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Deep Neural Network model for convergence of Visual Fatigue and Computer Vision Disability

Jeevanandam Jotheeswaran, Surbhi Jain

Abstract**: *The expanded utilization of blue screens in the work environment and home has realized the advancement of various health concerns. Numerous people who uses blue screens such as Computers, Tablets, Mobiles and Etc., report an elevated level of occupation related grievances and side effects, including visual fatigue and stress. The complex of eye and vision issues identified with close to such usages are called as "computer vision syndrome". In this research work, we study and understand the flow level of a user, while using a smart phone. The study of the flow level will majorly depend on the eye-activity of the user. The data mentioned below is carefully recorded after examining the activity of eyes including the size of the pupil, blink rate, and blink duration. The purpose of this study is to understand the connection between the flow level and the activity of the eyes. A clear understanding of this connection could prove to be very useful information in the computer vision field. Additionally, this can also help a lot to understand about Visual Fatigue caused by Digital Medium***

Keywords: Deep Neural Network. Visual Fatigue, Computer Vision Syndrome, Machine Learning, Deep Learning

I. INTRODUCTION

In the era of digitization, the Smart phones and other display screens have become a necessity rather than a utility. It is rare to see a mobile owner to go out without their mobile phones. The education sector has adopted the online and digital technology to a greater extent in terms of delivery of contents to assessments. Whenever people use the smart phone or gadgets, their eyes are glued to the device. When people devote their undiluted attention to our devices, there are certain consequences. If their eyes are observed closely, it will be noticed that the number of times they blink is different from the way they blink normally. There have been various studies from time to time to understand and observe this phenomenon closely. It was uncovered during detailed studies, the eye activity changes completely when people use their smart phones or computer devices.

It was uncovered in a research the duration of the blink also changes from time to time. On closer observance, it was found the size of the pupil also changes at times. These changes in the activities of the eye are indicative of the level of attention and concentration of the user. In short, the flow level of a user highly affects the eye activity. It will be easier to increase and/or decrease the flow level of a user if we could understand various factors responsible for blink rate, blink duration, pupil size, etc. Increasing or decreasing the flow level could help us manipulate visual fatigue caused by the device. Furthermore, it will help the developers and analysts to design software that would be less harmful.

There have been many studies to understand the difference between the reading ability of e-books and paper books. Wilson, Landoni, and Gibb (2003) conducted a study in which they found paper books provide a higher level of satisfaction and greater usability as compared to e-books. In 2010, Biedert, Bushcher, and Dengel suggested saccade length and fixation duration time were indicators of legibility. They demonstrated it becomes tougher to read when the fixation completion time increases and the saccade length decreases. Leyland et al. (2013) and Hooper and Hannafin (1986) claimed if the range recognized by the eye increases, fixation completion time reduces and saccade length increases. This results in quicker reading and lengthy statements.

Kang, Jung, and Lee (2010) argued while reading a long line, the saccade length increases and the eye cannot move to the other line. Whereas, Iqbal, Zheng, and Bailey (2004) and Recarte et al. (2008) claimed the dilation of pupil is a consistent assess for the mental workload. But, Al-Omar, Al-Wabil, and Fawzi (2013) and Na ̈a ̈ta ̈nen (1992) argued pupils were largely prejudiced by ambient illumination. Gao et al. (2013) and de Waard and Studiecentrum (1996) also utilized blink rate as the indicator of mental workload.

Gao et al. (2013) and Fogarty and Stern (1989) suggested that lowering blink rate means there is a rise in visual demand. Furthermore, Stern, Boyer, and Schroeder (1994) suggested blink rate will use to know fatigue indicator. Siegenthaler, Wurtz, and Groner (2010) observed the reading ability of e-book devices and a paper book using an eye tracker. The eye tracker proved quantitatively assesses efficiency and reading ability. And the experiment showed that there was no significant change in total reading time and reading speed among different reading devices. They also concluded changing font sizes in the e-book devices could render users with better legibility than e-books.

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***** Correspondence Author
Jeevanandam Jotheeswaran*, ACOE, Amity University, Noida, India. Email: jeevanandam@amity.edu
Surbhi Jain, Univo EdTech LLP, Noida, India. Email: surbhij@univo.amityonline.com

II. LITERATURE SURVEY

An experiment was conducted on 8 male and 8 female subjects to determine the change in reading ability in paper books and e-books by using an eye tracker. All the participants belonged to the age group 20-30 and did not have any eye problems. In this experiment, the conditions of paper books and devices were controlled. The cable-type Dikablis Eye Tracking System eye tracker (Ergoneers) and an eye gaze display to scale gaze movement were used. Sampling occurred at a frequency of 25 Hz to measure the coordinates of gaze movements.

