A Machine Learning based Eye Tracking Framework to Detect Zoom Fatigue

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Keywords: Eye Tracker, Zoom Fatigue, Machine Learning, SVM, KNN, Ada-Boost, Logistic Regression, Decision Tree.

Abstract: Zoom Fatigue is a form of mental fatigue that occurs in online users with increased use of video conferencing. Mental fatigue can be detected using eye movements. However, detecting eye movements in online users is a challenge. This research proposes a Machine Learning based Eye Tracking Framework (MLETF) to detect zoom fatigue in online users by analysing the data collected by an eye tracker device and other influencing variables such as sleepiness and personality. An experiment was conducted with 31 online users wearing an eye tracker device while watching a lecture on Mobile Application Development. The online users were given an exam followed by a questionnaire. The first exam was based on the content of the video. The online users were then given a personality questionnaire. The results of the exam and the personality test were combined and used as an input to five machine learning algorithms namely, SVM, KNN, Decision Tree, Logistic Regression and Ada-Boost. Results of the five models are presented in this paper based on a confusion matrix. Results show promise for Ada-Boost for detecting Zoom fatigue in online users with an accuracy of 86%. This research demonstrates the feasibility of applying an eye-tracker device to identify zoom fatigue with online users of video conferencing.

1 INTRODUCTION

Detecting Zoom Fatigue is a vital concern with the emergence of virtual connections among online users (Riedl, 2021). Attending video calls or conferences leads to a draining of mental energy among online users. This triggers early exhaustion of the brain known as ”Zoom Fatigue”. Machine learning models have been used to detect mental fatigue in online users performing different tasks such as on the construction site (Li et al., 2020), driving (Cheng et al., 2019), and so on. In addition, to the data collected by the eye tracker device, subjective assessments of mental fatigue are captured by different tests such as Karolinska Sleepiness Scale (KSS) (Jonsson and Brown, 2021) test, SSS (Stanford Sleepiness Scale) test, and NASA-TLX (NASA- Task Load Index see (Lowndes et al., 2020)). These tests capture the calculation of Sleepiness, alertness, and cognitive load of the brain respectively. The data collected from both eye tracker and different tests samples are processed through machine learning such as SVM (Support Vector Machine), KNN (K-Nearest Neighbor), Logistic Regression, ANN (Artificial Neural Network), and FFN (Fast forward Neural Network).However, this research doesn't capture the impact of online interactions on brain fatigue. Arising out of the COVID19 pandemic, people are more inclined to interact online on platforms such as zoom which can also be represented by Computer Mediated Communications (Nadler, 2020). To predict “zoom fatigue” in online users in order to help reduce the exhaustion of the brain is a challenge. The aim of this research is to investigate to what extent zoom fatigue can be detected in online users using an eye tracker device during video conferencing. The major contribution of this research is a Machine Learning based Eye Tracking Framework (MLETF). The Machine Learning based Eye Tracking Framework combines the eye tracker device and the Ada-Boost machine learning algorithm in order to identify features that lead to zoom fatigue

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Patel, A., Stynes, P., Sahni, A., Mothersill, D. and Pathak, P.
A Machine Learning based Eye Tracking Framework to Detect Zoom Fatigue.
DOI: 10.5220/0011075800003182
In *Proceedings of the 14th International Conference on Computer Supported Education (CSEDU 2022) - Volume 2*, pages 187-195
ISBN: 978-989-758-562-3; ISSN: 2184-5026

such as blink behaviour, gaze point and fixation time, saccade (speed of eye movements), and velocity.

2 RELATED WORK

This section, critically discusses the research conducted on the eye tracker device and the detection of zoom fatigue.

Mental fatigue is one of the main causes of accidents and mishaps in the workplace for different domains such as medical, driving, construction, and so on. There are many different ways to detect mental fatigue in online users such as through electroencephalographic (EEG) signals (Acı et al., 2019); (Wu et al., 2020), physiological sensors (Monteiro et al., 2019), drivers' facial patterns (Cheng et al., 2019), and wearable Eye Tracker device (Li et al., 2020); (Yu et al., 2020); (Yamada and Kobayashi, 2018); and (Gao et al., 2015).

