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Identification of Mentalstress using Machine Learning Technique Based on Eye Features

Pradeep N[1], Eshwari N[2]
[1, 2]*Department Computer Science and Engineering, BIET Davanagere*

Abstract: Health monitoring technology in everyday situations is expected to improve the quality of life and supporting aging populations. One of the mental stress is health identification of individuals due to association with cognitive performances and health outcomes in younger and older adults. Here, we propose a model to identification of mental stress of younger and older adults in natural viewing situations. Our model includes two unique aspects: (i) Feature sets to better capture stress in natural viewing situations and (ii) An automated feature selection method to select a feature subset enabling the model to be robust to the target's age.
To test our model, we collected eye-tracking image from younger and older adults as they before and after performing cognitive tasks. In our model detected the accuracy in this project.
Keywords: Cognitive tasks, Eye tracking and cognitive tasks

I. INTRODUCTION

Innovation technology for monitoring of health in a shrewd domain, for example, versatile working environments and savvy houses has been progressively perceived as a method of improving wellbeing results just as intellectual and social behavioural act [1]. Particularly considering the developing interest for monitoring of health for more grown-ups because of a quickly aging populace, checking innovation is relied upon to help maturing set up and help empower people to deal with their own health, with the double point of expanding personal satisfaction and decreasing medical expenses [2].

Prior readings on healthiness intensive care require behavioural types in speech, motion, and gaze as a worth of inferring individual's state, for instance physical conditions [3], stress [4,5] and mental workload [6], measuring behavioural characteristics, such as sleep quality [7] and social activities [8], and screening for neurodegenerative diseases, for example dementia [9–12], depression [13], and Parkinson's disease [14]. These monitoring technologies can keep track of daily changes in health also finds begin signs of disease. Being capable of inferring unutilized information related to an individual's healthiness holds promise for providing good health are and enhancing well-being. One aspect of an individual's regular health status that has yet to be utilized is mental stress, which refers the to feeling people might experience during or after cognitive activities [15]. Mental pressure is becoming an increasingly serious health and social problem, and it comes at a huge public health cost [16]. In the workplace, mental fatigue or stress is known to affect cognitive and behavioural performance [17]. In fact, mental fatigue or stress has been suggested as one off the most frequent causes of accidents and errors in the workplace [18].

Recent analyses have reported that the cost of stress-related accidents and errors in the US may reach as a high as $31.1 billion [19,20]. From the perspective of an individual's health, mental stress is a warning sign of harmful accumulations of stress that can have a detrimental effect on one's health [21]. Furthermore, in the context of health of the elderly, it has garnered increasing attention as recent longitudinal studies have shown an association of mental stress with cognitive decline and daily functional deficits din later life [22,23]. revious studies on monitoring mental fatigue by using unobtrusive methods have primarily focused on using eye- tracking measures during cognitive tasks such as driving [18,24,25,35,36]. Some studies investigated how eye-tracking measures change with the duration of the cognitive task to identify sensitive measures indicating an increase in mental stress [26–28]. Others built models by combining these eye-tracking measures and succeeded in detecting mental stress during a specific cognitive task [29,30,33,34].

A model equipped for distinguishing mental worry from eye-tracking information in regular survey circumstances would stretch out the extent of utilization to checking weakness in different ordinary circumstances. Besides, it could be utilized to construe pressure incited by explicit psychological visual undertakings, yet additionally different factors, for example, intellectual sound-related assignments (cognitive auditory), various cognitive tasks, or unexpected frailty [18, 40, 41]. Likewise, late investigations have called attention to the need to test whether past models for deducing mental weariness or stress utilizing eye-tracking measures can be applied to maturing populaces since age-related changes in eye-tracking measures have been accounted [29,31,32].

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A. Problem Statement

As mentioned above, mental stress has become important for monitoring the health of older adults ; thus, a model that enables us to monitor mental fatigue or stress in a wider age group including older adults would be very useful.

We collected eye-tracking data from 18 participants while they watched video clips and tested whether our model could detect mental stress induced by auditory cognitive tasks. With eye-tracking data of individuals watching only 30 s worth of video, our model could determine whether that person was stressed or not . To make a comparison with a model based on the existing work, we also built a model with only feature sets used in a previous study. We also collected eye-tracking data from 11 additional participants while they watched video clips without engaging in cognitive tasks, and confirmed that our model captured changes resulting from mental stress induced by the cognitive tasks, not just sequence effects of repetitive video watching as shown in figure 2.

