A Machine Learning based Eye Tracking Framework to detect Zoom Fatigue

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A Machine Learning based Eye Tracking Framework to detect Zoom Fatigue

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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 individuals by analysing the data collected by eye tracking device and other influencing variables (such as sleepiness, personality, etc). An experiment was conducted with 31 participants, where they wore an eye tracker device while watching a lecture on Mobile Application Development. The online users were given by two questionnaires, one with the summary and test from the content of the video and the second a personality questionnaire. The classification performance analysis of the supervised learning algorithms showed Ada-Boost was the most suitable algorithm to detect Zoom fatigue in individuals with accuracy of 86%. The result of this research demonstrates the feasibility of applying wearable eye-tracking technology to identify zoom fatigue with online users of video conferencing.

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

1 Introduction

Detecting Zoom Fatigue is a vital concern with the emergence of virtual connections among individuals. Attending video calls or conferences leads to draining of mental energy swiftly among individuals, which triggers early exhaustion of the brain known as "Zoom Fatigue". Previous studies have endeavored many approaches using machine learning methods to detect mental fatigue in individuals for both physical and mental activity for different scenarios such as environment, construction site (Li et al. (2020)), driving (Cheng et al. (2019)), etc. In addition to the data collected by the eye tracker device, subjective assessments of mental fatigue were captured by different tests such as KSS (Karolinska sleepiness scale see Jonsson & 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). The main focus of the previous research in the field of mental fatigue is related to the participants performing different tasks such as construction sites, driving, etc. This research doesn't capture the impact of online interactions over the early exhaustion of the brain. Due to this ongoing pandemic, people are more inclined to use online interactions by using online platforms such as the zoom application, which can also be represented by CMC or Computer Mediated Communications (Nadler 2020 Nadler (2020)). It is very vital to predict "zoom fatigue" in individuals so that we can help reduce the exhaustion of the brain which may lead to long-term sickness or weakness and prevent the development of zoom fatigue in individuals.

The aim of this research is to investigate to what extent zoom fatigue can be detected in online users using 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. Features such as blink behavior, gaze point and fixation time, saccade(speed of eye movements), and velocity are extracted from data rising out of eye tracking device. Our main objective in this research paper is to collect the output of eye tracker device and determine zoom fatigue in an individual. By detecting the zoom fatigue using the proposed MLETF we will be able to understand the most effective and the least effective variable which causes Zoom Fatigue. If we will be able to determine and avoid the most effective variable leading to Zoom Fatigue then, the impact of Zoom Fatigue in an individual can be reduced.

The major contribution of this research is to detect zoom fatigue and classify the variables impacting the mental strain caused by zoom fatigue. The proposed model in this research paper helps us to determine the variables that affect the individual zoom fatigue the most, avoiding the same can help prevent zoom fatigue. This is a new and common issue, which is rising and affecting crowd of all ages and gender globally. Also, if the individual can detect zoom fatigue in an early stage, effective measures can be taken to prevent the growth of mental strain and improve their health.

Further in this research is further divided into the following sections. Section 2 of this paper is Related Work which focuses on machine learning approaches on detection of zoom fatigue and previous work carried out in this domain. Section 3 describes the MLETF in detail. In section 4 the design of the proposed framework and in section 5 the step by step implementation is described. Section 6 evaluates the experiment, methodology, and description of data in this research. Section 7 presents the discussion for the experiment and analysis and section 8 concludes and discusses the future work in this research.

2 Related Work

In this section, we will critically discuss the research conducted on eye tracker device and the detection of zoom fatigue. The papers reviewed for this research have been published from 2012 to 2021. These studies will help in understanding the previous researches and their findings and limitations. Section 2.1 discusses the related papers in the detection of mental fatigue. Section 2.2 provides an overview of the previous research paper with a measure of eye tracking and section 2.3 describes the understanding of zoom fatigue.

2.1 Detection of Mental Fatigue

Mental fatigue is one of the vital causes of accidents and mishaps in the workplace for different domains such as medical, driving, construction, etc. There are many different ways to detect mental fatigue in individuals. In the research paper Li et al. (2020), a method was proposed to detect multiple levels of mental fatigue of construction workers, where the data was collected from wearable eye tracker device. The data were analyzed and classified as three levels of mental fatigue using TICC (Toeplitz Inverse Covariance-Based Clustering) method. According to the research, SVM performed the most efficiently with accuracy between 79.5% and 85% varying with construction and other subjective scenarios. Similarly in the research paper Acı et al. (2019), data extracted from electroencephalographic (EEG) was used for the detection of mental fatigue in individuals. The data was collected for 5 participants, with a total of 25 sets of data, which was further analyzed using machine learning algorithms for the detection of mental fatigue, such as KNN, SVM, and Adaptive Neuro-Fuzzy System method. The research paper Cheng et al. (2019), focuses on detecting driver fatigue by exploring the driver's facial patterns. For this research, 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 to detect their level of alertness and mental fatigue. Machine learning algorithm logistic regression showed the most accuracy with 83.7%.

