. Section V concludes the paper with discussions and future recommendations.

2. Literature survey

In our previous study [10], we had reported stress level analysis in students based on their gaze parameters observed while performing mathematical tasks. Pupil diameter and blink frequency were observed as good indicators of cognitive load, which in turn increase the individual's stress. The eye fatigue of students' could also be indicated based on the fixational qualitative score.

It is essential to understand the engagement of learners during online learning [11]. During the online learning process, it is not easy to understand attendees' attention, involvement, and concentration [12]. Eye tracking measures and techniques draw researchers' attention in understanding learners' online learning engagement [13].

The influence of emotion on eye behavior is explained in [14] [15]. The significant effect of negative images was observable in participants' visual attention and eye tracking features. The negative images had higher saccade amplitude, longer saccade duration, and higher saccadic velocity. It indicates the presence of longer, faster, and larger saccade in negative images [16]. A solid center bias was observed in positive images than in negative images. There was a remarkable difference in eye tracking measures while watching pleasant and unpleasant images. Eye gaze measures are good indicators of depression in an individual [17]. Pleasant and unpleasant images were used as a stimulus, and it has been noticed an attentional bias toward sad images for depressed participants.

The sympathetic nervous system, a part of the autonomic nervous system, is responsible for the human body's stress response [18]. When a person has stress or mental effort, it makes corresponding changes in the body like an increase in the heart rate, stimulating sweat production, dilation in pupil diameter, and increase in the breath rate. So

Table 1: Summary of Literature survey.

Paper	Stimuli	Eye Tracking metrics	Algorithms	Observations
[10]	Mathematical Questions	Pupil diameter Blink frequency	t- test	Pupil diameter and blink frequency were observed as good indicators of cognitive load
[23]	Simulator - Military aviation environment	Pupil diameter Fixation Saccade count	One way ANOVA t- test	Estimating pilot's cognitive load.
[21]	Video, Questionnaires	Pupil measures Blink Saccade Fixation Gaze allocation Eye movement directions Saliency based metrics	Friedman non-parametric ANOVA	Mental fatigue detection
[22]	Stroop Test	Pupil diameter Pupil dilation deviation Pupil dilation acceleration	Fuzzy SVM	Mental stress recognition
[24]	Difficult and easy mental calculations	Inter-trial and intra-trial changes in pupil diameter	ANCOVA	Significant difference in eye measures during easy and difficult tasks.
[28]	Solving coding problems on whiteboard and paper	Fixation Saccades blinks	Naive Bayes, Random Forest, Multi Layer Perceptron, SVM, KNN, Logistic Regression, Decision Tree	Prediction of stressful technical interview settings
[25]	Excavation operating simulation system	Pupil diameter Blink rate Blink duration Gaze count	Toeplitz Inverse Covariance-Based Clustering (TICC) SVM, LDA, decision tree, KNN, Boosted Tree	Monitor the mental fatigue
[31]	Baseline- Sit and relax Mental Arithmetic (MA) test Stroop Colour Word Testing	Pupil diameter	2 samples t –test	Predictor of mental stress

the pupillary responses are good indicators of mental efforts and cognitive load [19]. The eye blinks are correlated with stress and can be used to monitor the mental load of a person who intensively uses the monitor [20].

A mental fatigue detection model was proposed to support the aging population based on the eye gaze measures [21]. Various features have been derived and considered for detecting mental fatigue based on the eye movement direction, gaze allocation, saliency model, blinks, oculomotor and pupil diameter. Age-related changes could also be extracted from the eye tracking measures while watching the video.

The stress recognition based on the pupil diameter and pupil diameter acceleration has better accuracy compared to other physiological measures like Electrocardiogram (ECG) and Photoplethysmography (PPG) [22]. The Stroop test was used to induce stress in the participants, and a fuzzy support vector machine was used for the classification of "stress" and "relaxed" states. The study on estimation of cognitive load of pilots indicated that eye gaze measures have a remarkable role in detecting an individual's cognitive load [23]. The flight simulator with the various stress-inducing task has been used as the stimulus. The statistical analysis of the features of saccade, fixation, and pupil diameter showed a correlation with cognitive load. A person's cognitive load can increase while performing a complex task compared to an easy one. Significant variations in pupil diameter and microsaccades were observed in a mental arithmetic task performed to classify the low and high cognitive load [24].