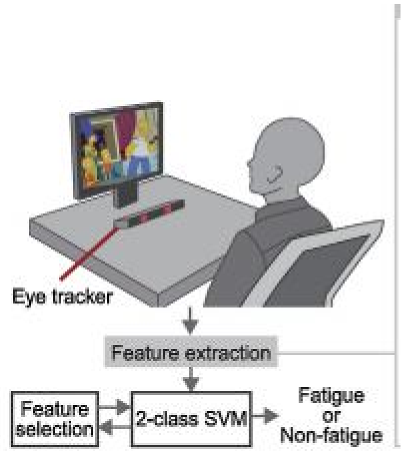

Fig. 1 Methodology of the Proposed System

B. Objectives

The main objectives of the project contains 2 different characteristics:

1) To better capture stress in natural viewing situations.
2) To automated feature selection method to select a feature subset enabling the model to be robust to the target's age.
3) To input the dataset video or images are converted from the face dataset.
4) To extract eye regions are pupil pattern of diameter and number of eye blinks subjected to face detection using viola jones method.
5) To output Classification done by using SVM classifier to detect the person is stress or not .

C. Proposed System

The proposed methodology is shown in the above figure 1, the images are collected from the videos and from the images the pre-processing methods are applied to decrease the noises in the images. Pre-processed images is enhanced using the contrast enhancement method. The eyes are segmented from the image using the viola-jones method. From the segmented image the six features are collected. The obtained features are trained using the classifier called as SVM (Support Vector Machine). The decision of the classifiers is to decide whether the system is stress (fatigue) or not stress (non-fatigue).

II. LITERATURE SURVEY

A model equipped for identifying mental worry from eye-tracking information in characteristic survey circumstances would stretch out the extent of use to checking weakness or worry in different ordinary circumstances. In addition, it could be utilized to construe pressure incited by explicit intellectual visual errands, yet additionally different factors, for example, psychological sound-related undertakings, numerous subjective assignments, or unexpected frailty.

Late examinations have called attention to the need to test whether past models for deriving mental pressure utilizing eye-tracking measures can be applied to maturing populaces since age-related changes in eye-tracking measures have been accounted for .

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As referenced above, mental pressure has gotten significant for checking the soundness of more seasoned grown-ups ; accordingly, a model that empowers us to screen mental worry in a more extensive age bunch including more established grown-ups would be exceptionally valuable.

These eye-tracking measures have been tentatively tried for the most part for individuals beneath 50 years old. Interestingly, numerous investigations have detailed age-related changes in eye-following measures including measures utilized for deriving mental exhaustion or worry in past examinations, for example, understudy distance across and reactions, eye development examples, and saccades. For instance, huge scope concentrates on age-related changes in saccade elements announced that saccadic boundaries including idleness and speed are moderately steady all through the centre a long time up to age 50, yet then change in later years be that as it may, no examination has researched the subject of whether eye-following measures can be utilized to derive mental worry in more seasoned grown-ups.

Truth be told, mental examinations have indicated that focused on members experienced issues continuing consideration and disregarding insignificant data , supporting the speculation that eye development may be progressively influenced by base up consideration when an individual is stressed.

The most developed psychophysiological measures are electroencephalography (EEG) and eye-following measures. EEG gauges that catch changes in cerebrum waves have been demonstrated to be substantial biomarkers of stress. In particular, different investigations have demonstrated that as an individual becomes focused on, moderate wave movement, for example, theta and alpha action increments over the whole cortex . In spite of the fact that EEG measures have high precision for disconnected pressure observing, they require the tedious use of prominent EEG sensors to the leader of the individual, and in this way, it is hard to utilize them for wellbeing checking applications in regular circumstances, at any rate for the present.

Then again, eye-tracking measures have a favourable position in their inconspicuousness, and they were utilized by the greater part of the past examinations and applications meaning to screen mentalpressure. The eye-tracking measures for deriving mental weariness regularly incorporate lists related with understudy measures, squinting, and oculomotor-based measurements.