Many approaches for the detection of mental fatigue have been proposed using various methods, for example, Wearable Eye Tracker device, EEG signals, or Psychological sensors. In research, Wu et al. (2020) a model for detection of mental fatigue in pilots was proposed by collecting the output of EEG (electroencephalogram) signals. The EEG signal provides four basic fatigue indicators, which are compared with the autoencoder proposed model, derived from the local characteristics of the pilot. The result of the research shows that the proposed model for the detection of mental fatigue in pilots gives a good performance. The research Yu et al. (2020) and Cui et al. (2021), proposes a model for detection of eye tracker device using the data collected from eye tracker device, with combining the value of PERCLOS with other fatigue characteristics(such as FOM, frequency of Open Mouth). The result of the experiment showed that the proposed model was able to achieve an accuracy of 98.6%. The research Monteiro et al. (2019) proposes a deep learning framework for the detection of mental fatigue using the data collected from physiological sensors. The result of the experiment showed that the deep learning models have the ability to extract the feature which provided a high level of accuracy in the detection of mental fatigue in individuals. The research Yamada & 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 individuals with cognitive loads.

2.2 Mental fatigue and measures of Eye Tracking device

The education system has also transformed towards e-learning and virtual classes for students, to analyze adaptive e-learning in the field of education, a framework was proposed in research Barrios et al. (2004). This framework helps the students to adapt the concept of e-learning and assure their accuracy and reliability as knowledge recipients. Similarly, research Ivanović et al. (2017) and Paul et al. (2019), discusses regarding the students adaptive and understanding of the e-learning system. The result shows that the eye measures such as eye movement, gaze, blink impact 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 KSS(Karolinska Sleepiness Scale), 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 individuals. 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.

2.3 Zoom Fatigue

The research paper Morris (2020) gives us an understanding of how mental fatigue is related to zoom fatigue and what are the causes and dynamics. Mainly this is caused by exhaustion with online communication. This is a type of mental fatigue that has increased with encouragement with lockdown and social distancing, where everyone is connected using an online mode of 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 individuals. The result highlights the impact of zoom fatigue and its rapid growth and impact on individuals. The research paper Fauville et al. (2021), proposes a ZEF (Zoom Exhaustion and Fatigue) Scale, which provides a quantitative and detailed understanding of zoom fatigue and the scale for fatigue detection. A total of 395 individuals 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.

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 individual 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 we need the participants to only focus on online video communication and absence of physical activities. Hence, by this research, we can understand to what extent the eye tracking device data can be used to detect Zoom fatigue in an individual. In the next section, we will see the details of the Research Methodology sued in this research.

3 Research Methodology

In this section, we will discuss the experiment setup, process, and data collection, and transformation. In order to detect and evaluate zoom fatigue using different machine learning methods, we performed experiments using an eye tracker device. Thirty-one participants consisting of 12 female and 19 male between the ages group of 22 and 35 took part in this study. All participants had good vision and normal health, with prior knowledge of Basic Java applications. The participants provided written consent before the experiment.

3.1 Experimental procedure

In this research eye tracker device was used to record the eye movement and different stimuli of the participants while watching an online lecture. The eye tracker device consists of a scene camera and two IR cameras, as we can see in fig.1. The eye tracker glasses have a rate of 60 Hz, and an accuracy of 0.5 degrees. The dimension of the glasses is 173 X 58 X 156 mm, which is extendable and video resolution of 1280x960p @ 24FPS. The eye tracker device can record the participant's gaze point, blink count, fixation count, and saccade count.

