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PAPER

An Application of Computer Vision Techniques to Study the Relationship between Mental Stress and Pupil Diameter among University Students

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ABSTRACT

Stress is a state of mental tension, which helps us to cope with challenges in our life. It makes us progressive when it is positive, but excessive negative stress that perseveres for a long time leads to a state of depressiveness. Longer stressed stage of a human being changes the size, functionality and frequency of response of many internal and external body parameters. By applying computer vision techniques, these changes of body parameters can be tracked to get useful information about the mental stress for a stress affected person. Many studies show the pupil diameter varies significantly with the effect of stress. Our work is based on the study of variation of pupil diameters of stress affected and not affected university students. With the application of different supervised machine learning algorithms, we have observed that the pupil dilates more in case of stress affected students than non-stressed students. We have also found that the pupils of the students dilates more when they were in positive emotional states than their negative emotional states. This work will be helpful for researchers who are working in the field of emotion detection and recognition and affective disorder analysis.

KEYWORDS

harr features, mental stress, pupil diameter calculation, machine learning analysis, statistical analysis

1 INTRODUCTION

Physical health is directly proportional to emotional well-being. Proper monitoring and regular observation of emotional health is necessary to keep our physical health fit and fine. Affective computing is a branch of science which deals with the study and analysis of our emotional and mental states. Different body parameters (both external and internal) i.e., eye blink, pupil size, head position and movements, hand movements, heart beats etc. are affected with the variation of mental status.

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The life of a modern person is filled with hectic schedules in office, home and society, which makes him stressed on a daily basis. Researchers mentioned that homeostasis is a process through which the living things maintain a stable environment for surviving and stress always threatens this homeostasis [1]. Continued period of stress can damage different tissues and can invite many vital diseases. Researchers claimed that anxiety affected persons, when passing through a longer period of stressful life, most of the time suffer with major depression [2,3]. The authors have specified some of the stress symptoms such as disorder in eating and sleeping habit, feeling a lack of energy, continuous headache, always feeling hopeless and feeling guilty unnecessarily. If a person experiences these symptoms for longer period of time, he/she is considered as being in an emotionally distressed condition [4]. The effects of stress are noticeable when it continues for a long term. It disturbs almost all the human organs like respiratory system, cardiovascular system, gastrointestinal, nervous, and reproductive systems etc. [5]. If the intensity of stress increases from a certain threshold level, it may cause cognitive and behavioural disorders. Stressful people experience a weakened immune system for which they suffer with constant illness [6]. Academic related stress reduces motivation level in adolescents and makes them sleepless for many nights, which causes health hazards to them. It is specified that real time monitoring of stress level using wearable sensors like Vital Jacket, Affectiva Q-sensor, EmotivEpoe device, LG watch Urabane 2 etc. can be an efficient way of stress measurement in human body [7,8]. Automatic measurement of stress level in a human body can be accomplished by considering different body parameters like EEG, ECG, Blood Volume Pulse (BVP), electrical activity of the muscles, respiration etc. [9]. Researchers have mentioned that the mental stress can be detected by analysing the respiratory signals extracted by a bio-radar with the help of time, frequency and Recurrence Quantification Analysis (RQA) features with a detection accuracy of 94.4% [10]. Ultra-short Heart Rate Variability (HRV) features and short Heart Rate Variability (HRV) features are widely used by the research community for automatic assessment of mental stress [11]. Different machine learning algorithms are proved to be very effective for automatic assessment of mental stress as reported by the researchers [12,13]. Multimodal dataset consisting of ECG signals, PPG signals and pupil video data of stressed and relaxed subjects have been analysed by different soft computing methods for automatic assessment of mental stress [14]. Researchers have used the heart rate variability as a measure to track the activity of automatic nervous system using neuro fuzzy technique, which gives sufficient amount of indication on mental stress of a human being [15].

We have basically studied the variations of pupil diameter in stress-affected people under different emotional states in comparison to non-stress affected people. The paper is organized as follows: Section 2 presents Related Literatures; Section 3 gives an overview of Materials and Methods; Section 4 represents the Results and 5 is Discussion and Conclusion.

