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Suspicious Behavior Detection in Smart Class Room: Computer Vision Approach

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Abstract: This paper represents an approach to develop an intelligent system particularly suitable for examination hall which helps to identify the student's cheating behavior and track it. In a smart classroom scenario, the built-in video camera of each computer will capture continuous frames and feed it to our developed system for tracking suspicious behaviors. We have detected targeted person's body movement using Canny Edge Detector for slow, very slow and high dynamics with optimal accuracy. We are also proposing an approach to track the fraud candidates by detecting the age and gender of the examinee and matching it with the pre-stored age and gender. Texture variation of wrinkle density in the forehead, eye lids and cheek area has been considered as a clue for age and gender classification. We have also tried to build a real time emotion detection system. Canny edge detector shows best accuracy when the examinee takes 3, 4 or 5 second for a proper movement. Our intelligent system works perfectly in happy, fear, surprise and neutral emotions detection and provides better accuracy to detect 21 to 35 and 36 to 50 age groups. It also shows optimal accuracy to classify examinee of different age and genders.

Keywords: *Neural Network; Suspicious Activity Recognition; Edge Detection; Age; Gender and Emotion detection.*

Introduction: Traditional examination hall monitoring and controlling system includes a lot of manual works where dealing suspicious activities of students are one of the challenging issues. Although vigilance team are always on duty to ensure the quality of the environment of any examination hall, since few decades ago, examination hall monitoring and controlling system has been evolved which are basically based on Video Surveillance System [1-3] or Staged Matching Technique [4]. With such system, often vigilance team can monitor examination hall remotely. But real time detecting and controlling students' suspicious activities within an examination hall aren't still possible with only the video surveillance system. Thus, it is crucial to develop an intelligent system particularly suitable for autonomously detecting and controlling students' suspicious activities within an examination hall. To meet the demand, so far some researchers are dealing this issue and trying to develop some system.

There have been a lot of psychological experiments and studies regarding the students' behavior in the examination hall [5-7] which ensures the necessity of a real time cheating detection system. Some of the existing researches on real time exam hall monitoring (For example, [8-9]) depend on feature detection, eye tracking or head tracking process to detect suspicious activities of students in examination hall. Some of them have also

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used one webcam and a microphone for the purpose of monitoring the visual and acoustic environment of the testing location [10]. Some use Active Shape Model (ASM) [11] and Vector Field of Image Gradient [12] together for Visual Focus of Attention detection [13]. Another research also builds a centralized system [14] so that all the examination monitoring activities can be done effectively and efficiently. But no research has been conducted to detect the proxy student by means of age and gender detection and to detect the student's suspicious behavior by means of emotion detection. There have been several works for human motion and emotion detection [15], [16]- which are generally very costly and the data collection procedure is not user friendly to be applied in examination hall. Moreover, no works has been done to detect the very slow movements that frequently occur in the examination hall.

Since, Bangladesh is a developing country; our aim is to build a robust system that cans tract examinee's suspicious behavior at a reasonable cost. The main purpose of this study is to identify the student's cheating behavior in the examination hall and control it in an intelligent way. To achieve this task, in our approach, we have considered the scenario of smart class room where each of the examinee will be provided with a laptop to sit for the examination. The laptop must have a built-in camera or the examinee will be provided with external USB camera. The camera will capture real time video and the system developed within each of the laptop wills analysis each frame for suspicious behavior. At first we have detected targeted person's suspicious movement using canny edge detector. Now-a-days, sometimes it happens that proxy candidate sit for exam in the exam hall as a replacement of the original candidate. To avoid this problem, to identify a particular examinee, we have tried to detect the age and gender of the examinee and matched it with the prestored age and gender for each of the examinee. Any deviation from the prestored age of the examinee along with his/her gender will be a hint of proxy candidate. In general, students should be impartial and his/her behavior should be neutral in the exam hall. So to detect the suspicious behavior, we have tried to build a real time emotion detection system. If an examinee shows his or her abnormal behavior (rather than being neutral) then we carefully inspect the selected individual. In this study we also contrasted the efficiency of the above-mentioned techniques. Our intelligent system is efficient because it overcomes important drawbacks of the existing systems namely cost, simplicity and shows optimal accuracy. It is a system that will make examination hall more organized and reduce the cost of deploying human invigilators. The system can be customized for all kind of smart examination hall room and can be implemented with lesser effort.