A. Stress Detection Technology

Numerous endeavours at creating pressure recognition innovation have concentrated on either deciding feelings of anxiety by utilizing explicit test undertakings, i.e., qualification for-obligation tests or checking associates of worry during intellectual errands. The previous kind of approach utilizes neurobehavioral assignments for evaluating official capacities, for example, carefulness or deftness; their test undertakings commonly take up to 10 min and have no work on/learning impacts. For instance, these test assignments are performed previously andadditionally sincerely busy driving so as to assess pressure. Despite the fact that this empowers one to appraise a person's psychological pressure paying little mind to what sort of cause actuated the psychological pressure, it requires the individual to play out the test task each time the psychological pressure assessment is to be made.

B. Mental Stress Detection Model

Based on the related work depicted in the past area, we chose to concentrate on six kinds of eye-tracking estimates that would be valuable for surmising mental pressure: highlight sets identified with student measures, flickering, oculomotor-based measurements, look designation, eye development headings, and a saliency model. The first three capabilities were utilized in quite a while on mental worry during psychological errands . The other three capabilities have been utilized for portraying eye developments in common review circumstances just as construing cerebrum sicknesses, in spite of the fact that they have not been utilized before for recognizing mental pressure. Besides, we explored age-related changes in eye-tracking estimates that have been utilized for deriving mental worry in past investigations. To assemble a model competent distinguishing mental worry of people including more youthful and more seasoned grown-ups, we have to recognize eye following highlights that empower the model to be hearty to age-related changes through a component choice strategy.

C. Haar method

HAAR implies High Altitude Aerial Reconnaissance. Picture preparing and examination dependent on the constant or discrete picture changes are great procedures. The picture changes are broadly utilized in picture sifting, information depiction, and so on. It likewise presents a technique for picture investigation by methods for the wavelets–Haar range. Haar Cascade classifier depends on the Haar Wavelet method to examine pixels in the picture into squares by work. Haar course classifier depends on Viola Jones identification calculation which is prepared in given some info faces and non-faces and preparing a classifier which recognizes a face in eyes utilizing Dlib library work.

D. Local Binary Pattern (LBP)

Nearby picture surface descriptors are broadly utilized in picture examination. The local binary pattern (LBP) is a surface descriptor that is straightforward and effective. LBP has been used in numerous applications in picture preparing field, for example, face acknowledgment, design acknowledgment and highlight extraction. In this project, a changed LBP technique was proposed to extricate surface highlights. The proposed calculation was actualized on numerous computerized pictures and the nearby structure highlights of these pictures were acquired. A few picture acknowledgment tests are directed on these highlights and contrasted and different calculations. The aftereffects of the proposed calculation demonstrated that the advanced picture was spoken to in an exceptionally little size and moreover the speed and precision of picture acknowledgment dependent on the proposed technique was expanded altogether.

E. Support Vector Machine (SVM)

Managed ML calculation which can be utilized for arrangement of given yields. It finds an ideal limit between the potential yields. It takes care of grouping issue such anticipated the yield of given issue.