(Li et al., 2020),proposed a method to detect multiple levels of mental fatigue of construction workers. The data was collected from a wearable eye tracker device. The data were analysed and classified based on three levels of mental fatigue using Toeplitz Inverse Covariance-Based Clustering (TICC) method. According to the research, SVM performed the most efficiently with an accuracy of between 79.5% and 85% that varied depending on construction and other subjective scenarios.

(Cheng et al., 2019), detected driver fatigue by exploring the driver's facial patterns. A driving simulator-based experiment was conducted with 21 participants, where features such as blink rate, blink duration, PERCLOS, closing speed, and several yawns were collected in order to detect their level of alertness and mental fatigue. A PERCLOS drowsiness metric is the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures ("droops") rather than blinks. Logistic regression showed the most accuracy at 83.7%.

The research (Yu et al., 2020) and (Cui et al., 2021), proposes a model for detection of mental fatigue using the data collected from eye tracker device, with combining the value of PERCLOS with other fatigue characteristics such as frequency of Open Mouth (FOM). The result of the experiment showed that the proposed model was able to achieve an accuracy of 98.6%.

The research (Yamada and Kobayashi, 2018) and (Gao et al., 2015), proposes a framework for detection of mental fatigue with data collected from eye tracker device, and other measures such as natural viewing situation and automation of feature selection method. These proposed models resulted in providing better accuracy for evaluating and detecting mental fatigue in online users with cognitive loads.

Following national health guidelines as a result of COVID19, institutes of higher education such as the National College of Ireland (NCI) decided that there was no further face to face lectures. The education system transformed to online learning through virtual classes for students. Eye tracking has been used in online learning (Barrios et al., 2004); (Ivanović et al., 2017); (Joe Louis Paul et al., 2019).

(Barrios et al., 2004) proposed a framework for adaptive e-learning through eye tracking. (Ivanović et al., 2017) focused on the integration of eye tracking technologies and methods in an e-learning system. (Joe Louis Paul et al., 2019) investigated eye gaze tracking based adaptive e-learning for enhancing teaching and learning in virtual classrooms. Results suggest that eye measures such as eye movement, gaze, blink impact on the understanding and reliability of the e-learning system. The understanding of the framework and adaptive e-learning provides us information that how an eye tracker device and data collected from them can help us detect zoom fatigue with online mode of communication.

The research (Salvati et al., 2021) discusses the evaluation of Mental fatigue in drivers by comparing the indicative data from Karolinska Sleepiness Scale (KSS), and post-processing data from PERCLOS. Similarly, the paper (Schleicher et al., 2018) discusses the evaluation of mental fatigue with eye movements, and Oculomotoric parameters. The result showed that the blinks frequency, count, and duration are directly related to the mental fatigue of online users. In paper (He et al., 2017), a model has been proposed for validation of Google Glass-based drowsiness detection. The result of this experiment showed that the eye blinks, and longer response time showed a direct impact on mental fatigue.

Neuroimaging studies suggest that that mental fatigue is associated with reduced electrophysiological signals related to error monitoring (Boksem et al., 2006), and reduced functional connectivity of brain networks associated with orienting one's attention to external stimuli (Esposito et al., 2014), with increases in functional connectivity of brain networks associated with mind wandering.

(Morris, 2020) suggests an understanding of how mental fatigue is related to zoom fatigue mainly caused by exhaustion with online communication. The research paper (Nadler, 2020), discusses the causes of zoom fatigue, from the online mode of communication, and the effect of cognitive load over online users. The research paper (Fauville et al., 2021), proposes a Zoom Exhaustion and Fatigue (ZEF) Scale, which provides a quantitative and detailed understanding of zoom fatigue and the scale for fatigue detection. A total of 395 online users participated in the survey, which showed the impact of 5 features which are social, emotional, gesture, general and visual in the detection of zoom fatigue.