Wearable eye trackers were used for detecting the mental fatigue of construction equipment operators [25]. The Excavator operation environment was simulated to understand the mental fatigue of the participant. Clustering based on Toeplitz Inverse Covariance was used to classify the three levels of mental fatigue. The eye measures blink rate, blink duration, pupil diameter, and gaze position were sensitive to mental fatigue states. Each participant's distribution of gaze points is analyzed to understand the visual attention range that has a crucial role in operational safety.

The enormous data obtained using an eye tracker has a lot of sensible information. Computational procedures and machine learning techniques could extract meaningful patterns from the physiological data obtained from the eyes

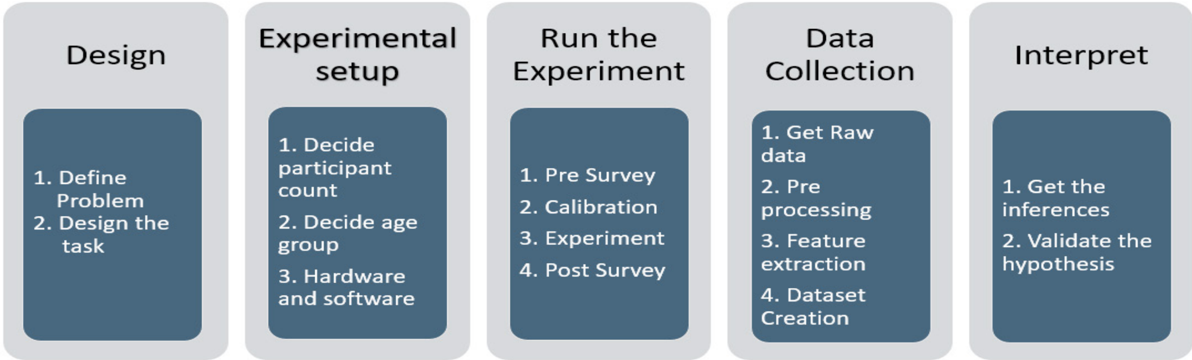


Fig. 1: Steps in Eye Tracking Study.

and can be related to different cognitive and emotional states of an individual [26]. An intelligent system can monitor and measure the user's mental state and support psychological well-being by reducing stress [27] [28]. The changes in emotions and perceptions may vary depending on his physiological and cognitive processing [29]. Physiological signals obtained from the eye are involuntary and help in continuous and consistent real-time monitoring of an individual. Its noninvasive data collection is an added benefit; therefore, it can indicate the stressful state of an individual more efficiently than other modalities.

Based on the studies on various related works, it has been observed that different models and methodologies have adopted eye gaze measures for detecting emotion, stress, cognitive load, mental fatigue, and different mental states [30]. A comparative analysis on the related work is presented in the Table 1. Compared to other models or techniques in detecting the stressful state of a person, the proposed model IntelEye could recognize the cause of their change in mental states by identifying the gaze in the corresponding scene of the video.

3. System Model

As people with mental disorders are increasing, mental health monitoring has become a necessity. Mental stress or workload can negatively affect a person's thoughts, behavior, and emotions. Eye tracking technology caught the researchers' attention in mental health monitoring, providing unobtrusive and continuous monitoring of mental health indicators.

The proposed model IntelEye continuously monitors the eye's vital parameters and indicates the user's stressful state while watching calm and stressful videos. Machine learning algorithm K Nearest Neighbor(KNN) has been applied to predict the stressful state of the user. The following research questions were formulated to understand the changes in eye tracking measures.

RQ1: Is there any significant difference in eye tracking measures while watching calm and stressful videos?

RQ2: Can eye tracking measures indicate the physiology of autonomic reactions?

3.1. Data Acquisition

The data collection procedures followed the five essential steps: design, experimental setup, run of the experiment, data collection, interpret as shown in Fig. 1.

1. Design: As part of the design of the experiment, the research questions and the supporting null hypothesis have been formulated. The stimuli for the experiment were selected as calm and stressful videos.
2. Experimental setup: The data was collected from the hospital employees (n=6, mean age=33.5, SD=5.6, age range= 26 to 42). SMI REDn Professional remote eye tracker with a sampling frequency of 60Hz was used for data collection. Experiment suite 360 software was used for extracting the features from raw eye gaze data.