2 RELATED WORKS

Researchers have developed a framework to detect mental stress of a person by analysing their facial expressions under different emotional states like sad, anger and fear with the help of convolutional neural networks [16,17]. By analysing different physiological features with implementation of machine learning algorithms researchers have developed many efficient systems to detect mental stress of human being [18]. Our mental health conditions are directly reflected by our eyes. Researchers have successfully detected the affective states of a person by considering pupil dilation and thermal facial features [19]. Researchers have considered many physiological parameters like EEG, ECG, EDA, EMG, heart rate, pupil diameter, speech, skin temperature etc. for successful mental stress detection [20]. Like other substantial features, eye blinks carry a strong association with our mental status. Researchers have successfully verified the relationship between eye blinks with mental status in their work [21]. Many studies were done previously by the researchers to show the correlation between different eye parameters with mental status of a person, some of the studies have been mentioned by the authors [22]. Researchers have investigated and mentioned that the pupil dilates more for a stressed person than the normal one in low intensity of light [23]. It has been substantiated that pupil diameter is a distinctive feature for automatic discrimination between normal and stressed persons, specified by the researchers in [24,25]. Researchers have successfully predicted the existence of mental stress in people by using EEG signals by applying machine learning framework [26]. Excess use of digital devices like laptop, desktop and cell phones increase the stress levels in humans. Mental stress in these persons can be detected by tracking their pupil diameters. By applying digital filtering methods, researchers have detected mental stress in individuals by considering their pupil diameter variations [27]. Researchers has examined the use of a multimodal voice-image feature fusion model for emotion identification that is based on the transformer architecture. Along with this, an improved probabilistic matrix factorization (PMF) model has been created to provide personalized content suggestions for learners. Their goal is to offer a more precise and successful method of health teaching [28]. Like pupil diameter, eye gaze can provide sufficient information about the stress level in humans. Researchers have analysed in their paper how stress level increases with increment of cognitive load by observing their eye gazes [29]. Researchers have found that the mental stress is correlated with pulse rate and pupil dilation when individuals are exposed to virtual environment [30]. Mental stress has been successfully detected by researchers from different eye tracking data such as gaze-bin and entropy by using machine learning, deep learning techniques [31].

In this paper, we have investigated the variations of pupil diameter with respect to positive emotions like joy and surprise and negative emotions like sad and disgust. Along with this we have also studied the state of pupil diameter in case of stress affected persons under these emotional states.

3 MATERIALS AND METHODS

Our observations are based on the data collected from the experiment, which was conducted in an institutional laboratory with the supervision of expert psychologists. Fifty students (both male and female) within the age between 21–26 had taken part in the experiment. Specifically, the students who had been visiting the psychologists regularly for routine check-up or for issues related to their mental health had taken part in the experiment. Before initiation of the experiment, consent form has been collected from the participants and approval from institutional ethical committee has also been obtained. Throughout the experiment, the participants were asked to perform two different tasks. In the first task, they were asked to answer a set of 21 questions within a period of one hour. The questions were associated with their academic career, personal life and family life problems etc. During the second task, the participants were asked to watch emotional stimuli videos corresponding to six basic emotions like sad, joy, disgust, fear, anger and surprise. Each participant was invited to watch a single stimuli video per day. After watching each video, each participant was asked to fill up a self-assessment form, which is a feedback type form, that contains self-expressed emotional scores ranging from zero to five. Out of 50 participants, 44 subjects were chosen for experimental analysis. The rejection of participants was on the basis of discontinuity for appearing each of the defined tasks, suffering with cold and cough, which is responsible of causing unnecessary variations of eye blinks, pupil diameters etc. Each of the participants were rated as stressed or non-stressed by the expert psychologists based on their answers of first round questions and by observing their past records of routine check-up. The participants are rated as "stressed" or "non-stressed" with the help of DASS-21 scale given in Table 1, which is explained in [32]. The face videos of each participant were recorded during their performance of second task (video watching phase) with a web camera with specifications 30 fps at 1280 x 720. The recorded videos of the participants were stored in .mp4 format with x264 codec.

Table 1. DASS-21 cut-off scores

Severity Level	Depression	Anxiety	Stress
Normal	0–9	0–7	0–14
Mild	10–13	8–9	15–18
Moderate	14–20	10–14	19–25
Sever	21–27	15–19	26–33
Extremely Sever	28+	20+	34+

3.1 Selection of stimuli videos

To elicit emotions inside the students, six basic emotional videos of sad, fear, disgust, anger, joy and surprise were being used. These video clips have been selected by referring [33]. Each stimulus video contained 2 mins. of relaxing scenes and 10 mins. of specific emotional scenes. The initial relaxing scenes are helpful to make the participants calm and relax before entering into an emotional world. The stimulus videos were rated by the participants to show how are intense they are to drag them into a specific emotion. The average intensity level of different stimulus videos are as follows: the anger videos 0.56, disgust 4.28, fear 1.43, joy 4.72, sorrow 4.19 and surprise 3.15.

3.2 Proposed work

Our objectives are in two folds i) to study the relationship between mental stress and variation in pupil diameter ii) to investigate the effect of positive and negative emotions on pupil diameter. Figure 1 shows the framework of our work. The framework is basically consisting of three major stages. Stage-I is comprised of two rounds. Round-I was the question-answer round and round-II was the emotional video watching phase. Stage-II involved the pupil diameter calculation of all the participants and building up the pupil diameter database. Stage-III was associated with the analysis of the database in both statistical and machine learning approach. Based on the responses of participants from round-I (question answer) tasks and with the analysis of their past medical consultation history, the participants were rated by the psychologists as "stressed" or "not stressed". In round-II, all the rated participants were invited to watch the stimulus videos of different emotions. During video watching phase, the facial expressions of all participants were being recorded by a web camera. From the recorded facial videos, the pupil diameter of all the participants were calculated and analysed for finding out the relationship between the pupil diameter with mental stress. The basic steps involved for measuring the pupil diameter are i) face detection ii) eye detection iii) pupil detection iv) pupil diameter calculation.