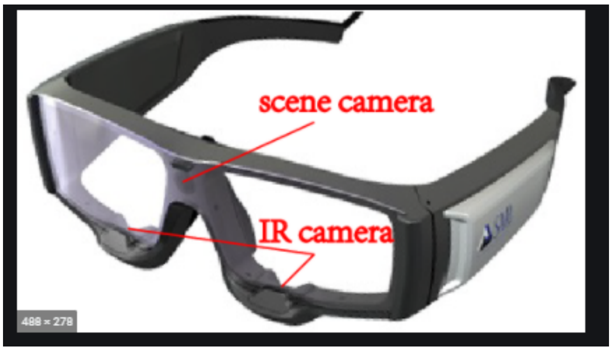

Figure 1: SMI Eye tracker glass

The experiment was conducted in four-step, as we can see in fig.2. The participants 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 participants was stored and analyzed by BeGaze software by *Gaze Intelligence*. This provides us details of gaze points, count of fixation, blink frequency, and saccade.

Further, the participants are asked to fill two sets of questionnaires, first, is the test based on the learning of the video lecture and the second is the questionnaire to collect

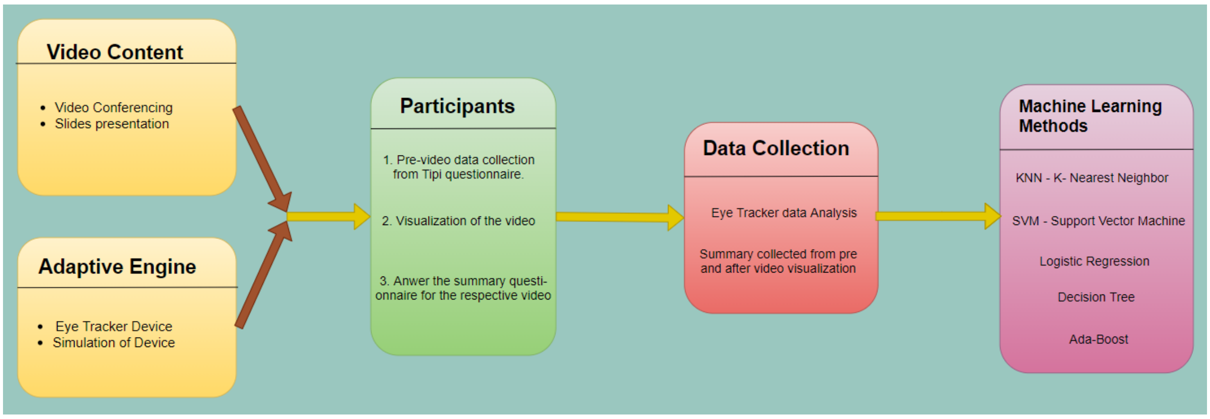

Figure 2: Research Framework

subjective and personality details of the participants. 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 TIPI(Ten Item Personality Inventory) 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 are 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 participants which are Extraversion, Agreeableness, Conscientiousness, Emotional Stability and Openness to Experiences.

3.2 Data Acquisition

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 a 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 around 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.

3.2.1 Data Collection

Under this section, we will describe the process of data collection in detail. 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 participants, 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 participants 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.

3.2.2 Data Preparation

For the implementation of this research Data pre-processing and transformation are very vital steps. In this section, we will discuss the steps involved in transforming the data into the appropriate format for further implementation. All the steps for data transformation and pre-processing 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, we checked for missing values and the presence of outliers in our dataset. Then in the second stage data transformation was performed. In this step, the data was analyzed 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 eye tracker consists 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.

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 (BeGaze software by Gaze Intelligence) 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