III.SYSTEM DESIGN

A. System Architecture

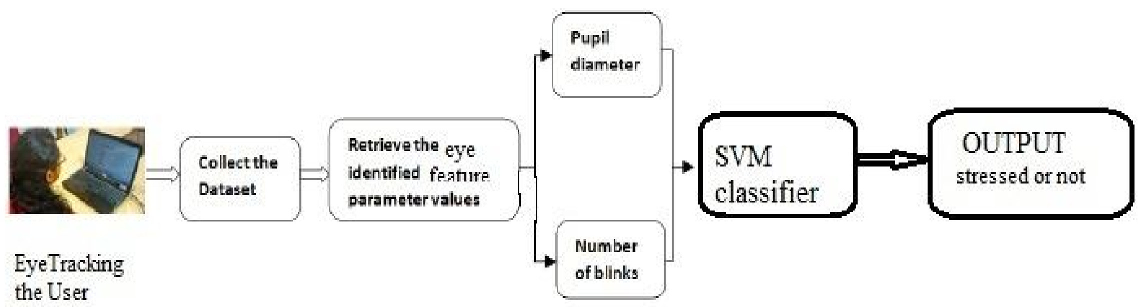

Fig. 2 Architectural diagram for Proposed System

It performs different level of operations, the steps are

1) *Input:* The dataset face video or image are implemented as input video. The input video are taken in the format .avi.
2) *Pre-processing:* In the pre-processing step we can implement the video to frame conversion and then those frames are frame resize are performed.
3) *Face Detection:* Each frames are subjected to face detection. Detection of face is done using the Viola jones method. It is the specific method of Haaryfeature-based cascade classifier, to capture the facial images which any effective method is proposed by viola jones method using Dlib library fuction. Then the Eyes are extracted from the image.
4) *Feature Extraction:* In this step, take the eye pupil pattern of diameter, to measures size of pupil area changes before and after performances. To shows square box of the image detected. It extract the eye regions, features in the frames. It performs the scientific mathematical calculations, from the features of parametric values. To capture the video from user using to detect haar cascade classifier here image of the optimization method of OpenCV. Which provide the eye positioning algorithm provided by the Dlib library and image will be obtained. It calculated the horizontal vertical pixel values is calculated maximum value as regarded as the center point. A pure image selected.
5) *Classification:* In this step ,finally We will classification is done using SVM classifier to detect or identified the person is Stressed or not stressed The output is displayed on the screen.

B. FlowChart

The methodology applied for performing the stress analysis is as shown in the below figure 3. In order to determine the stress we are collecting the features which decides the stress level.
The below figure 3 shows the proposed flowchart. The steps are as follows

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1) Collect the video.
2) Convert the video into frames: using the looping and opencv2 we are going to extract the images from the video.
3) Obtain the input image: select the each image for feature selection process.
4) Pre-processing: apply the filters to expel the commotion from the input picture.
5) Feature extract from the face: detect the eyes and remove the background.
6) Features selection: using LBP- Local Binary Pattern, Haar are the features collected.
7) Classifier: A classifiers is employed to make the decision.