Dikablis Analysis & Recorder, along with D-Lab Analysis software were used for scaling, extraction and analysis of data. The gaze movement coordinates are used to measure by the eye tracker to check the reading ability of e and paper books. By using these coordinates, fixation duration time, saccade length, and blink rate are derived.

$$R_k = \frac{110(X_k - X_{\min})}{X_{\max} - X_{\min}},$$

Table 1: Axis Representation

S.no	Axis Depiction	Description
1	R_k	The x-axis coordinates of paper book and e-book (mm);
2	X_{max}	x-axis value among measured coordinates of gaze which are minimum
3	X_{min}	x-axis value measured coordinates of gaze which are minimum
4	X_k	The x-axis coordinates needed to be obtained among measured coordinates of gaze.

Saccade length and fixation duration time were calculated using their definition from typical literature.

The formula for fixation duration time is:

$$\bar{T}_{\text{fixation}} = \frac{\Sigma T_i}{N_{\text{fixation}}},$$

Where,

TFixation: average fixation time;

Ti : i^{th} fixation time;

Nfixation : number of fixation occurrences.

The formula to calculate Saccade length is:

$$\bar{L}_{\text{saccade}} = \frac{\Sigma L_i}{N_{\text{saccade}}},$$

Where,

Lsaccade : average saccade length;

Li : each saccade length;

Nsaccade : number of saccade occurrences.

Blink rate was calculated as:

Blink rate = Number of times eyes are closed

(Total reading time – total time turning over pages).

To study the issues, the subjects were asked to rate their discomfort on a scale of 0 to 10, where 0 was ‘most comfortable’ and 10 stood for ‘most uncomfortable’. The results showed that reading an e-book was more uncomfortable than reading a paper book. The main reason behind this could be linked to the Visual Fatigue arising due to staring continuously at the screen of the device.

Similarly, there have been various studies regarding the user’s flow level for smart phone games by studying the blink rate, pupil size, and blink duration. Based on these studies, there have been a lot of eye flow manipulation which can affect the user either positively or negatively. A study by Cho and Shin (2002) revealed people prefer to blink few times while they associated with a game comparing to file typing. They reasoned it is because playing games is more enjoyable and requires higher concentration.

Kim et al. (2007) reported the difference of flow is dependent based on task done .The level of flow depends on the blink rate and a low blink rate is indicative of a relatively higher level of flow. Lee et al. (2012) concluded an individual interest benchmark and the amount of focus can be accomplished through pupil’s size. The size of the pupil grows in accordance with the level of interest and concentration. It is understood that a higher level of interest and concentration may also increase the level of Visual Fatigue.

A study was conducted to measure a user’s flow level in three different types of smart phone games. The experiment was conducted on a total of 25 subjects without any vision problems [3],[4]. They used an eye tracking device called Face Lab to measure the blink duration, blink rate, and pupil size of the individual. It does eye-tracking and quantify pupil response and blink rate at same time. After recording these measures, the subjects were asked questions from a questionnaire.

The three types of games used are

- Puzzle,
- Dot To Dot, And
- Colouring.

The initial range was taken as the first ten seconds of the game and the final range was the last ten seconds of the game. Everyone are asked to play all three games and their flow was recorded separately. The SAS 9.2 (SAS Institute Inc.) was utilized to analyses of variance (ANOVA), then Tukey's Studentized Range (HSD) Test at a significance level of 0.01 and 0.05.

Pupil Size

The size of the pupil was noted whenever the participant’s eyes were open. The time frame of blinking was not calculated for the average size as the eyes were closed during that time.

Blink Rate

The blink rate was measure per minute with the help of the following equation:

$$e_c = \frac{c_l e_l + c_r e_r}{c_l + c_r} \qquad \text{for } c_l + c_r > 0$$

where,

e_l : Left eye closure value

e_r : Right eye closure value

e_c : Both eyes closure value

c_l : Confidence of left eye closure value

c_r : Confidence of right eye closure value

Blink Duration

Blink duration is the addition of the mutual blinking time ratio to the number of blinks. To maintain the accuracy of the experiments, all the experiments were conducted in isolated rooms with similar atmosphere. It was concluded that the puzzle game had the highest level of flow followed by dot to dot and then coloring. It is understandable, that puzzle game was the most interesting game and it required the maximum concentration among the three.