3.3 Methodology

With the help of advanced technologies, the process of psychological state determination of a person becomes easier and faster. The analysis of different eye related parameters like eye blink, eye gaze, pupil diameter variations are proved to be very effective in this determination process. This process of analysis of eye parameters is followed by detection processes like automatic face detection and eye detection, which is shown in Figure 2.

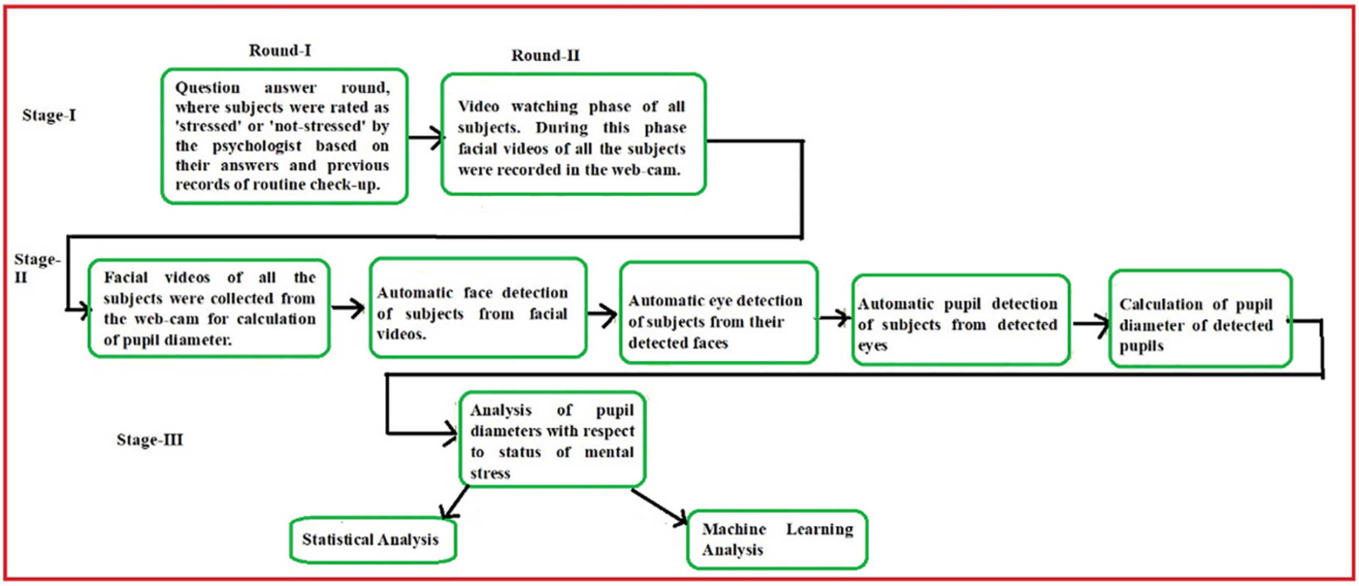

Fig. 1. Framework to study the variation of pupil diameter under different emotions with mental stress

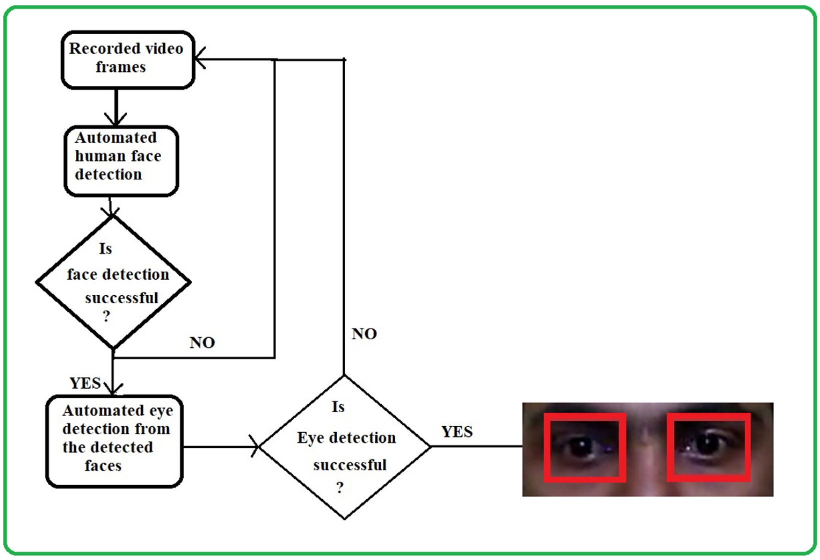

Fig. 2. Automatic face and eye detection steps

Face and eye detection. Haar cascade algorithm is proved to be an efficient algorithm for face and eye detection from images and videos. This algorithm uses Haar-like features and cascades them to detect the face and eye [34]. This algorithm is lain forward by Viola Jones for fast and accurate detection process, which is mentioned in [35]. This is a machine learning algorithm, where a cascade function is trained with many positive and negative images. Haar-like features are used to extract original features form the positive and negative images. Haar features are formed like a rectangular structure with LxB pixels. The Haar-like features are calculated as per equation (1).