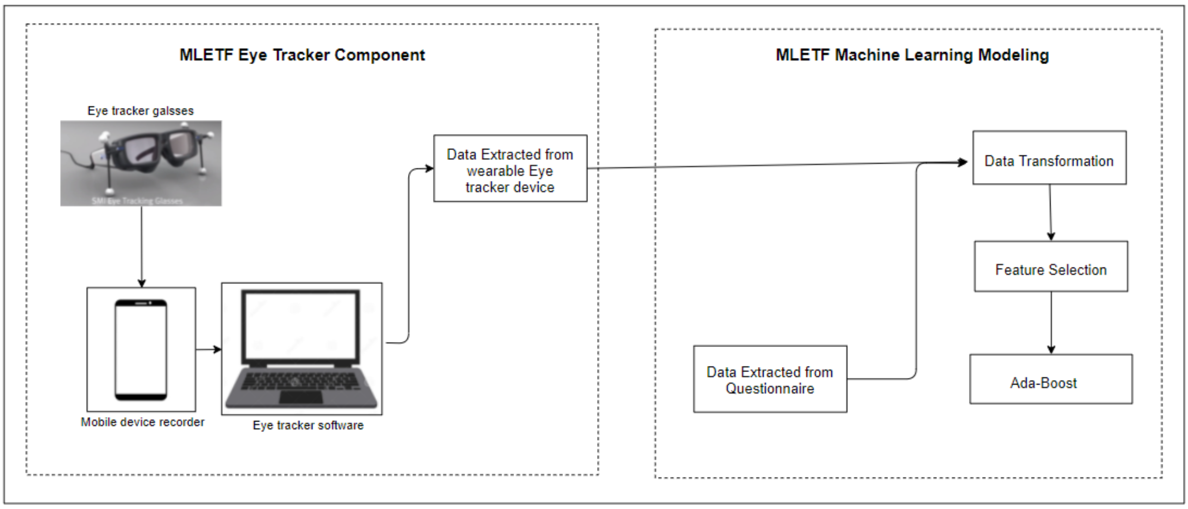

Figure 3: Machine Learning based Eye Tracking Framework Architecture Design

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 participants after experiment through Microsoft and google forms. The responses from participants 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 Ada-boost 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, Emmotional 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

This section will discuss the detail of the experiments conducted in this research. It elaborates and evaluates the experiments and the MLETF. The aim of this research is to detect zoom fatigue using the proposed MLETF, hence, we will perform some machine learning algorithms over the data to compare and analyse the extent of prediction from the data collected from eye tracker device and questionnaire including personality and summary test. Below are the series of experiments performed beginning with the state of art.

6.1 *Experiment 1 : Implementation of data collected from eye tracker device*

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 is divided into an 8:2 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 to it the total amplitude, velocity, and latency of the saccade are also included.

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

Table 1: Results of Experiment 1

Table 1 shows us the results obtained by the machine learning model 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%. In next experiment we will see 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: Implementation of data collected from eye tracker device and PERCLOS*

The aim of this experiment is to investigate accuracy can be improved using the calculated PERCLOS, that is percentage of total blink duration to total duration. In experiment 2 we will investigate accuracy of different machine learning algorithm for prediction of zoom fatigue using data collected from eye tracker device and calculated PERCLOS. The dataset is divided into an 8:2 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.

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

Table 2: Results of Experiment 2

Table 2 we see the results obtained by different machine learning models for experiment 2. From this table, we see that based on the data extracted from eye tracker device and calculated PERCLOS machine learning algorithm 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.

6.3 *Experiment 3: Implementation of data collected from eye tracker device and questionnaire*

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. In experiment 3 we have implemented different machine learning algorithms with the data collected from the eye tracker device and the response collected from the questionnaire. The dataset is divided into an 8:2 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.

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

Table 3: Results of Experiment 3

Table 3 we see the results obtained by different machine learning models for experiment 3. From this table, we see that the machine learning algorithm Ada-boost has achieved a 86% accuracy 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. In the next experiment, we will see 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: Implementation of data collected from eye tracker device, PERCLOS and response from questionnaire*

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. In experiment 4 we have implemented different machine learning algorithms with the data collected from the eye tracker device, the calculated PERCLOS, and the response collected from the questionnaire. The dataset is divided into an 8:2 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.

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

Table 4: Results of Experiment 4

Table 4 we see 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. Here, we see that 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. This will help us to understand the contribution of the research in this domain. 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. In section 6, Evaluation we have demonstrated four experiments to detect zoom fatigue in individuals. We have implemented five machine learning algorithms (SVM, Logistic Regression, KNN, Decision Tree, and Ada-Boost) to compare the performance for the detection of zoom fatigue in our research. In the first experiment, we are using the data collected from the eye tracker device, for the detection of zoom fatigue in the participants, the result showed that KNN has achieved an accuracy of 71%.

We see in the second and fourth experiments we have included PERCLOS, 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 the third experiment, we have used the dataset with the combination of data collected from the eye tracker device and the questionnaire. 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.

In this research we have evaluated the data extracted from eye tracker device and questionnaire response by the participants, but there are other factors which might effect these findings. Zoom fatigue in individuals 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 impact the zoom fatigue in the individuals. Also, during experiment there was no specific distance maintained between the participants and the computer screen. One of the reason for development of Zoom fatigue is the increased intensity due to close up eye contact with the computer screen. In the next section, we will see the key findings, conclusion, and future work for this research.

8 Conclusions and Future Work

This research proposes a MLETF for the detection of zoom fatigue in individuals, 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 showed the most accuracy in prediction of zoom fatigue with Ada-Boost as the accuracy of 86% and SVM, Logistic regression and Decision Tree with accuracy 71%.

Overall, we see that MLETF are capable of predicting zoom fatigue in individuals 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 participants.

We can also evaluate the impact of video length, screen and eye distance in 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 individual'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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