III. METHODOLOGY

As discussed earlier, prolonged use of computers, tablets, eBook reader, mobile phones, etc may cause eye related issues which are called as Computer Vision Syndrome (CVS) or Digital Eye Strain (AOA, 2016). Headaches, blurred vision, dryness of the eye, ocular fatigue, double visions, etc are the symptoms of CVS (Blehm, 2005). It is common knowledge that headaches originate in the brainstem due to interaction with the trigeminal nerve (carries innervations to the head and to the eyes). Prolonged use of digital devices cause ocular motor imbalances which triggers visually induced dysphoria and CVS is a form of it. Due to a surge in the usage of digital devices, the need and challenges for eye care are increasing rapidly.

The problem of CVS is growing tremendously with more and more people complaining about this problem every month. The need for a treatment or a solution to this problem is necessary. There are some people who might suggest that a reduction in usage of digital devices might help to eradicate this problem. However, that is not a feasible option for the people competing in the modern era [5]. The digital media of today fulfils most of the requirements of an urban person ranging from bill payments to entertainment, from infotainment to cab bookings, etc. Avoiding a digital device will lead to many inconveniences for the urban population.

A study by Dong Ju Kim1, Chi -Yeon Lim2, Namyi Gu3, and Choul Yong Park1 in the year 2016 examined visual discomfort induced by using high-resolution smart devices. Fifty-nine volunteers were asked to play a game or watch a movie on a tablet computer. All the participants were healthy adults between the ages of 20-60, out of which 19 were male and 40 were females. The participants were to watch the smart devices from a viewing distance of 40 cm for one hour.

The findings showed viewing smart mobile devices for 1 hour significantly increased mean total asthenopia score which ranged from 10 to 51 (the highest possible total asthenopia score was 60). It showed all the participants suffered from mild-to-moderate asthenopia at baseline. The problems such as sore/aching eyes, watery eyes, irritated eyes, tired eyes, and hot/burning eyes increased after using the gadgets. It is to be noted that even using state-of-the-art, high pixel density technology aggravated asthenopia. Tear film break-up time (TBUT) decreased. However, total ocular wave front aberration remained unchanged.

It is estimated that 64% to 90% of system users do CVS. When using system for more than 4-5 hours can make eye discomfort. Then, dry eye syndrome is very normal for people who work on computers and 60% of people use video monitors, then electronic books readers with a liquid crystal display (LCD) monitors possess marked visual fatigue. There are two possible causes of CVS such as decreased blink rate and increased accommodative effort.

However, the exact functioning of CVS remains unclear. Focusing continuously on a computer or a smart screen may entail continuous accommodation effort without blinking for an extended period. When people with computer, blink rate decreases and was lead to eye discomfort score. Then one study says viewing distance for a mobile device is 36.2 cm and it is lesser than reading books (40 cm). Then it is also said that a shorter distance needs accommodation and convergence more. The study says increased tear evaporation with decreased blinking and enhanced accommodative effort might leads to dry eye aggravation with increased ocular irritation and pain.

The other possible reason of CVS can be the blue light by light-emitting diode (LED) display. Nowadays many concerns raised about hazardous effects of blue light range that will affect both the cornea and the retina. Still blocking blue light with a special lens decreased visual fatigue.

It has been noticed there have been various questionnaires to assess the visual fatigue of VDT (visual display terminal) operators. A study was aimed to design a proper and more comprehensive questionnaire that encompasses all the aspects of visual fatigue of the VDT users [1],[2]. Physiologic parameter (CFF change) was used as a criterion to determine the cut-off points of visual fatigue. The study was conducted by Hassan Rajabi-Vardanjani, Ehsanollah Habibi1, Siyamak Pourabdian1, Habibollah Dehghan1, and Mohammad Reza Maracy2 in the year 2011.

To minimize the risk of errors, 248 participants were examined in ocular health and uncorrected reflective errors. The participants involved in the test were also trained how to respond to the flickers of light emitting diode (LED). The visual fatigue of each user was measured both before and after the test by both the questionnaire and VFM-90.1 (visual fatigue meter).All participants were banned from any kind of eye work such as working in front of monitors, watching television and studying about 15 minutes prior to the study. After 15 minutes, the participants returned straight to their jobs and were busy at work
for 60 minutes at least.