(Kacur et al., 2019) presented their work to detect schizophrenia disorders based on Rorschach Inkblot Test and an eye-tracker system. The method extracts and evaluates the overall time period in defined regions as well as the path an image is scanned through by an individual using Markov chain. The key features were vectors of final probabilities and transition matrices. The KNN method was used to classify the extracted features into positive (schizophrenia disorder) and negative (a healthy individual) classes. The dataset consisted of 44 individuals (22 patients, and 22 healthy individuals). Depending on features and settings the detection accuracy was in the interval of 62% to 75%.

Recommendation systems have been used to provide personalized learning to the learners. These systems generally consider learners' information such as individual characteristic, learning style, knowledge background, etc. (Intayoad et al., 2017) propose the context-aware recommendation system that considers the social context also. The social context is the interaction between learning objects (LO) and the learners. K-nearest neighbor and decision tree are used for analysing and classifying the learning path of the learners having scientific and non-scientific backgrounds. The training datasets were gathered from studying two different content modules of basic computer skill course - Introduction to Information Technology (module 1) and Office Programs (module 2). The transactions of the click stream were stored in weblogs. These transactions presented the interaction pattern which is the numbers of times that a student accesses particular LOs where the contents were stored and represented. Each module consisted of three lessons. Each lesson was composed of several LOs. At the end of each module, there was a module examination. There were 5526 training data items from module1 and 21,146 items from module2. According to the results of classification task, KNN and DCT obtain almost equal over all accuracies of pass and fail student classification for both module1 and module2. However, the accuracy of the classification from module2 is higher than those of module1 for both classifiers. It can be concluded that DCT is more suitable than KNN for this data set. Even in case of high diversity of the dataset, DCT had been very accurate.

(Ungureanu et al., 2020) studies and illustrates some approaches to evaluating the cognitive load and emotional state of students during a learning process. They analyze the emotional state during learning, evaluating the visual effort, and assessing the cognitive load level, all induced using software applications or electronic devices. The paper elaborates experimental sessions, choosing the proper stimulus and equipment, recording, and pre-processing methods for the involved physiological information. It uses AdaBoost, KNN and SVM artificial intelligence techniques for feature selection and data classification to achieve the best calibration, appreciation, and monitoring of a learning process. Russel's 2D model (arousal and valence) was used to measure the level of emotions. The machine learning techniques were used to classify the emotions into the pleasant, unpleasant and neutral emotional categories. Entropy was the only hyper parameter used to improve the performance. In all experiments, AdaBoost obtained the best misclassification rates (0.06% for a multimodal approach, when 100 of the decision trees and 30% of the whole data set was used for training).

In conclusion, the state of the art indicates that several machine learning models such as SVM, KNN, Decision Tree and Ada-Boost are used for detection of mental fatigue with data extracted from wearable eye tracker device. The state of the art indicates that the many different features such as PERCLOS, KSS (Karolinska Sleepiness scale), SSS (Stanford Sleepiness scale) etc has impact over mental fatigue. Current research indicates that mental fatigue in an online user can be detected using wearable eye tracker technology while performing different physical activities, such as driving, construction work, pilot, etc. However, for detection of zoom fatigue the online users are required to focus on online video communication and lack of physical activities. Hence, this research to understand what extent the eye tracker device data can be used to detect Zoom fatigue in an online user.

3 EXPERIMENTAL PROCEDURE

In this research the eye tracker device was used to record the eye movement and different stimuli of the online users while watching an online lecture. The eye tracker device consists of a scene camera and two IR cameras, as shown in fig.1. The eye tracker glasses can record the online user's gaze point, blink count, fixation count, and saccade count. A saccade is a quick, simultaneous movement of both eyes between two or more phases of fixation in the same direction. Saccade is associated with the eye's jumping from one location to the next. Thirty-one online users consisting of 12 females and 19 males between the ages group of 22 and 35 took part in this study while watching a video based on Java Web Mobile Application development of length 25 minutes. All online users had good vision and normal health, with prior knowledge of Basic Java and no knowledge of mobile app development. The online users provided written consent before the experiment.