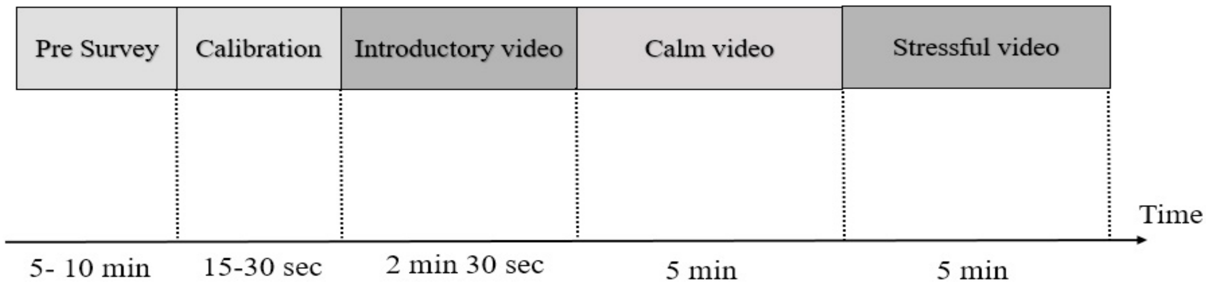


Fig. 2: Time Chart of Experimental Setup.

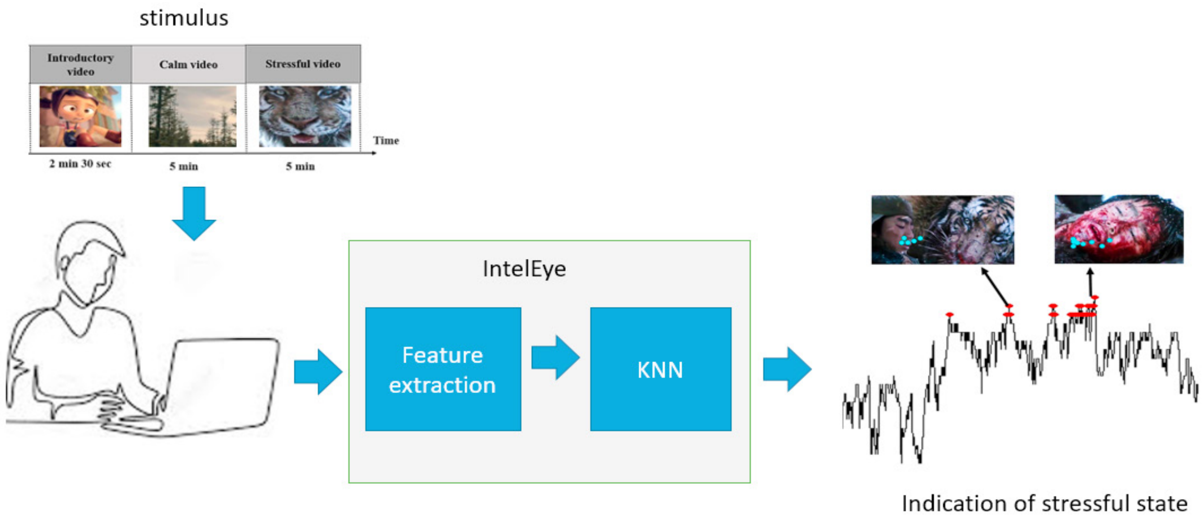


Fig. 3: System Architecture of IntelEye.

3. Run Experiment: The time chart of the experimental setup is shown in Fig. 2. The data collection procedures were explained to each participant, and written consent was obtained during the pre-survey. As shown in Fig. 3, the participant will be asked to sit comfortably in front of the system. The remote eye tracker will be placed in front of the system. The distance from the screen to the participant's eye was maintained at 50 to 60cm. The participant's face was parallel to the screen. The lighting condition is maintained consistently throughout the experiment. 9-point calibration was performed before the starting of each experiment, and the data was collected only after successful calibration. An introductory video was played initially for 2 minutes and 30 seconds to train the participant and familiarise them with the environment. The data collected during the introductory video was not considered for the analysis. The video, which was considered as the most relaxing film, was selected as the calm video [32]. A short video of a tiger attacking scene was selected as the stressful video. The calm and stress videos each were presented for a duration of 5-minutes each.
4. Data Collection: The raw data obtained included the participant's gaze coordinates and pupil diameter. The features fixation duration, blink duration, fixation dispersion X coordinate and fixation dispersion Y coordinate were extracted from those raw data. The extracted features and the pupil diameter were considered for the data analysis. The cumulative features fixation rate and blink rate for the entire duration of calm and stressful video were also considered for the analysis. Pupil diameter is the diameter of the pupil in the millimeter. The pupil diameter of the adults in bright light varies from 2 to 4 mm, and during dark, it ranges from 4 to 8mm. A Group of gaze points closer in time, and distance is the fixation. The time duration of fixation is the fixation duration, and it is measured in milliseconds. It provides the details of how long a person gazed at a location,

and a longer fixation duration indicates the interest in viewing that location. If the eye closure lasts for more than 10 milliseconds, it is considered a blink. The time duration of a blink is blink duration and is measured in milliseconds. Fixation dispersion indicates the distribution of gaze points in the X and Y direction. The distance between the most distant fixation points is known as fixation dispersion and is measured in terms of pixels [33].