$$Haar_{feature} = \sum_{i\in(1......M)} l_i . RecSum(x, y, l, b, \theta) \tag{1}$$

Where, $RecSum(x, y, l, b, \theta)$ represents the pixel sum of the rectangle with x and y are the coordinates, l and b are the dimensions and θ is the rotation of the rectangle, specified in [36,37]. Figure 3 shows different Haar feature formation procedures with different orientations and Figure 4 represents prototypes of different Haar features used for facial structures and facial parameters. Haar features are like the convolutional kernel. Each feature is unique and has a single value, which is obtained from the subtraction of sum of pixels under white rectangle from the sum of pixels of black rectangle. Finally, the combination of Adaboost learning algorithm and cascade classification technique successfully detect the required feature by discarding the non-face images with high accuracy [38].

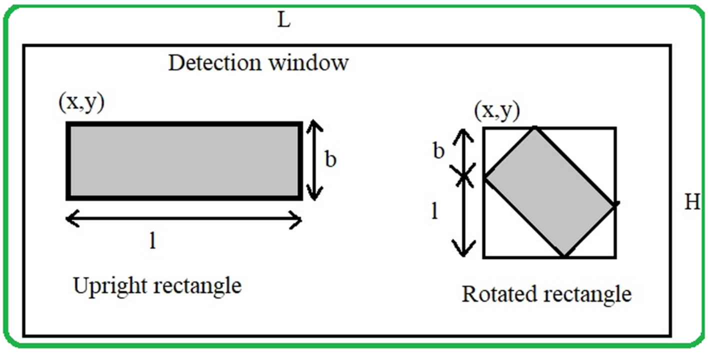

Fig. 3. Different Haar features with different orientations

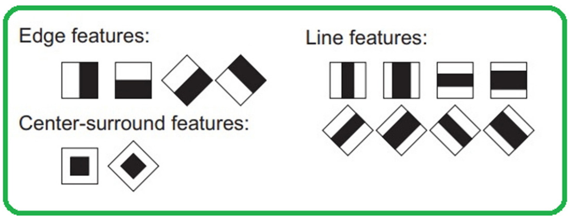

Fig. 4. Haar feature prototypes

Pupil detection and pupil diameter calculation. Once the eyes have been detected from the video frames, the task of pupil detection for each of the participants had been processed. Binary thresholding technique is adopted to detect pupils of each participant. In binary thresholding method, all the pixel values of the concerned image are compared with a threshold value. Then the whole image space is divided into two categories, one that is higher than the threshold value and another that is lower than the threshold value. This binarized image can be formed by the following equation.

$$bin(x,y) = \begin{cases} 0, for\ Im(x,y) \le Threshold \\ \qquad Otherwise\ 1 \end{cases} \tag{2}$$

Where, *bin* (x, y) is the converted image and $Im(x, y)$ is the intensity value of the pixels at the (x, y) location of the considered image, as in [39]. Applications of morphological operations are carried out to detect the edge of the pupils. The key element in morphological operation is a structuring element. The structuring element moves across the whole input image and produces an output image by comparing each pixel of input image with its neighbourhood, as in [40]. The circles can be formed in the specific region of pupils by Hough transform method. It is a very powerful tool to detect lines or circles in an image. When the radius is unknown for a circular image, a 3-D Hough space is created. The parametric space corresponds to an accumulation matrix with the parameters a, b and R. i.e., A (a, b, R). Each point (x_i, y_i) of the perimeter of a circle in image space will produce a cone-like structure in parametric space as in Figure 5. Then a new circle with a new radius will be created at the level of 'r'. By following the above procedure, the pupils of each participant have been detected. Detected pupil of one person is shown in Figure 6. In most of the cases, we got pupil diameter same for both the eyes for a single person in different emotional conditions. But in some cases, the diameter for both the eyes are a little different for a single person. So, the overall pupil diameter for a single person is considered by taking the average of the pupil diameters of both the eyes.