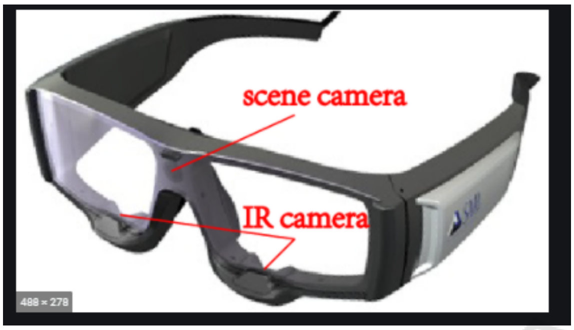

Figure 1: SMI Eye tracker glass.

The experiment was conducted in four-step, as shown in fig.2.The online users wore the eye tracker device while watching the lecture video of twenty-five minutes. The lecture used in this experiment is on mobile application development using java. The response from the online users was stored and analyzed by BeGaze software *Gaze Intelligence*. This provides us details of gaze points, count of fixation, blink frequency, and saccade.

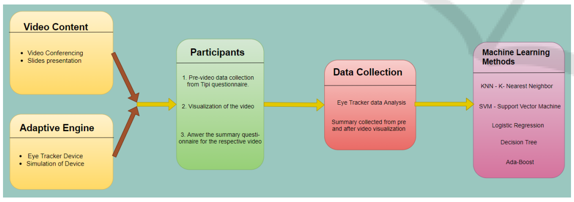

Figure 2: Research Framework.

Further, the online users are asked to complete two sets of questionnaires. First, is a test based on the content of the video on mobile application development. The second is a questionnaire that collects subjective and personality details of the online users. The questionnaire based on the learning of the video lecture contains easy, medium and hard questions from the video. The personality questionnaire contains gender, age and Ten Item Personality Inventory (TIPI) questionnaire, sleepiness and cognitive load analysis such as KSS (Karolinska Sleepiness Scale) and SSS (Stanford Sleepiness Scale) is collected. TIPI Questionnaire contains a total of ten attributes or characteristics such as Extroverted, enthusiastic, Critical, quarrelsome etc, the response of these attributes is measured from a scale of 0 to 7. The result of calculation over the response from TIPI questionnaire will provide 5 personality traits of the online users which are Extraversion, Agreeableness, Conscientiousness, Emotional Stability and Openness to Experiences.

The dataset for this research is collected from the experiment conducted, by monitoring and recording the eye movement, performance, and answer to the questionnaire by the participants. The dataset is stored in an Excel (xlsx) format. There are two data files containing details extracted from the eye tracker device and the response of the questionnaire respectively. The data file with eye tracker device responses contains 32 columns with information about eye stimulus during the experiment. The second data file with 17 columns contains the information about personal detail, test result, and Tippi questions response. The dataset collected for this research satisfies the ethical and privacy requirements.

The data file with responses from the eye tracker experiment contains details like Visual Intake, Saccade, and blink attributes. For all these attributes the detail such as count, frequency, total interval, average interval, maximum interval, and the minimum interval was extracted from summary metrics option from the eye tracker device software. The count and frequency of attributes are measured in decimal and the intervals are measured in milliseconds.

The second data file contains details collected from the response to the questionnaire by the online users, which contains age, gender, SSS (Stanford Sleepiness Scale), KSS (Karolinska Sleepiness Scale), Test results from the experiment, and answer to social cognition and Tippi questionnaire. The SSS and KSS are measured in decimals ranging from one to nine and one to ten respectively. The online users can get the highest of 12 marks in the test based on the video. These two data files are further merged using the participant assigned unique identification. The next subsection will discuss data quality, transformation, and feature selection in detail.

All the steps for data transformation and preprocessing are performed using Python Jupyter Notebook. This phase in the research deals with data exploration and insights such as missing or wrong data, calculation of new attributes, and transformation of data. Firstly, as a part of data exploration, dataset is checked for missing values and the presence of. Then in the second stage data transformation was performed. In this step, the data was analysed and the categorical variables were standardized, such as gender. The unit of measurement of intervals in the dataset was in milliseconds and seconds which was normalized to seconds. The normalization of the data will improve the performance of the model. In the third step new variable was created for PERCLOS, that is the percentage of the time interval for which the eye was blinked or closed by the total time interval of the experiment. Finally, the Pearson correlation matrix was plotted to understand the correlation between the variables, and the variables with the highest correlation values were omitted from the dataset before implementation.