5. Interpret: The eye tracking measures are considered idiosyncratic and specific to each person. So the eye gaze data obtained for one person may differ from others, but it follows similar variations while watching the calm and stressful videos. The data received during the calm video was considered as the baseline period and labeled the data based on the baseline threshold. Machine learning algorithm KNN has been applied to indicate the stressful state of a person as shown in Fig 3. The proposed model IntelEye could predict when the person is in a stressful condition and which video frame is responsible for changing his mental state. The model could also indicate the position in which the person was focused during the stressful situation.

A person's visual attention is defined as selecting specific visual content from an image or video for further processing [34]. Visual attention is monitored for psychology, education, and neuropsychology research. Emotional or perceptual factors in an image can influence the visual attention of the observer. The violent scenes in the video can make the observer stressed and escalate physiological arousal. Those changes can be monitored with eye tracking technology. When the user inspects the images or video, their viewing pattern or focus of attention can provide insight into the cause of the stressful state. IntelEye provides the user's gaze position, specifying what content in the image triggers the stress in the participant.

4. Result Analysis

The proposed model, IntelEye, could predict the stressful state of a person while watching the video based on their eye gaze features like pupil diameter, fixation duration, Fixation dispersion x-axis, fixation dispersion y-axis, and blink duration. Each feature obtained from the participant is analyzed and compared across the calm and stressful video watching time. Fig. 4 shows the boxplot of all the features of all the participants. Each feature had a significant difference between calm and stressful video watching time. All the participants had an increase in their pupil diameter at certain places while watching the stressful video. It has been observed that participants had a longer fixation duration while watching calm videos than during stressful video watching time. The fixation dispersion of the X and Y axis were increased during the stressful video-watching time. The blink frequency and blink duration were less during the stressful video watching time compared to the calm video. There was an increase in fixation frequency while watching the stressful video. The changes in eye gaze measures are the stress indicators during stressful video watching time.

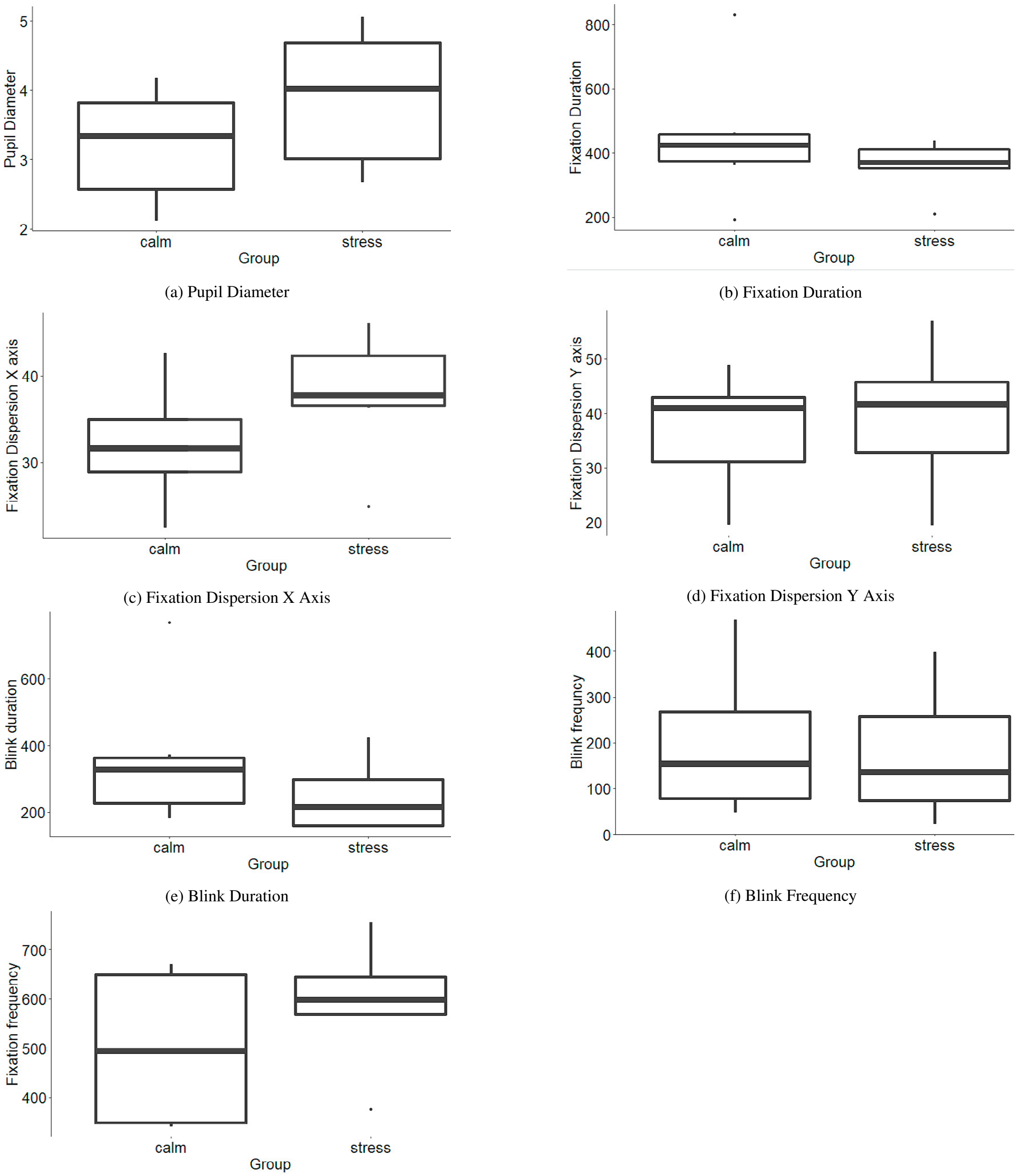
Fig 5 shows the plot of all features of all the participants. The red color vertical line indicates the separation of calm and stress video. The plots clearly show the increase in pupil diameter during stressful video watching time. The fixation duration and blink duration were more during calm video watching time.