Methods: Human cheating behavior is very common in the examination hall. It is very difficult to detect examinees' cheating activities and bypass the legal activities. Our present research work is divided into two consecutive subsections as follows: -

The block diagram of our proposed intelligent system is illustrated in Figure-1:

Moving Edge Detection: To detect the random body movement (comprises of very high or slow dynamics) of examinee with optimal accuracy, we propose the following techniques-

Apprpach-1: Low and High Dynamics: At first a video sequence of f frames are taken by the video camera to our system. Then the system started to compute their corresponding edges by means of Canny Edge Detector [18]. At the first stage, we detected the moving objects by means of detecting the moving edges. Let us consider that the moving edges are denoted by Edgem. Now we considered three consecutive frames denoted by {In-1, In,In+1} to perform mathematical operation.

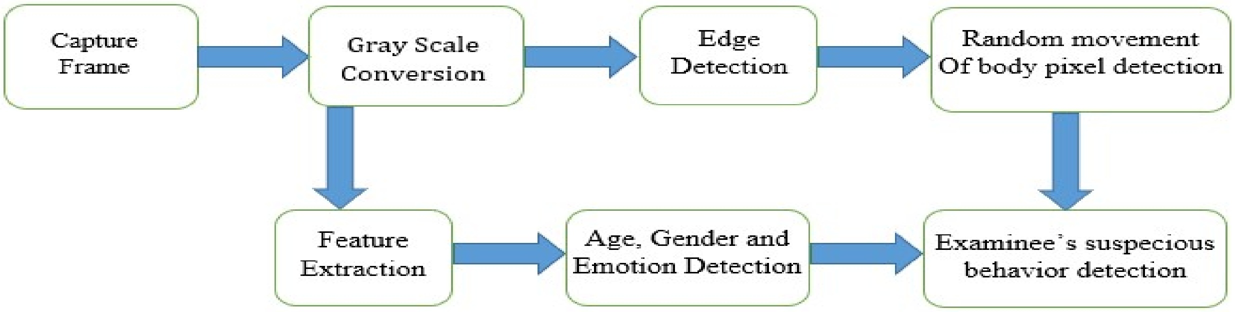


Figure-1: Block diagram of the proposed system

At first we computed two difference images by considering the central frame after subtracting from its two neighbors. That means, $(I_l = \lfloor I_n - I_{n-1} \rfloor$ and $I_2 = \lfloor I_n - I_{n+1} \rfloor)$. We only considered those pixels that will result in positive value in these difference images. Value zero is set for the negative pixels. Now from I_l and I_2 we can easily get the moving pixels. But we may see, they may not match with each other and lacks in finer details of the edges (see figure 3). They are also having some background noises and δ edges which is related to the speed of the movement, see Figure-4 (bottom). We performed AND logical operation on these two resulting images to remove the δ edges which is expressed as follows -

Final Image, $I_{final} = I_l \cap I_2$

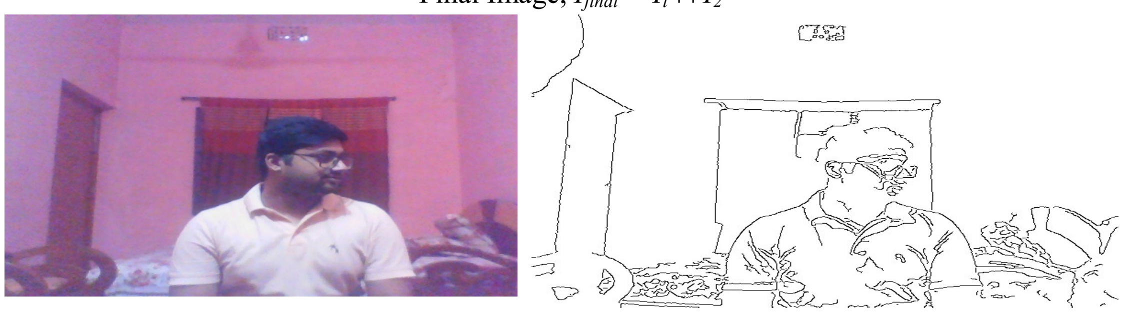


Figure-2: (left) Original frame. (right) Edge representation computed by the Canny edge detector.

Figure-3: Derivation of difference and final images with low dynamics

Figure-3(right) shows an illustration of the resulting I_{final}, corresponding to Figure-2, computed after merging Figure-3(left) with Figure-3(center). During those experiments, the speed was very low. So the two difference images I_l and I_2 doesn't have any δ edges, but they are corrupeted by some noisy edges.