4 DESIGN

The Machine Learning-based Eye Tracking Framework (MLETF) architecture combines Eye Tracker Components and Machine learning classification models as shown in fig. 3. The components of consist of eye tracker glasses, mobile device recorder and eye tracker software (beGaze), which are discussed in details in section 4.1. In section 4.2, the components of Machine learning classification models are discussed.

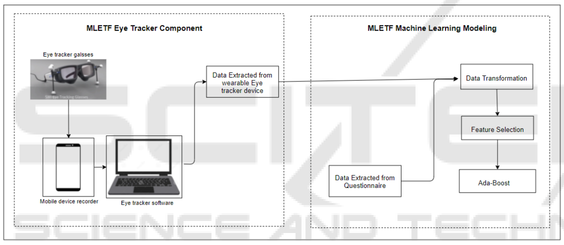

Figure 3: Machine Learning based Eye Tracking Framework Architecture Design.

4.1 MLETF Eye Tracker Component

There are basic three components of eye tracker device, glasses, mobile recorder and eye tracker software. The eye tracker glasses has three mounted cameras which will record the movement and stimulus of eyes of the online user. This stimulus will be recorded using the mobile device recorder. The recorded response is stored in an external storage device using mobile. Then the recorded video is updated in the eye tracker software for further processing and extraction of different attributes and features from eye tracker device. The features extracted from eye tracker device are gaze point, visual intake duration, visual intake frequency and count, saccade count, saccade amplitude, saccade amplitude, saccade velocity, saccade latency, blink count, blink duration, and blink frequency. The extracted data from eye tracker device are loaded into excel file for further analysis.

4.2 Machine Learning Models

The machine learning model of the MLETF framework contains data transformation, feature selection from the data extracted from eye tracker device and questionnaire, which is further used for implementation of Ada-Boost. The data is extracted from two questionnaire presented to the online users after experiment through Microsoft and google forms. The responses from online users are exported from these forms and are stored in excel format file. For detection of zoom fatigue, the dataset collected is divided into ratio of 8:2 for train and test split. Further AdaBoost is implemented over the selected feature from the dataset.

5 IMPLEMENTATION

The MLETF (Machine Learning based Eye Tracking Framework) was implemented using Python Programming Language, Jupyter Notebook as IDE (Python 3.8.5). Python Libraries such as Pandas, Numpy, os and scikit learn (sklearn) were used. The two data files were extracted using read excel containing data extracted from wearable eye tracker device and questionnaire, which were merged using unique identification number for experiments. Additional attributes were created and calculated for tipi and PERCLOS calculation, such as Extraversion, Agreeableness, Conscientiousness, Emotional Stability, Openness to work and PERCLOS. Furthermore, the dataset was divided into 8:2 ratio for train and test split using library scikit learn and import train test split, with random state as 123 and shuffle as true. Furthermore, 5 Machine Learning models SVM, KNN, Logistic regression, decision tree, Ada-boost) were implemented on the trained dataset using the scikit learn python library.

6 EVALUATION

The aim of this research is to detect zoom fatigue using the proposed MLETF. Machine learning algorithms are implemented over the data collected from the eye tracker device to compare and analyse the extent of detection of Zoom fatigue. Multi-class classification models are used with 3 levels (negligible sign of fatigue, slight fatigue and zoom fatigue) of fatigue are taken into account(Salvati et al., 2021). Below are the series of experiments performed beginning with the state of art.

6.1 Experiment 1: Comparison of SVM, LR, KNN and Ada-Boost with Eye-tracker Data

The aim of this experiment is to investigate accuracy of different machine learning models for prediction of zoom fatigue using the data collected from eye tracker device. The dataset was divided into an 80:20 split ratio for training and test data with data shuffling as random. The dataset for this experiment contains the total count, count of frequency, duration of visual intakes, saccade, and blinks. In addition, the total amplitude, velocity, and latency of the saccade are also included.