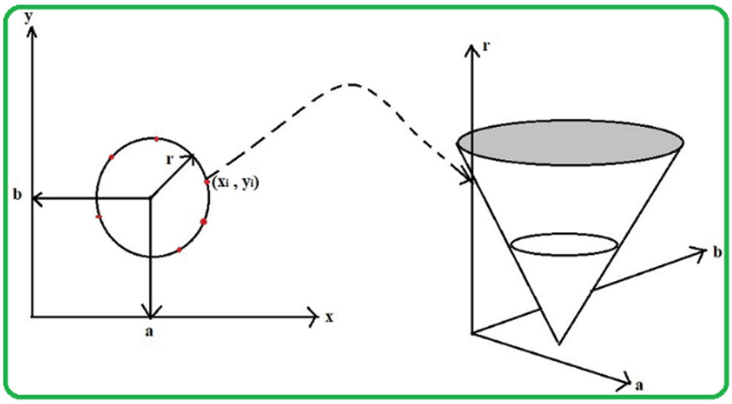

Fig. 5. Circle formation by Hough transform method for unknown radius

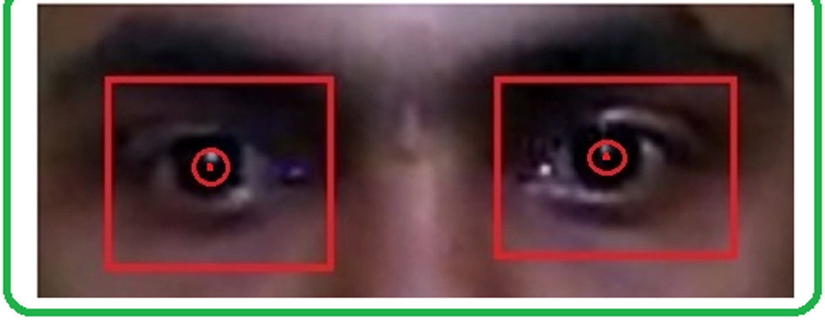

Fig. 6. Pupil detection by Hough transform method

4 RESULTS

The pupil diameter database has been created by measuring the diameters of pupils of each and every participant under different emotional states. Our analysis is moving forward to find out i) whether the pupil diameters vary with respect to different emotions and ii) is there any difference between the pupil diameters of stress affected people and normal people. The pupil diameters have been calculated for the emotions of sad, joy, disgust and surprise. The mean of pupil diameters has been calculated for each emotion of all the valid participants for comparison purpose. Figure 7 represents the mean of pupil diameters of all the participants under the considered emotions. The average value of pupil diameter of all 44 participants under sad emotional state is 3.933, for disgust emotion, it is 4.088, whereas for joy state, it is 1.947 and for surprise state it is 2.273. All the pupil diameters are in mm scale. Generally, the sad and disgust emotions are considered as negative emotions and joy and surprise emotions are treated as positive emotions. The average pupil diameters of the participants are shown in Figure 7. It shows that the diameters are larger in sad and disgust emotions in comparison to the diameters for joy and surprise emotional states. It can be said that pupils are dilated during negative emotional states and pupil diameters are smaller during positive emotional states. Previous studies also reveal that pupil diameter becomes larger for negative emotions and becomes smaller for positive emotions [41,42]. Figure 8 shows the average pupil diameters of both stress affected and normal people under different emotions such as sad, joy, disgust and surprise. The average pupil diameter for stress-affected people under sad emotional state is 5.241 and for normal people, it is 2.626, for disgust emotion. The average pupil diameter for stressed persons is 5.387 and for normal persons, it is 2.790. Under joyous state, the average pupil diameter for stressed persons is 2.296 and for normal persons, it is 1.599, likewise for surprise emotional state the average pupil diameter for stressed persons is 2.562 and for normal persons is 1.984. All the measurements are in mm scale. The results shown in Figure 8. reveal that under each of the selected emotional states, the pupil diameter for stressed affected people are larger than the normal people. Studies reveal that the automatic nervous system of our body dilates our pupil when it copes with any challenging situations i.e., in case of excessive stressful situation [19,43–45]. Our findings have been validated in two ways i) statistical analysis ii) machine learning analysis.

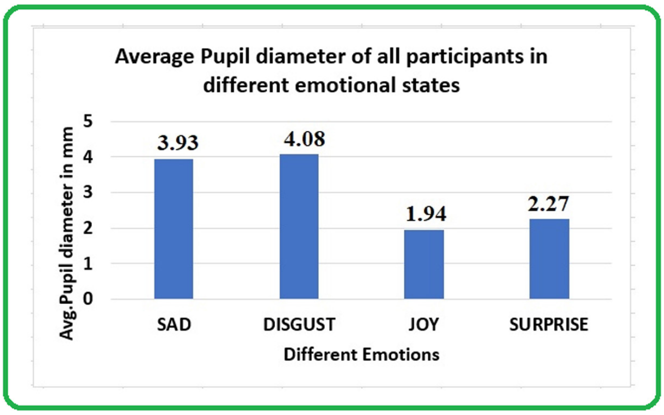

Fig. 7. Average values of pupil diameters of all subjects under different emotional states