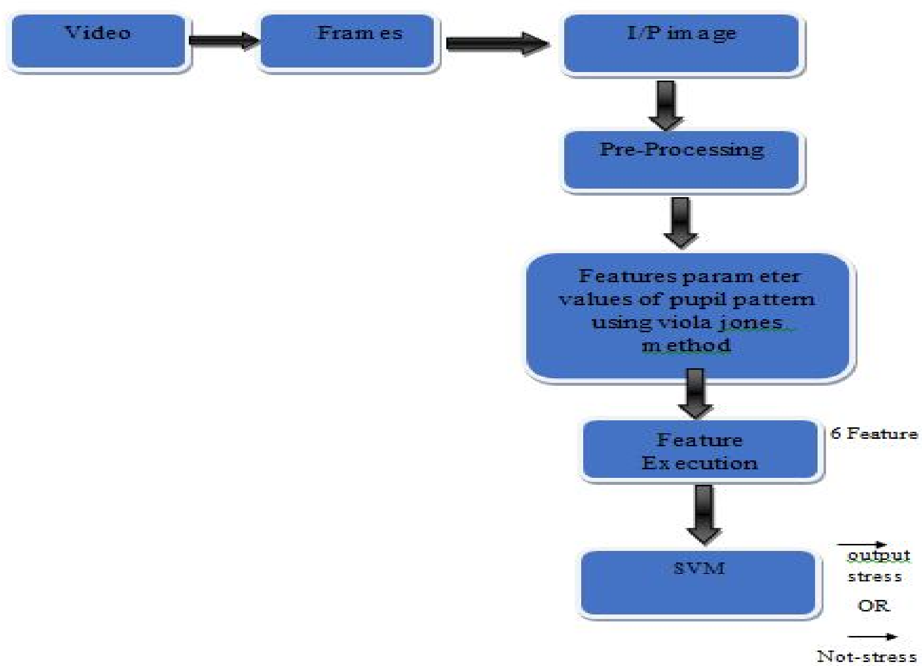

Fig. 3 Flowchart of Proposed System

IV. RESULTS AND SCREENSHOTS

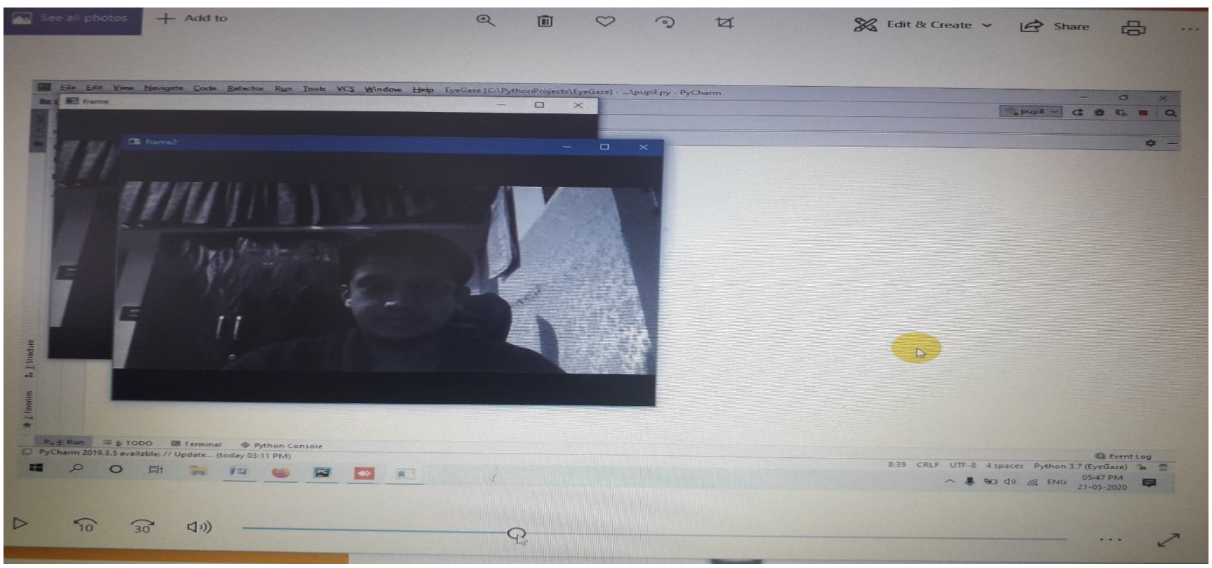

Fig. 4 Shows input the image video in a system

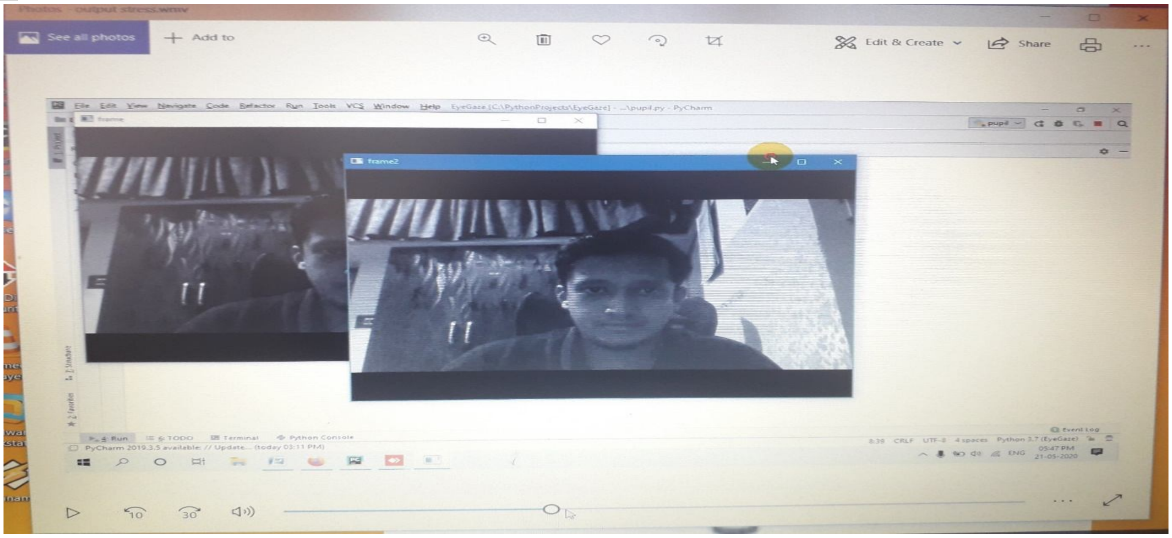