The research questions RQ1 and RQ2 are answered based on the data collected during calm and stress video as stimuli. The following null hypothesis has been formulated to answer the research question.

H01: There is no significant difference in eye tracking measures during calm and stressful video watching time.

Welch Two Sample t-test is performed on the features obtained during the calm and stressful video-watching time, and the P-value has been analyzed. The mean of all features during the calm and stressful video and the P-values are shown in Table 2. Most participants showed a significant difference in their features during the calm and stressful videos and obtained P-value < 0.05. The P-value indicates that the null hypothesis can be rejected and accept the alternate hypothesis. So it concludes that there is significant difference in features during both the video watching time and it answers the research question RQ1.

The Autonomic Nervous System (ANS) is responsible for physiological changes in the body during stressful events. The sympathetic nervous system responsible for stress response will activate the physiological signals in the body [35]. As a result, while watching stressful videos, there can be changes in eye gaze measures. The experimental results show that stress generated while viewing uncomfortable scenes influences the eye measures. Since the eye gaze measures showed a significant difference during calm and stressful videos($p<0.05$), it can be proved that eye gaze measures can indicate the autonomic reactions in the human body(RQ2).



(a) Pupil Diameter

(b) Fixation Duration

(c) Fixation Dispersion X Axis

(d) Fixation Dispersion Y Axis

(e) Blink Duration

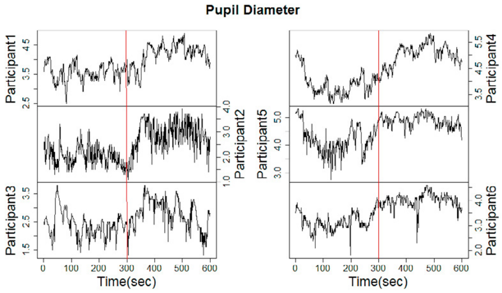
(f) Blink Frequency

(g) Fixation Frequency

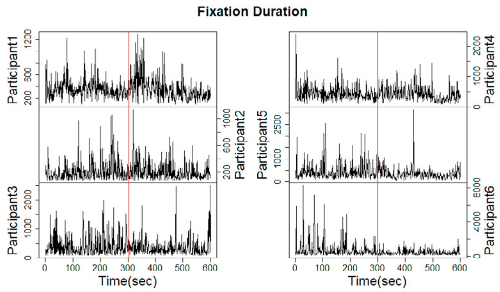
Fig. 4: Boxplot of all features during calm and stressful video watching time.