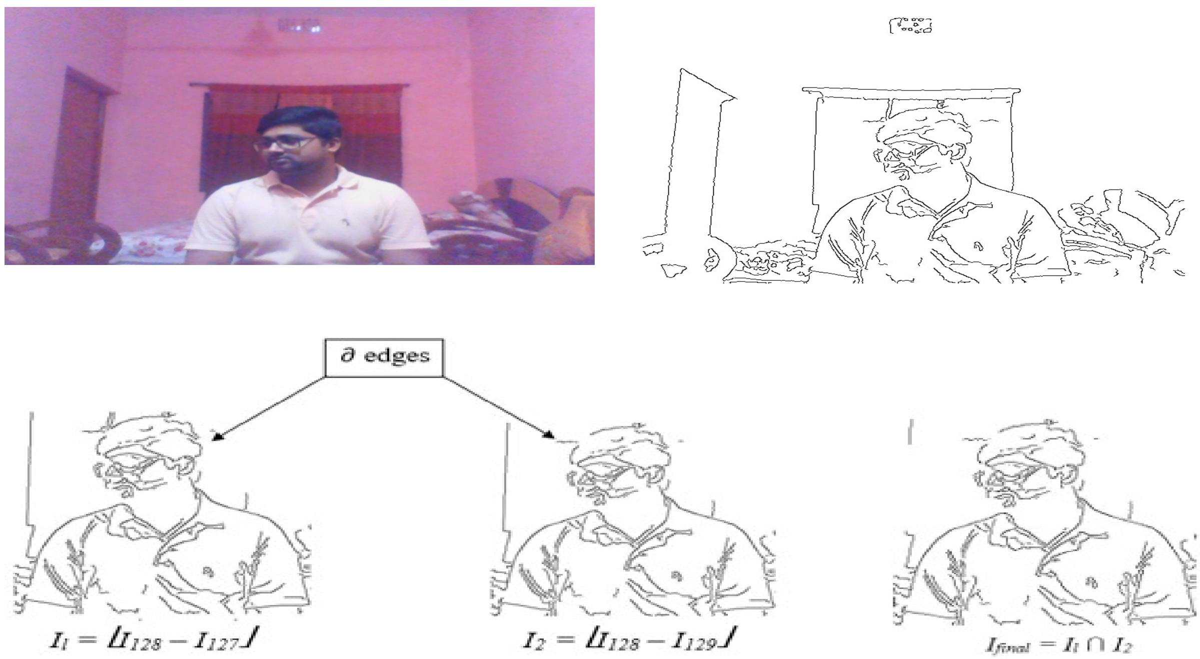


Figure-4: Derivation of difference and final images with high dynamics

Figure-4 indicates the result obtained with a scene containing a movement having higher dynamics. From the figure it is clear to us that now they are having some δ edges. As like we discussed earlier, the final image I_{final} is again corrupted by noise.

Approah-2:Very Low Dynamics: Now we present a solution to the problem to detect the body movement with very low dynamics with the help of Canny edge detector. Let us consider that we have detected the moving edeges for a particular frame In(located at nth position) with the process as described in approach-1. Now we set a variable, m=0 and also consider all the images located at n±m locations. Using the technique in approach-1, we computed the edges from all In±m images. Now all of the resulting edge images are merged together by OR operation to derive the missing edges caused by low dynamics and derive Iultimate1. Now we increased the value of the variable m and perform the same operations as discussed above and derive the image, Iultimate2 after OR operation. Next we performed the OR operation on the above two ultimate images to detect the smallest movements with finer details. The whole operation is continued untill no new information about the edge can be extracted from Iultimate. Figure-5 show the Original frame(left), Moving edges extracted after one iteration(middle) and Moving edges extracted after two iterations (right).