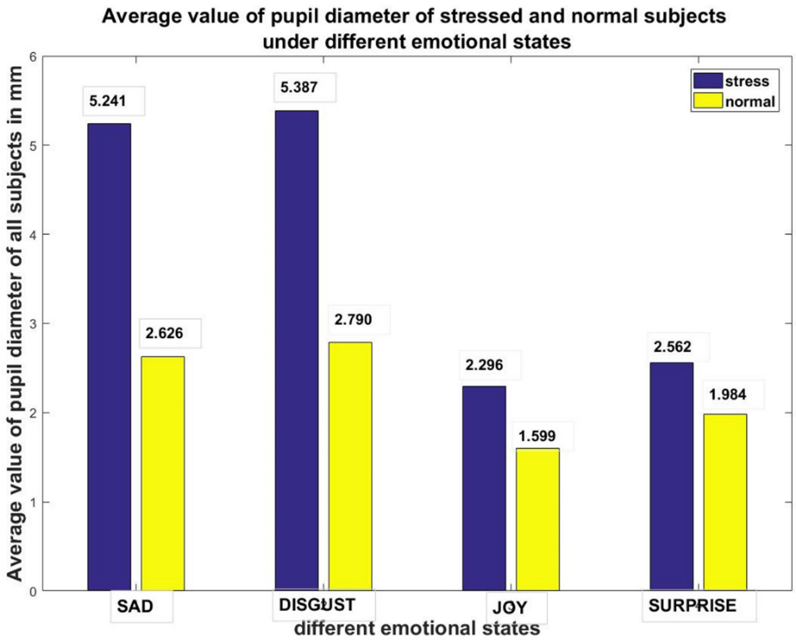

Fig. 8. Average values of pupil diameters of stressed and non-stressed subjects for different emotional states

4.1 Statistical analysis

To validate our findings, we have set two null hypotheses for two different observations. The null hypotheses are represented as follows:

H_{01}: There are no differences in the mean of pupil diameters among the participants for positive (joy and surprise) and negative emotions (sad and disgust).
H_{02}: There are no differences in the means of pupil diameter between stressed and normal persons.

We have applied one way within subject ANOVA to test the authenticity of H_{01}.

The Shapiro-Wilk normality test has been performed before the performance of one way within subject ANOVA. Table 2 shows the details of normality test.

Table 2. Shapiro-Wilk normality test to verify the normal distribution of the pupil diameter data in all emotions of all the subjects

Emotions	Shapiro-Wilk		
	Statistic	df (Degree of Freedom)	*'p-Value'*
Sad	0.116	44	0.159
Disgust	0.106	44	0.200
Joy	0.118	44	0.137
Surprise	0.124	44	0.189

By following Table 2 for sad emotion, the Shapiro-Wilk test showed normally distributed data with W (44) = 0.116, p = 0.159. Likewise for disgust emotion, the Shapiro-Wilk test showed normally distributed data with W (44) = 0.106, p = 0.200

and for joy emotion, the Shapiro-Wilk test showed normally distributed data with W (44) = 0.118, p = 0.137. Similarly for surprise emotion, the Shapiro-Wilk test showed normally distributed data with W (44) = 0.125, p = 0.189. In each of the cases, 'p' values are higher than the significance level ($\alpha = 0.05$), which suggests that the assumed hypothesis that the data are normally distributed is accepted. Along with the normality test, the Mauchly's test of sphericity has also been observed, which is represented as $x^2(5) = 301.709$, p = 0.102. This is indicating that the assumption of sphericity had not been violated and the ANOVA statistics can be considered. Table 3 shows the results of one way within subject ANOVA for N = 44. Results showing that Wilk's Lambda = 0.045, F (3,129) = 116.275, P < 0.00016, partial $\eta^2 = 0.73$. Wilk's Lambda = 0.045 is less than the significance level ($\alpha = 0.05$), which shows that the group means are well separated and $\eta^2 = 0.730$ i.e., large Eta square, indicates a large effect size, which shows the individual groups are well separated by their means. The results of ANOVA test indicates that the pupil diameters of all participants at positive emotional state (joyous and surprise) and negative emotional states (sad and disgust) are significantly different and the pupil dilates more in case of sad and disgust emotional states than the joy and surprise emotional states.

An independent t-test was conducted to explore the differences between stressed and normal subjects by considering their pupil diameter variations under different emotional states like sad, disgust, joy and surprise. A significance level of 0.05 was utilized. Descriptive statistics are presented in Table 4. The stressed group (N = 22) was associated with a pupil diameter of mean (M) = 5.24, standard deviation (SD) = 0.878, whereas the normal group (N = 22) was associated with a smaller pupil diameter with mean (M) = 2.626, standard deviation (SD) = 0.639 for sad emotional state with t (42) = 11.285 and p < 0.001. In case of disgust emotional state, stressed group (N = 22) was associated with a pupil diameter of mean (M) = 5.387, standard deviation (SD) = 0.852 and the normal group (N = 22) was involved with a smaller pupil diameter of mean (M) = 2.79, standard deviation (SD) = 0.627.