Table 1: Results of Experiment 1.

Machine Learning model	Accuracy
SVM	0.43
Logistic Regression	0.43
KNN	0.71
Decision Tree	0.29
Ada-Boost	0.29

Table 1 shows the results obtained by the machine learning models for experiment 1. This table shows that KNN was able to achieve the highest accuracy of around 71% from the dataset collected by the eye tracker device, followed by SVM and Logistic Regression with 43%. The next experiment shows to what extent the accuracy in prediction of zoom fatigue can be improved with the addition of calculated PERCLOS, that is percentage of total blink duration to total duration.

6.2 Experiment 2: Machine Learning Models with Eye-tracker Data and PERCLOS

The aim of this experiment is to investigate if the accuracy can be improved using the calculated PERCLOS, that is percentage of total blink duration to total duration. The dataset was divided into an 80:20 split ratio for training and test data with data shuffling as random. The calculated attribute PERCLOS is the ratio of the time interval for blink by the total time interval is also included.

Table 2 shows us the results obtained by different machine learning models for experiment 2. This table shows that KNN has achieved a total of 57% accuracy in the detection of zoom fatigue. Followed by SVM, and logistic regression with an accuracy of the model as 43%. The PERCLOS doesn't provide any positive impact for detection of zoom fatigue. In the next experiment, we will see to what extent the accuracy in the prediction of zoom fatigue can be improved with the addition of data extracted from the questionnaire.

Table 2: Results of Experiment 2.

Machine Learning model	Accuracy
SVM	0.43
Logistic Regression	0.43
KNN	0.57
Decision Tree	0.29
Ada-Boost	0.29

6.3 Experiment 3: Machine Learning Models with Eye-tracker Data and Questionnaire Dataset

The aim of this experiment is to investigate accuracy can be improved by addition of data extracted from questionnaire with data collected from eye tracker device. The dataset is divided into an 80:20 split ratio for training and test data with data shuffling as random. The dataset for this experiment contains a combination of the data collected from the eye tracker device, such as total count, count of frequency, duration of visual intakes, saccade, and blinks. In addition, data from questionnaires such as age, SSS, gender, and score obtained from the summary test of the experiment is also added.

Table 3: Results of Experiment 3.

Machine Learning model	Accuracy
SVM	0.71
Logistic Regression	0.71
KNN	0.57
Decision Tree	0.71
Ada-Boost	0.86

Table 3 shows the results obtained by different machine learning models for experiment 3. This table shows that Ada-boost has achieved an accuracy of 86% in detection of zoom fatigue with learning rate as 3 for the data extracted from eye tracker device and questionnaire. Followed by SVM, Decision Tree, and logistic regression with an accuracy of the model as 71%. And KNN shows the lowest accuracy for this experiment with an accuracy of 57%. The personal information such as age, response to SSS (Stanford sleepiness scale), and the output from the eye tracker test provide a good impact in the detection of zoom fatigue. The next experiment, investigates to what extent the accuracy in the prediction of zoom fatigue can be improved when we consider the data extracted from the eye tracker device, questionnaire, and calculated PERCLOS.

6.4 Experiment 4: Machine Learning Models, with Eye-tracker Data, PERCLOS and Questionnaire Dataset

The aim of this experiment is to investigate accuracy can be improved by addition of PERCLOS and data collected from questionnaire with data extracted from eye tracker device. The dataset is divided into an 80:20 split ratio for training and test data with data shuffling as random. The dataset for this experiment contains a combination of the data collected from the eye tracker device, such as total count, count of frequency, duration of visual intakes, saccade, and blinks. In addition, data from questionnaires such as age, SSS, gender, and score obtained from the summary test of the experiment and PERCLOS is also added.

Table 4: Results of Experiment 4.