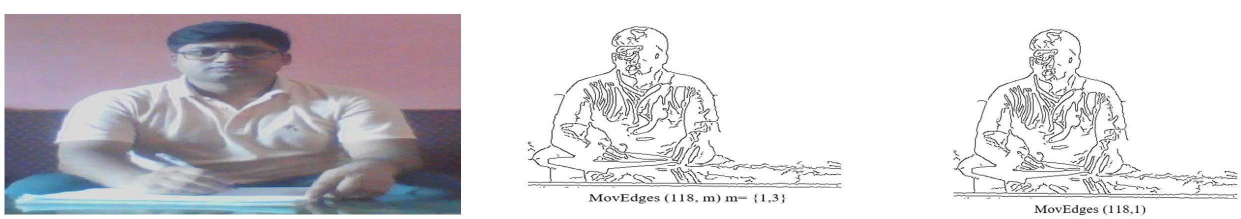


Figure-5: Illustration of Approach-2

Examinee's Body Movement Detection: We combined approach-1 and approach-2 to build our system to track examinee's suspecious body movement. At first a frame is captured (starting with a timer=0) from the video sequences taken from webcam of each examinee. We set a threshold value of black pixels remaining at the moving edges to be considered for a suspecious movement. Then we implemented approach-1 to detect the moving edges represented by black pixels in the white screen.. We counted the number of black pixels and compared with the threshold value. If it surpasses the threshold value, then we considered it for a suspicious movement. If not, we implemented approach-2 because the movement may be too slow to be detected by approach-1. Again we counted the number of black pixels and and compared with the threshold value to detect the suspicious movement. If nothing is detected, we increased timer and start from the beginning. The follwong flowchart describes the above techniques:

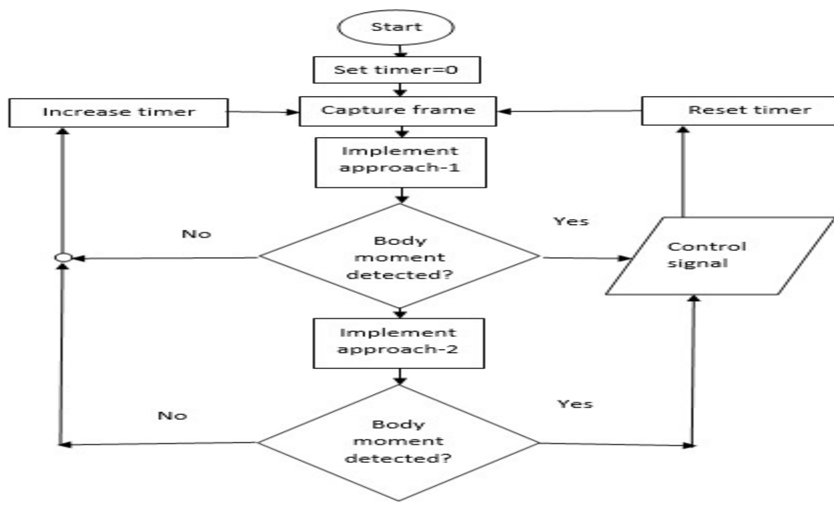


Figure-6: Programming flow chart to detect body movement of the examinee

Age and Gender Detection: Famous facial databases like FERET database [19] and FGNET database [20] and some images are collected by the authors have been used to train our Neural Network that works as a classifier embedded in our intelligent system. Texture variation of wrinkle density in the forehead, eye lids and cheek area have been used as a clue to detect the age of the target person. The images dataset contains the images of both genders (male and female) and images of persons with different ages. We have divided the ages into different age groups like 8-20, 21 to 35, 36 to 50 and 51 to 65. Our proposed algorithm consists of three main steps: Pre-processing, Feature Extraction and Classification.

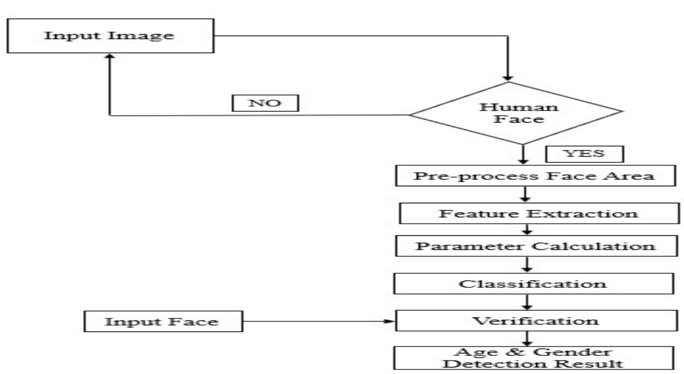


Figure-7. Flowchart to detect Age and Gender

Input Image: Input image is the source image which is used to classify age and gender. Images with different formats are acceptable. Our system will not accept images of children less than eight years of age.

Preprocessing: Our experimental data is highly sensitive to lighting and illumination condition. It is also corrupted by the source noise. Thus, before forwarding to the classification stage, detected face images must undergo a preprocessing step. It is described below-

•Resize Detected Face Image - The images collected from the initial face detection are in various sizes. Therefore, the first step in preprocessing to standardize the data set is to modify each image into a standard width and height (e.g. 255 * 255 in this research).