5. Discussion

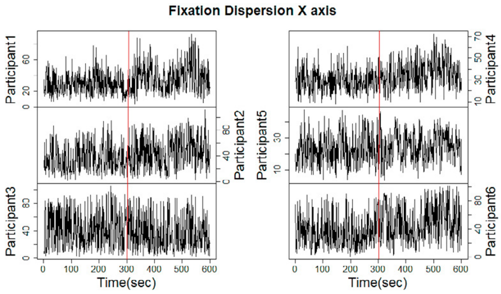
Various studies on eye tracking measures could prove a significant difference in eye tracking measures while performing a specific task that induces stress [10] [16] [17]. The studies could identify various eye measures as indicators of stress [20], cognitive load [19], depression [17], fatigue [25] and dementia. But those studies lack the indication of the cause of those mental illness. Understanding the factors that affect mental health is as important as



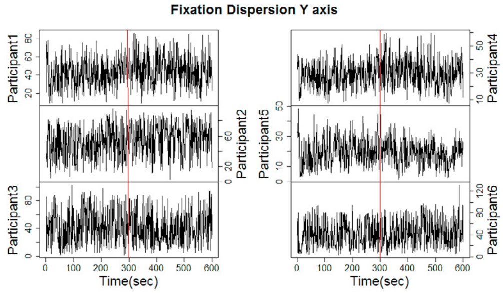
(a) Pupil Diameter



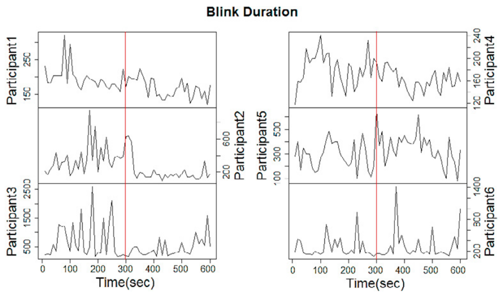
(b) Fixation Duration



(c) Fixation Dispersion X Axis



(d) Fixation Dispersion Y Axis



(e) Blink Duration

Fig. 5: Plot of all the features during calm and stressful video watching time.

detecting mental illness. Eye tracking technology can provide insight into conscious responses from the subconscious processing while watching any particular stimulus. Observing the reactions on which element they dwell on over time can understand which component of the stimulus triggered the brain. IntelEye tries to understand the subconscious processing of an individual while watching calm and stressful videos from the response obtained by analyzing the eye tracking measures. By observing the eye tracking measures, IntelEye could indicate the gaze and the video frame, which made them more stressed while watching a video. It is significant compared to other reported works.

6. Conclusion

This study investigates the variations in eye gaze measures during calm and stressful video watching. The sympathetic nervous system gets activated by stress, which triggers the body's physiological changes. During the study, the changes in eye gaze measures were observed while watching the stressful videos and could prove that eye gaze measures are good indicators of autonomic reactions. The Welch Two Sample t-test was performed on the features and obtained a P-value<0.05 for most participants. It indicates significant differences in eye measures while watching calm and stressful videos. The proposed model IntelEye, a non-invasive model, could recognize the stressful states using the KNN algorithm while watching the videos. The perception of uncomfortable scenes in the video can make an

Table 2: Results of the Statistical Analysis.

Feature	Participant	Calm Video (Mean)	Stressful Video (Mean)	P-Value	Remarks
Pupil diameter	P1	3.575	4.192	<0.0001	Reject Null Hypothesis
	P2	2.119	2.674	<0.0001	
	P3	2.398	2.733	<0.0001	
	P4	3.898	5.059	<0.0001	
	P5	4.180	4.857	<0.0001	
	P6	3.105	3.859	<0.0001	
Fixation Duration	P1	363.260	350.917	>0.005	Reject Null Hypothesis
	P2	191.103	220.250	<0.005	
	P3	402.175	385.663	>0.005	
	P4	453.631	410.566	<0.005	
	P5	461.315	352.404	<0.0001	
	P6	829.930	438.377	<0.0001	
Fixation Dispersion X axis	P1	29.204	37.275	<0.0001	Reject Null Hypothesis
	P2	35.290	43.649	<0.0001	
	P3	42.678	38.272	<0.0001	
	P4	28.813	36.302	<0.0001	
	P5	22.427	24.916	<0.0001	
	P6	34.019	46.088	<0.0001	
Fixation Dispersion Y axis	P1	41.983	46.497	<0.005	Reject Null Hypothesis
	P2	48.883	56.950	<0.0001	
	P3	43.212	40.093	>0.005	
	P4	28.139	30.440	<0.005	
	P5	19.455	19.404	>0.005	
	P6	40.083	44.308	<0.005	
Blink Duration	P1	195.987	157.498	<0.0001	Reject Null Hypothesis
	P2	372.734	163.580	<0.0001	
	P3	768.498	422.997	<0.005	
	P4	181.943	159.951	<0.005	
	P5	331.798	268.668	>0.005	
	P6	323.594	307.674	>0.005h	

individual stressed. IntelEye could also identify the uncomfortable scene that stressed the individual by extracting the corresponding frame from the video. The participant's gaze position at that time is highlighted based on the fixation detection.