The highest score of changes recorded in visual fatigue (CFF changes) was assessed (−4.1) and the highest questionnaire changes were 5.83. The assessed visual fatigue was estimated by questionnaire on a Likert scale and CFF changes are based on the Hertz. The results correlation between tools was examined by the Pearson's correlation ($r = -0.87$ and $P < 0.001$).The flicker variations in this study have been between (0) and (−4.1) Hz and all points in the variation range have been assumed from −0.2 to the next point with 0.1 intervals.

The cutting points and a ROC curve were drawn for each of the sensitivity-specificity curves. The first cutting point was (−0.5) Hz that is the equal to 0.65 in the questionnaire. The second cut point was (−2.2) Hz that is the equal to 2.36 in the questionnaire. The third cut point was (−3.4) that is the equal to 3.88 in the questionnaire. The questionnaire was assessed and reassessed several times to check its credibility. It was found that the questionnaire offered a much detailed and more comprehensible analysis of visual fatigue. Several measures were taken to negate any errors during the study.

There have been various recommendations for relief from CVS including proper body positioning, lighting conditions, and taking rest breaks, etc [6],[7] A study was conducted to find a more effective treatment for CVS by addressing problems of alignment between the mid-peripheral and central visual tracking systems. The results of a prospective clinical study of spectacles with contoured prismatic correction are also discussed in this study. These results also demonstrate the efficacy of this treatment in a subset of patients with CVS. No changes were made to the focus, add power, or light filtration (no blue light blocker used) for this study. The contoured prism was used to account for misalignment of visual tracking systems at all distances.

A total of 22 patients diagnosed with CVS were involved in the study between the ages of 17 and 51. Twenty of these patients were females while two were male. The participants were typical computer users suffering from Computer Vision Syndrome. The Neurolens Measurement Device was used for the measurement of misalignment. The device also analyzed the critical elements of ocular fusion, including pupillary distance, heterophoria, accommodative converge to accommodation ratio, alignment of binocular peripheral and central fusion, and central fixation disparity.

Data from the device provides objective measurements of the precise amount of prismatic correction needed to give patients perfect alignment of ocular fusion at a distance, intermediate and near. These data are then used in the manufacture of customized, corrective Neurolens spectacles. The evaluation of the spectacles was done after a series of evaluations and tests performed over a period of less than three months. After the 30 day visit, 7 out of 22 patients received a second set of lenses with a contoured prism enhancement. 6 out of the seven who received enhancements reported a greater improvement with the second pair versus the first pair of lenses.

The validated CVS questionnaires were scored at each visit to determine how much improvement was made in reducing each patient's symptoms. The study also calculated the average subjective improvement based on patient responses. The findings suggested Neurolens measurement and Neurolens treatment are effective in relieving symptoms associated with CVS. The results indicated that all the 22 patients (100%) had a positive response to the treatment and all these patients were willing to suggest Neurolens treatment to their friends and family.

There was no significant change between 30 and 60 days. However, a considerable change was noticed after 60 days, which suggests the treatment effect was durable and persistent. This shows that Neurolens treatment could prove to be an effective solution for the people suffering with CVS

IV. PROPOSED VISUAL FATIGUE DETECTION

Automate Platform to detect the students with CVS as shown in flow diagram from Image Recognition:

Using features from images of eyes of the students we can extract following features [6][8]:

- Blink Rate
- Blink Duration
- Dependent variable indicating whether a student is suffering from CVs

1st Step: - First step involves calculation of blink rate and blink duration in 5 minute. Blink data can be obtained by computer vision technique .i.e. Convolutional Neural NetworkConvolutional Neural Network can be build taking images of closed and open eye dataset as feature vector and classification variable as whether eye is closed or not.

Algorithm: An image is of greyscale or RGB scale for e.g. an image of 3*3*1 is of grayscale where 1 represents as greyscale and any value greater than 1 represents RGB image. Deep neural network passed through series of the layer on the image then returning the value of 0 and 1 according to the classification (Here 1 represents student with CV and 0 student without CV).

Convolutional Layer: It is the foremost layer to have features taken in the image. It is a mathematical operation like image matrix and a filter or kernel which gives the feature map are two inputs for the layer[10].

Stride : Number of pixels shifts over the input matrix.