Machine Learning model	Accuracy
SVM	0.71
Logistic Regression	0.71
KNN	0.57
Decision Tree	0.57
Ada-Boost	0.71

Table 4 shows the results obtained by different machine learning models for experiment 4. From this table, we see that the machine learning algorithm Ada-boost, SVM and logistic regression has achieved an accuracy of 71% in prediction of Zoom Fatigue. The PERCLOS has lowered the accuracy of machine learning algorithms and doesn't provide any positive impact in detection of zoom fatigue. Following the experiment, the next section will describe the key findings and discussion related to this research.

7 DISCUSSION

This section aims to discuss the above-performed experiment and the obtained results. The research begins with the collection of data from the experiment conducted with the eye tracker device and the questionnaire including personality as well as a summary test of the video.

Section 6, Evaluation demonstrates four experiments for detection of zoom fatigue in online users. Five machine learning algorithms SVM, Logistic Regression, KNN, Decision Tree, and Ada-Boost are implemented to compare the performance for the detection of zoom fatigue in this research. In the first experiment, the data collected from the eye tracker device, for the detection of zoom fatigue in the online users is used, the result showed that KNN has achieved an accuracy of 71%.

In the second and fourth experiments PERCLOS is included, which is the percentage calculation of total blink duration and total time interval. The result showed that the addition of PERCLOS in the dataset has reduced the performance of detection of Zoom Fatigue. But the previous research demonstrated that PERCLOS is a key attribute for detection of mental fatigue. This character of PERCLOS can be studied, for understanding why PERCLOS has reduced performance of MLETF but has demonstrated a good performance for detection of mental fatigue. Hence, the ratio of blink duration and total interval doesn't provide subsequent input for detection of zoom fatigue, but individually the blink duration and total interval provide good performance in the detection of zoom fatigue. In third experiment, the dataset with combination of data collected from the eye tracker device and the questionnaire is considered. The result of this experiment showed that Ada-Boost has achieved the highest accuracy in detecting zoom fatigue with 86%, and another machine learning algorithm has also shown better performance than other experiments. Where SVM, Logistic Regression, and Decision Tree have resulted in 71% accuracy.

The evaluation of the data extracted from eye tracker device and questionnaire response by the online users are considered in this research, but there are other factors which might affect these findings. Zoom fatigue in online users can be impacted by the length of the video. The video length for this research is 25 minutes, but by elongation or reduction of the video length will impact on the zoom fatigue of online users. Also, during experiment there was no specific distance maintained between the online users and the computer screen. One of the reasons for development of Zoom fatigue is the increased intensity due to close up eye contact with the computer screen.

8 CONCLUSIONS AND FUTURE WORK

This research proposes a MLETF for the detection of zoom fatigue in online users, this analysis was done with data collected from experiments using the eye tracker device, data collected from the response of questionnaire, and calculated field PERCLOS. The result of the experiment highlights that prediction of zoom fatigue from the data collected by eye tracker device and questionnaire has good accuracy for classification models such as Ada-Boost, Logistic Regression, SVM and Decision Tree. The feature set in the research contains 24 variables, which includes data from the eye tracker device, responses from the questionnaire, and calculated PERCLOS. The results of the experiment showed that the data collected by eye tracker device and questionnaire attained the highest accuracy in prediction of zoom fatigue with Ada-Boost at 86% and SVM, Logistic Regression and Decision Tree with an accuracy 71%. Zoom fatigue is a form of mental fatigue that can be hard on brains which makes brains exhausted quickly. By determining these features new measures can be practised or introduced for minimizing the effect of zoom fatigue.

Overall, the research shows that MLETF is capable of predicting zoom fatigue in online users by the data extracted from the eye tracker device and the response from the questionnaire. The future work of this research can be extended to the inclusion of more details from the eye tracker device, and the addition of personal and subjective traits of the online users. The impact of length of video, distance from the screen and eye can also be evaluated for detection of zoom fatigue. Depending upon the model and license of the eye tracker device, some attributes such as pupil dilation, pupil fixation, etc. can be extracted from the experiment, which might affect the prediction of zoom fatigue. Also, subjective and personal traits such as NASA-TLX can provide details and the effect of cognitive load over an online user's zoom fatigue. Moreover, this approach can be used to detect zoom fatigue in domains such as medical, engineer, driving, etc.

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