In the future, IntelEye can be integrated with the eye tracker software as a plugin tool and can be used in smart working environments to indicate employee's stress. The actual patients' data will help ensure the IntelEye model's efficiency.

Acknowledgements

We would like to thank Healthcare Global Enterprises Ltd. Cancer Center, Bangalore for the support in data collection for the project.

References

[1] Demmin, D.L. and Silverstein, S.M. (2020) "Visual impairment and mental health: unmet needs and treatment options." *Clinical Ophthalmology (Auckland, NZ)* **14**, p.4229.

[2] Wee, H.J., Lye, S.W. and Pinheiro, J.P. (2019) "An integrated highly synchronous, high resolution, real time eye tracking system for dynamic flight movement." *Advanced Engineering Informatics*, **41**, p.100919.

[3] Sano, A., Taylor, S., McHill, A.W., Phillips, A.J., Barger, L.K., Klerman, E. and Picard, R. (2018) "Identifying objective physiological markers and modifiable behaviors for self-reported stress and mental health status using wearable sensors and mobile phones: observational study." *Journal of medical Internet research* **20** (6), p.e9410.

[4] Naushad, V.A., Bierens, J.J., Nishan, K.P., Firjeeth, C.P., Mohammad, O.H., Maliyakkal, A.M., ChaliHadan, S. and Schreiber, M.D. (2019) "A systematic review of the impact of disaster on the mental health of medical responders." *Prehospital and disaster medicine* **34** (6), pp.632-643.

[5] Venugopal, D., Amudha, J. and Jyotsna, C. (2016) "Developing an application using eye tracker." *IEEE International Conference on Recent Trends in Electronics, Information Communication Technology (RTEICT)* (pp. 1518-1522).

[6] Harezlak, K. and Kasprowski, P. (2018) "Application of eye tracking in medicine: A survey, research issues and challenges." *Computerized Medical Imaging and Graphics* **65**, pp.176-190.

[7] Jyotsna, C., Amudha, J., Rao, R. and Nayar, R. (2020) "Intelligent gaze tracking approach for trail making test." *Journal of Intelligent Fuzzy Systems* **38** (5), pp.6299-6310.

[8] Krishnan, S., Amudha, J. and Tejwani, S. (2021) "Intelligent-based decision support system for diagnosing glaucoma in primary eyecare centers using eye tracker." *Journal of Intelligent Fuzzy Systems*, pp.1-8.

[9] Carter, B.T. and Luke, S.G. (2020) "Best practices in eye tracking research." *International Journal of Psychophysiology* **155**, pp.49-62.

[10] Jyotsna, C. and Amudha, J. (2018) "Eye gaze as an indicator for stress level analysis in students." *International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 1588-1593). IEEE.

[11] Dewan, M., Murshed, M. and Lin, F. (2019) "Engagement detection in online learning: a review." *Smart Learning Environments* **6** (1), pp.1-20.

[12] Narayanan, S.A., Kaimal, M.R., Bijlani, K., Prasanth, M. and Kumar, K.S. (2014) "Computer vision based attentiveness detection methods in e-learning." *Proceedings of the 2014 International Conference on Interdisciplinary Advances in Applied Computing* (pp. 1-5).

[13] Ramachandra, C.K. and Joseph, A. (2021) "IEyeGASE: An Intelligent Eye Gaze-Based Assessment System for Deeper Insights into Learner Performance." *Sensors* **21** (20), p.6783.

[14] Shu, L., Xie, J., Yang, M., Li, Z., Li, Z., Liao, D., Xu, X. and Yang, X. (2018) "A review of emotion recognition using physiological signals." *Sensors* **18** (7), p.2074.

[15] Soleymani, M., Pantic, M. and Pun, T. (2011) "Multimodal emotion recognition in response to videos." *IEEE transactions on affective computing* **3** (2), pp.211-223.

[16] Tang, W., Wu, S., Vigier, T. and Da Silva, M.P. (2020) "Influence of emotions on eye behavior in omnidirectional content." *Twelfth International Conference on Quality of Multimedia Experience (QoMEX)* (pp. 1-6). IEEE.

[17] Ding, X., Yue, X., Zheng, R., Bi, C., Li, D. and Yao, G. (2019) "Classifying major depression patients and healthy controls using EEG, eye tracking and galvanic skin response data." *Journal of affective Disorders* **251**, pp.156-161.