Padding : whenever filter does not fit perfectly there are two ways to fit the input image:

- Pad the picture with zeros
- Terminate the image part where the filter did not fit.

Pooling Layer: Next layer is pooling layer. When size of the image is too large we reduce the parameter by sampling. Max pooling find the biggest element from the rectified feature map. Average pooling also take the largest element. Addition of elements in the feature map called as sum pooling.

Next step involve flattening the image with feature map i.e. converting 3D image into 1D image using multiple convolutional and pooling layer then applying different function for final layer. Like sigmoid function in binary classification.

2nd Step: - Calculating the blink rate and blink duration from above technique

3rd Step: - Final step involves building logistic regression for binary classification to predict whether student is suffering from visual fatigue or not

Algorithm: - Logistic Regression is another technique used in machine learning mainly used for binary classification. Logistic regression come from the term logistic function. An S shaped curve which can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits using the formula 1 / (1 + e^-value).

Input values (x) are joined linearly using weights or coefficient values to predict an output value (y). The difference from linear regression is the output is a binary values (0 or 1) than a numeric value.

Logistic regression equation as follows

$$y = e^{(b0 + b1*x)} / (1 + e^{(b0 + b1*x)})$$

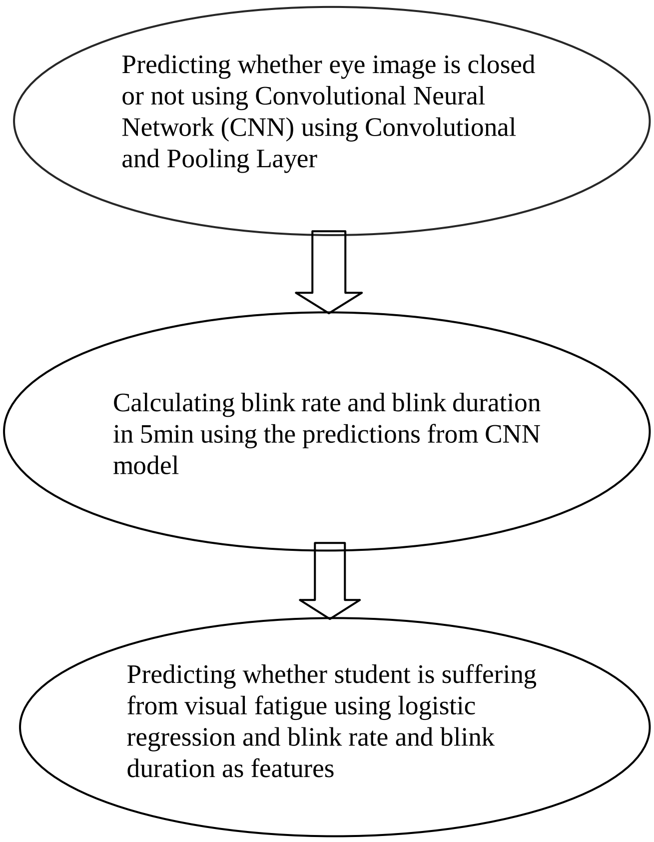
Where

y = Predicted output,

b0 = Bias or intercept term and

b1 = Coefficient for the single input value (x).

Each column in your input data has an associated b coefficient (a constant real value) that must be learned from your training data.



Flow Diagram:Visual Fatigue Convergence

V. RESULT ANALYSIS

Data Pre-processing:- Dataset contain images of 20000 student's eyes recorded after every 1 second while watching movie or using smart phones. The blink data can be obtained from images by using computer vision techniques as follows:-

Detecting the eye blink: First step involve detecting the eye blink. Using CNN model is built to detect whether image shows that eyes is closed or not.

Dataset of 30000 classified images as shown in Figure 1 have been taken with label as close or open. Then model is built with 4 hidden layers as convolutional layer input dimension as 64 and stride as 1.