Table 3. One way within subject ANOVA to check the differences in pupil diameter for all participants

Eye Measure	Emotional States of Both (Stressed and Normal) Subjects	Mean of Pupil Diameters (M) in mm Scale	F (3,129)	*p-Value*	Partial 'η^2'
Pupil Diameter	Sad	3.933	116.27	0.00016	0.730
	Disgust	4.088			
	Joy	1.947			
	Surprise	2.273			

with t (42) = 11.505, p < 0.001. For joyous emotional state, the stressed group (N = 22) was having pupil diameter with mean (M) = 2.30, standard deviation (SD) = 0.433 and the normal group (N = 22) has smaller pupil diameter with mean (M) = 1.6, standard deviation (SD) = 0.39 and t (42) = 5.613, p < 0.001. Likewise, for surprise state, the stressed group (N = 22) was involved with a pupil diameter of M = 2.56 (SD = 0.451) and the normal group (N = 22) was involved with a pupil diameter of M = 1.98 (SD = 0.33) with t (42) = 4.831, p < 0.001. These set of statistical results show that the pupils of stressed persons are dilated more than the normal persons under different positive and negative emotional states.

Table 4. Independent sample t-test results of pupil diameters of both non-stressed and stressed subjects in different emotional states

Eye Measure	Different Emotional States	Group Type	Mean Pupil Diameter in (mm)	Standard Deviation of Calculated Mean	*t*	*p-Value*
Pupil Diameter	Sad	Stressed	5.241	0.878	11.285	<0.001*
		Non-stressed	2.626	0.639		
	Disgust	Stressed	5.387	0.852	11.505	<0.001*
		Non-stressed	2.790	0.627		
	Joy	Stressed	2.296	0.433	5.613	<0.001*
		Non-stressed	1.599	0.389		
	Surprise	Stressed	2.562	0.451	4.831	<0.001*
		Non-stressed	1.984	0.333		

Note: *Significant at the 5% level.

4.2 Machine learning analysis

Advancement in the field of machine learning solved most of the critical problems not only in the field of engineering but also in other interdisciplinary fields. Machine Learning techniques help to classify even more complex and larger data sets within less than a second. Where human prediction is too hard to reach, artificial intelligence plays an important role in these places to get optimum solutions [46,47]. Researchers demarcated the influence of big data analysis on the healthcare of seniors. Sophisticated analytical techniques like data mining and machine learning algorithms enable the identification of subtle patterns and correlations that may serve as early warning signs for age-related illnesses by utilizing large and diverse datasets [48]. We have utilized some of the supervised machine learning algorithms like Baye's classification, K-nearest neighbours (KNN), Support vector machine (SVM) with kernel, Decision tree and logistic regression to make automatic classification of stressed persons and normal persons by considering the variation of pupil diameters under different emotional conditions. Also, we have approached the procedure to classify the persons with positive emotional states and negative emotional states by considering the variation in pupil diameters. Tables 5–8 present the classification results between stress affected and non-stressed persons under different emotional states. The pupil diameters under each of the emotional states has been taken as the individual predictor to each of the given classifiers. All the algorithms have performed well with appreciable accuracy, precision, recall and f1 score. Basically, under the sad and disgust emotional states (negative emotions), results are very good i.e., the classification accuracy is approaching to 94%.

Table 5. Classification results of different machine learning algorithms between stressed affected and non-stressed persons by considering their pupil diameter under sad emotional state

Classifier Type	Emotion (Sad)				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.001	0.95	0.93	0.94	94%
SVM with Kernel	0.001	0.94	0.95	0.94	94%
KNN	0.001	0.96	0.92	0.93	94%
Logistic Regression	0.012	0.95	0.94	0.94	94%
Decision Tree	0.012	0.95	0.93	0.94	94%

Table 6. Classification results of different machine learning algorithms between stressed affected and non-stressed persons by considering their pupil diameter under disgust emotional state

Classifier Type	Emotion (Disgust)				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.001	0.96	0.90	0.93	94%
SVM with Kernel	0.012	0.95	0.93	0.94	94%
KNN	0.012	0.95	0.94	0.94	94%
Logistic Regression	0.012	0.93	0.95	0.95	94%
Decision Tree	0.002	0.90	0.96	0.93	94%

Table 7. Classification results of different machine learning algorithms between stressed affected and non-stressed persons by considering their pupil diameter under joy emotional state