[18] Varas-Diaz, G., Subramaniam, S., Delgado, L., Phillips, S.A. and Bhatt, T. (2020) "Effect of an exergaming-based dance training paradigm on autonomic nervous system modulation in healthy older adults: a randomized controlled trial." *Journal of Aging and Physical Activity* **29** (1), pp.1-9.

[19] Buettner, R., Sauer, S., Maier, C. and Eckhardt, A. (2018) "Real-time prediction of user performance based on pupillary assessment via eye tracking." *AIS Transactions on Human-Computer Interaction* **10** (1), pp.26-56.

[20] Kraft, D., van Laerhoven, K. and Bieber, G. (2021) "CareCam: Concept of a new tool for Corporate Health Management." *14th PErvasive Technologies Related to Assistive Environments Conference* (pp. 585-593).

[21] Yamada, Y. and Kobayashi, M. (2018) "Detecting mental fatigue from eye-tracking data gathered while watching video: Evaluation in younger and older adults." *Artificial intelligence in medicine* **91**, pp.39-48.

[22] Mokhayeri, F. and Akbarzadeh-T, M.R. (2011) "Mental stress detection based on soft computing techniques." *IEEE International Conference on Bioinformatics and Biomedicine* (pp. 430-433).

[23] Babu, M.D., JeevithaShree, D.V., Prabhakar, G., Saluja, K.P.S., Pashilkar, A. and Biswas, P. (2019) "Estimating pilots' cognitive load from ocular parameters through simulation and in-flight studies." *Journal of Eye Movement Research* **12** (3).

[24] Krejtz, K., Duchowski, A.T., Niedzielska, A., Biele, C. and Krejtz, I. (2018) "Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze." *PloS one* **13** (9), p.e0203629.

[25] Li, J., Li, H., Umer, W., Wang, H., Xing, X., Zhao, S. and Hou, J. (2020) "Identification and classification of construction equipment operators' mental fatigue using wearable eye-tracking technology." *Automation in Construction* **109**, p.103000.

[26] Klaib, A.F., Alsrehin, N.O., Melhem, W.Y., Bashtawi, H.O. and Magableh, A.A. (2021) "Eye tracking algorithms, techniques, tools, and applications with an emphasis on machine learning and Internet of Things technologies." *Expert Systems with Applications* **166**, p.114037.

[27] Nourbakhsh, N., Chen, F., Wang, Y. and Calvo, R.A. (2017) "Detecting users' cognitive load by galvanic skin response with affective interference." *ACM Transactions on Interactive Intelligent Systems (TiiS)* **7** (3), pp.1-20.

[28] Behroozi, M. and Parnin, C. (2018) "Can we predict stressful technical interview settings through eye-tracking?." *Proceedings of the Workshop on Eye Movements in Programming* (pp. 1-5).

[29] Phasya, Adaptive software for physiological and cognitive states monitoring,(2021) https://www.phasya.com/en/technology.

[30] Kumar, V.S., Ashish, S.N., Gowtham, I.V., Balaji, S.A. and Prabhu, E. (2020) "Smart driver assistance system using raspberry pi and sensor networks." *Microprocessors and Microsystems* **79**, p.103275.

[31] Torres-Salomao, L.A., Mahfouf, M. and El-Samahy, E., (2015) "Pupil diameter size marker for incremental mental stress detection." *international conference on e-health networking application services (HealthCom)* (pp. 286-291). IEEE.

[32] Devan Joseph, (2015) "The World's Most Relaxing Film." https://www.businessinsider.in/a-new-short-movie-claims-to-be-the-worlds-most-relaxing-film-see-for-yourself/articleshow/47406648.cms

[33] Salvucci, D.D. and Goldberg, J.H., (2000) "Identifying fixations and saccades in eye-tracking protocols." *In Proceedings of the 2000 symposium on Eye tracking research applications* (pp. 71-78).

[34] Skaramagkas, V., Giannakakis, G., Ktistakis, E., Manousos, D., Karatzanis, I., Tachos, N., Tripoliti, E.E., Marias, K., Fotiadis, D.I. and Tsiknakis, M. (2021) "Review of eye tracking metrics involved in emotional and cognitive processes." *IEEE Reviews in Biomedical Engineering*

[35] Sharma, N. and Gedeon, T. (2012) "Objective measures, sensors and computational techniques for stress recognition and classification: A survey." *Computer methods and programs in biomedicine* **108** (3), pp.1287-1301.