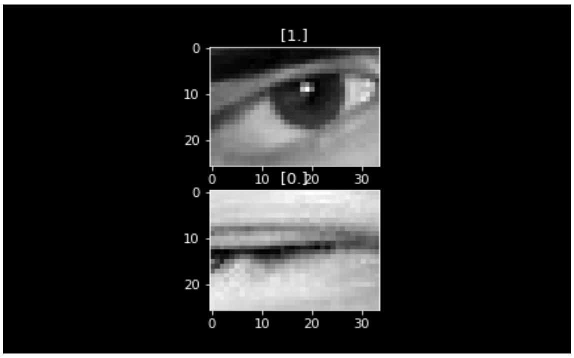


Figure 1: Detecting the eye blink

And activation function as relu for starting 3 layers and sigmoid for last layer since our problem statement involves binary variable. We have use max pooling for creating rectified feature map with pooling size=2. The images are flatten into one dimensional layer. We have also taken dropout layer as 0.2 probability i.e. each node is dropped with 20% probability to reduce over fitting. The model is compiled taking loss function as cross entropy and overall accuracy predicting that how model is performing. We have taken epoch as 20 where one epoch represents one forward and backward pass. Model summary is presented in Table 2. Overall accuracy of the model is 70% i.e. we are able to predict whether eye image is closed or open with 70% accuracy. And overall test accuracy is very high as shown in figure 2.Next step involves passing the student's images captured in every 1 sec recorded for 5 minutes the eye blink classification model to record no of times student blink and duration of the blink.

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 26, 34, 64)	640
max_pooling2d_5 (MaxPooling2	(None, 13, 17, 64)	0
conv2d_6 (Conv2D)	(None, 13, 17, 128)	73856
max_pooling2d_6 (MaxPooling2	(None, 6, 8, 128)	0
conv2d_7 (Conv2D)	(None, 6, 8, 128)	147584
max_pooling2d_7 (MaxPooling2	(None, 3, 4, 128)	0
conv2d_8 (Conv2D)	(None, 3, 4, 128)	147584
max_pooling2d_8 (MaxPooling2	(None, 1, 2, 128)	0
flatten_2 (Flatten)	(None, 256)	0
dense_9 (Dense)	(None, 512)	131584
activation_3 (Activation)	(None, 512)	0

```
_________________________________________________________________
dense_10 (Dense)             (None, 1)                 513
_________________________________________________________________
activation_4 (Activation)    (None, 1)                 0
_________________________________________________________________
dropout_2 (Dropout)          (None, 1)                 0
=================================================================
Total params: 501,761
Trainable params: 501,761
Non-trainable params: 0
```

Table 2:Model Summary

```
test acc: 1.0
<matplotlib.axes._subplots.AxesSubplot at 0x13113c7f0>
```

Figure 2:Confusion Matrix

Classification Model for predicting whether student is suffering from CV or not:-

Final step involve taking blink duration and blink rate as feature vector and building classification to model to predict whether a student is suffering from CV or not.

Data Description:-Dataset 0f 10000 students is taken which include blink rate and blink duration and other eyes features and depend variable as whether student is suffering from visual fatigue or not.

Model Building: - Logistic Regression can be used to classify that whether student is suffering from visual fatigue or not. Blink rate and Blink duration is taken as independent variable and dependent variable represents 1 if student is suffering from visual fatigue or not.

Here our problem statement involves predicting the visual fatigue with more accuracy so we tried to increase the sensitivity i.e. true positive rate. Overall accuracy comes out to be 80% while sensitivity comes out to be 75% i.e. we are able to predict the student with visual fatigue with 75% accuracy. Although specificity comes out to be 60% which is quite low with reference to table 3. Threshold value comes out to be 0.6 i.e. prediction probability greater than 0.6 consider as student suffering from visual fatigue. Area under ROC curve is 0.8 i.e. our model is able to classify the data points with 80% accuracy.

Table 3: Performance for Visual fatigue prediction

Method	Sensitivity	Accuracy
Convolutional Neural Network	78.77	70
Logistic Regression	80	75

VI. CONCLUSION

The objective of this research was to assess connection between visual fatigue and computer vision disability. Based upon the existing literature, it can be assumed that visual fatigue triggers general fatigue and a change in general fatigue subsequently affects our vision disability. Image recognition can be used to develop app to detect the person's vision disability from specially eye image of the student. Deep Neural network is used to build the model to classify the student with vision disability. Further chi square test is used to check the association between computer vision disability and use of smartphones. Increasing and/or decreasing a user's flow level will be easier if we can understand different factors that are responsible for blink rate, blink duration, pupil size, etc. Increasing or decreasing the level of flow might help us to manipulate the device's visual fatigue. It will also help developers to design less harmful software. In laboratory, visual fatigue measurements may not be sufficient to summarize, therefore the visual fatigue in real-world conditions and under different intra architectural and climatic parameters needed as future scope.

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