Fig. 5 Image converted into frames moving to right side

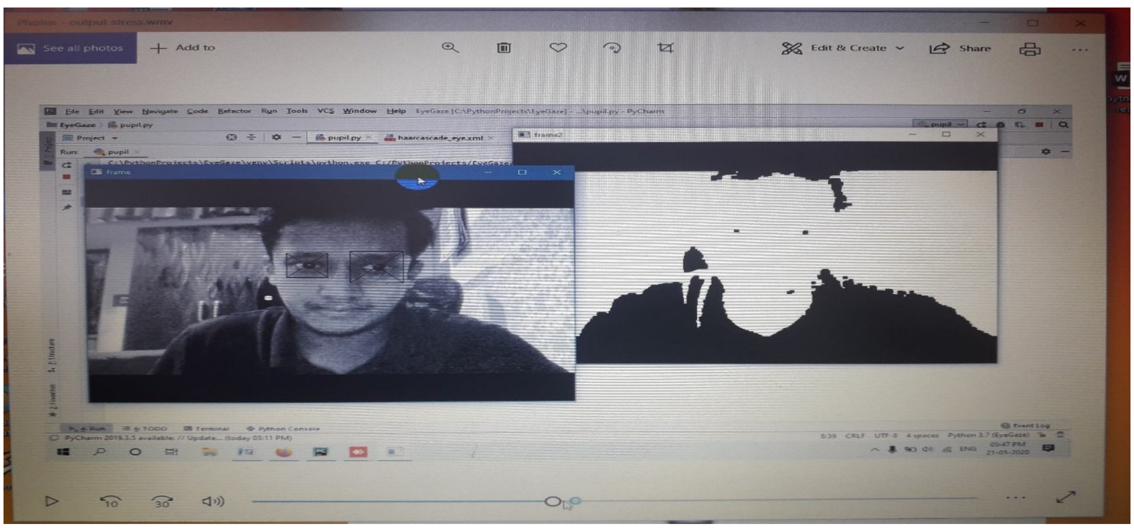

Fig. 6 shows system track eyes from the frames using viola jones method

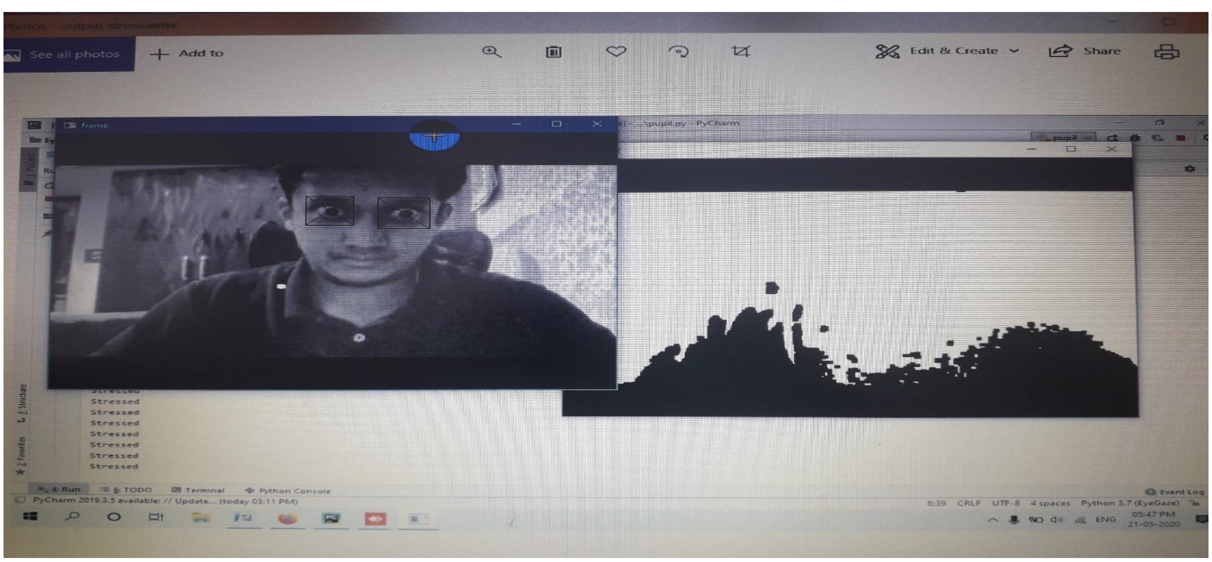

Fig.7 shows considers the eyes pupil diameter enlarges to display the output code