Classifier Type	Emotion (Joy)				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.001	0.84	0.85	0.81	81%
SVM with Kernel	0.001	0.78	0.82	0.75	75%
KNN	0.012	0.82	0.80	0.81	81%
Logistic Regression	0.012	0.89	0.89	0.88	88%
Decision Tree	0.002	0.82	0.80	0.81	81%

Table 8. Classification results of different machine learning algorithms between stressed affected and non-stressed persons by considering their pupil diameter under surprise emotional state

Classifier Type	Emotion (Surprise)				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.002	0.82	0.82	0.81	81%
SVM with Kernel	0.012	0.85	0.84	0.81	81%
KNN	0.002	0.89	0.89	0.88	88%
Logistic Regression	0.001	0.75	0.75	0.75	75%
Decision Tree	0.002	0.77	0.75	0.75	75%

Table 9 shows the classification results between stress affected and non-stressed persons, where the pupil diameters under sad, disgust, joy and surprise emotions are considered as four predictors to each of the learning algorithms. In this case, for each of the algorithms the accuracy score is approaching to 94%. Table 10 shows the classification results of different machine learning algorithms used to classify all the persons with respect to two different emotional conditions i.e., positive and negative emotional states by studying their pupil diameter variations. We have considered the sad and disgust states as negative emotional state and the joy and surprise states as positive emotional states. In this case the features applied to the machine learning algorithms are the pupil diameters of each person considered in two different conditions. In the first case, the pupil diameters of each subject are taken together for sad and disgust emotions and in second case, that is generally considered as positive emotional state are the pupil diameters of each subject taken from both joy and surprise emotional states The classification accuracy of each classifier is quite good. Specifically, logistic regression classification algorithm provides better accuracy than other classifiers.

Table 9. Classification results of different machine learning algorithms between stress affected and non-stressed persons by considering all four emotional states in combination

Classifier Type	Emotions (Sad, Disgust, Joy and Surprise)				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.001	0.93	0.95	0.935	94%
SVM with Kernel	0.001	0.93	0.95	0.935	94%
KNN	0.001	0.91	0.95	0.93	94%
Logistic Regression	0.012	0.875	0.96	0.91	94%
Decision Tree	0.012	0.945	0.94	0.935	94%

Table 10. Classification accuracy of different machine learning algorithms in the classification of positive and negative emotional states of all subjects based on their pupil diameters

Classifier Type	Pupil Diameters for Negative Emotions and Positive Emotions				
	Prediction Time in Sec.	Precision	Recall	f1 Score	Accuracy
Baye's Classification	0.001	0.85	0.84	0.84	84%
SVM with Kernel	0.001	0.88	0.86	0.87	87%
KNN	0.001	0.82	0.83	0.82	82%
Logistic Regression	0.006	0.84	0.92	0.86	88%
Decision Tree	0.012	0.86	0.87	0.86	85%

5 DISCUSSION AND CONCLUSION

Our work is basically prioritizing the study of mental stress by analysing the variations of pupil diameter under different emotional conditions. Throughout our work, we investigated that pupil diameter is a significant factor to study mental stress under different emotional states. As per previous studies [42–45], the pupil of human being dilates and also constricts under different psychological states as well as under different emotional states. The goal of our work is to study mental stress of human beings by considering pupil diameter as a factor under different emotional conditions. To achieve this task, we have built a pupil diameter database through an assessment process. The database is consisting of the measured diameters of pupils of both stressed and normal subjects. Different computer vison techniques have been used for automatic detection of faces, eyes and pupils of the participating persons. By analysing the database, we found that, the pupil of human beings dilates more under negative emotions like sad and disgust than the positive emotions like joy and surprise. We also found that the pupil diameter becomes larger in case of stressed persons in both positive and negative emotional conditions than the non-stressed persons. These findings were observed from experimental results given in Figures 7 and 8. The first experimental result has been proved to be significant through a very good ‘F’ value i.e., $F(3,129) = 116.27$ with $p < 0.00016$. The second finding also been significantly accepted through independent sample ‘T’ test, with appreciable ‘t’ values like for sad emotion $t(42) = 11.285$, for disgust emotion $t(42) = 11.505$, for joy emotion $t(42) = 5.613$ and for surprise emotional state we got $t(42) = 4.831$. We have applied different machine learning algorithms to classify stress affected persons from the non-stressed persons and to classify the persons with positive emotional states from the persons with negative emotional states by considering the pupil diameter of each person. The classifying algorithms provide significant accuracies like maximum 94% and with minimum classification accuracy of 75%.

Study of mental stress by analysing pupil diameter can be considered as one of the easy and efficient ways of detection process. If mental stress is detected at an earlier stage, it will help the affected persons not to suffer with depression at a later stage, which alternatively saves the person psychologically as well as physically. Our detection process can be adopted to check mental stress among university students in their routine check-up phase.

5.1 Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

5.2 Competing interests

We do hereby declare that we do not have any conflict of interest with anybody.

5.3 Funding

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