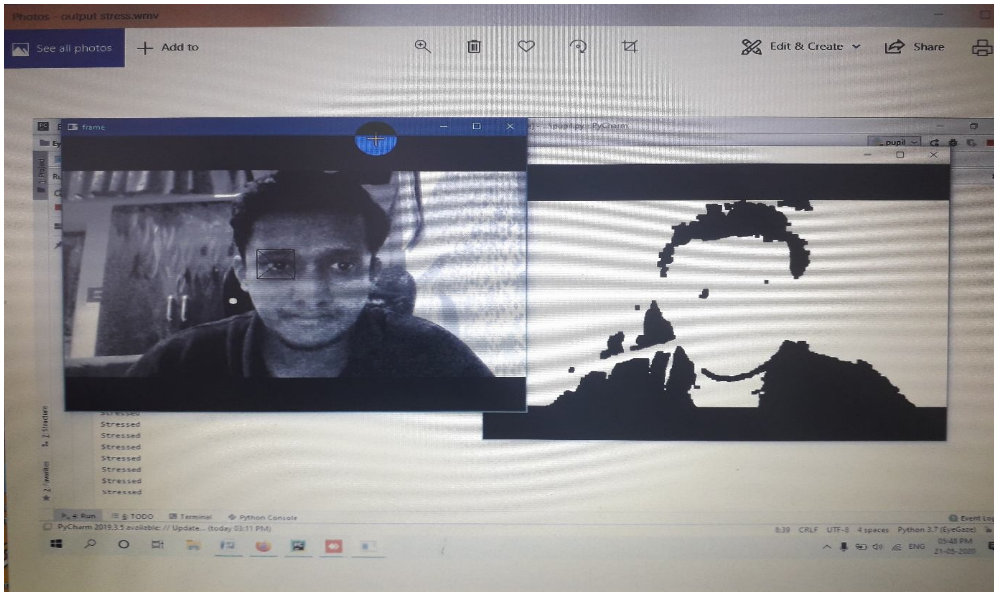

Fig. 8 shows captured the square of object right eye to predict the person stressed

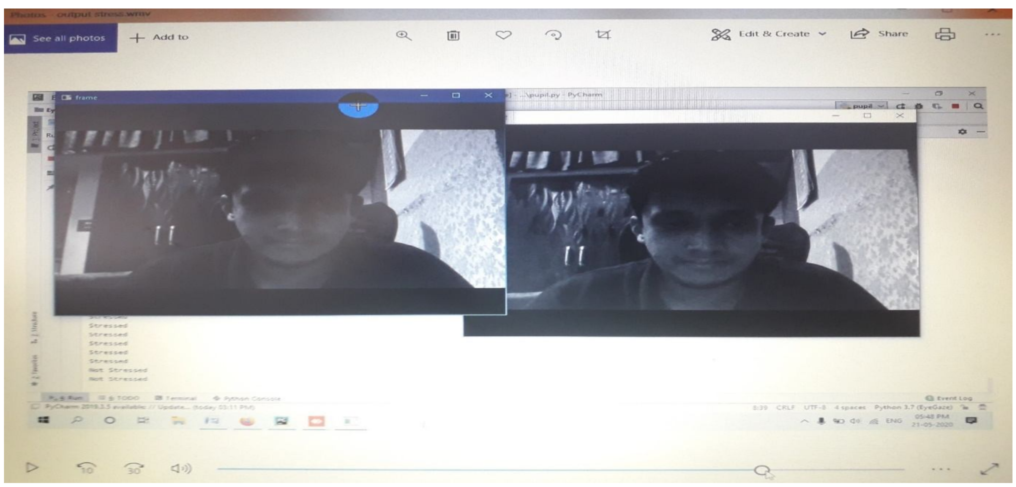

Fig 9: Normally the person eyes become predicted not stressed

V. CONCLUSION

As opposed to past examinations concentrating on distinguishing mental exhaustion or worry during psychological undertakings, we intended to build up a model empowering us to identify mental worry in common survey circumstances when an individual isn't performing intellectual assignments. Likewise, considering the expanding interest for wellbeing checking for more seasoned grown-ups, we additionally expected to make our model hearty to different age-related changes in eye following measures. To this end, we contrived stress identifying model including (I) to more readily catch mental worried in common review circumstances and (ii) a computerized highlight determination strategy to choose a component subset empowering the model to be hearty to the objective's age.

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