•Colour Conversion - The images used in this research were taken in standard colour format which is hard to process. Therefore, to overcome the complexity, all the images are converted into grayscale and finally do an equalization of the histogram to have a uniform distribution of the image intensity values. First the red, green and blue values of every pixel in the image are obtained and then the following formula is used to convert the RGB image into a grayscale image:

G(x, y) = 0.21R+0.7G+0.07B……..…………………………………………………………...………...(1)

• Noise Reduction - Dirt on camera lenses, imperfections in camera flash lighting that result in natural images taken from digital cameras creating noise. The transformed color images are sent to the filter for noise reduction. Gaussian smoothing is used in pictures to eliminate the noise. Gaussian smoothing function f (x, y) can be expressed as,

$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/(2\sigma^2)}$ ……………………………………………………………………………...(2)

This function can be used to calculate the weight for each pixel in the image. Assume the Centre point of the weight matrix is (0, 0). Then the nearest coordinate values can be represented as,

$(-1,1)$	$(0,1)$	$(1,1)$
$(-1,0)$	$(0,0)$	$(1,0)$
$(-1,-1)$	$(0,-1)$	$(1,-1)$

Then the weight matrix is calculated by setting a value to σ. The output weight matrix for a sample data set by using σ =1.0

0.0453	0.0556	0.0453
0.0556	0.0707	0.0556
0.0453	0.0556	0.0453

The sum of the weighted matrix is calculated using the formula:

$sum\ (w) = \sum_{i=1}^{9} \text{w(i)}$……………………………………………………………………............…(3)

Then the weighted average of the nine points is calculated by.

$\text{avg(w)} = \frac{w(i)}{sum(w)}$…………………………………………………………………………………………….(4)

The Gaussian blur for each point in the matrix is calculated by multiplying the colour value of each point by the weight average. Each colour value is between 0-255.

$G(i) = int(i) * avg(w)$..(5)

These values of the matrix help to calculate the Gaussian blur value for the center point.

$$blur(middle) = \sum_{i=1}^{9} G(i) \quad \text{......(6)}$$

By repeating the above steps for all the points in the image, the Gaussian blur for the face images can be calculated.

Feature Extraction: According to the research [21] Human face contains 66 feature points of landmarks by using images from the FG-NET database. Relevant characteristics that are important for classification should be extracted from the facial images.

Parameter Calculation: A set of parameters is required to identify age and gender. The description of the parameters is given below:

- ✓ Height of Eye = (X1 + X2) / 2
- ✓ Distance between Eye and Eye brow = (Y1 + Y2) /2
- ✓ Height of Nose (N) = b – (d + f) / 2
- ✓ Distance between Lip and Nose = h – b
- ✓ Width of Eyebrow = Q
- ✓ Distance between Eyes (E) = e – c
- ✓ Eye to Upper Lip Distance (L) = h – (f + d) / 2
- ✓ Ratio1 = Eye Distance /Nose Distance = E / N
- ✓ Ratio2 = Eye Distance / Eye to Upper Lip Distance = E / L

Two wrinkle parameters from each wrinkle area are also calculated:

Wrinkle Density ($W_{density}$) = No of all wrinkle pixels/ No of all pixels in the area

Wrinkle Depth (W_{depth}) = Total Canny Magnitude of wrinkle pixels/Total no of pixels in the area.

Classification: Classification is carried out in two principal steps. The gender classifier will first identify the corresponding gender of the query image. The image is then moved to the age classifier to identify the respective age group. Gender classification is basically done using variations in the shape of the features on the face and the age classification is based on variations in the texture of the wrinkle areas. Classification is performed using calculated neural network parameters. The neural networks are trained using data taken from nearly 10000 images of the two gender groups and different age groups which are images from frontal and nearly frontal faces. Figure-8 Shows the structure of the neural network used for age classification.

Emotion Detection Approach: Developing a real-time emotion detection system, we had to get different components working independently. We also analyzed several research papers to identify the basic problem and how we could improve the accuracy of our result. Our general approach summarizes below:

• Build Dataset: We gathered data sets from multiple sources from coded facial expressions and translated their labels and images into a common format.

• Pre-process Images: We've run software for facial detection to extract the face in each image. We then re-scaled them by cropping, and removed bad images manually. We also applied a Gaussian filter to the images as a preprocessing step for the CNN, and subtracted the mean image from each image of the training set. We also expanded the images to include reflections and rotations of each image in order to get more out of our limited training data, hoping that this would increase robustness.

• Construct CNN: In Caffe on AWS, we used pre-trained versions of AlexNet and LeNet, where we retrained the first and last layers. We also had to experiment with different methods and parameters of the learning rate in order to produce a non-divergent model.

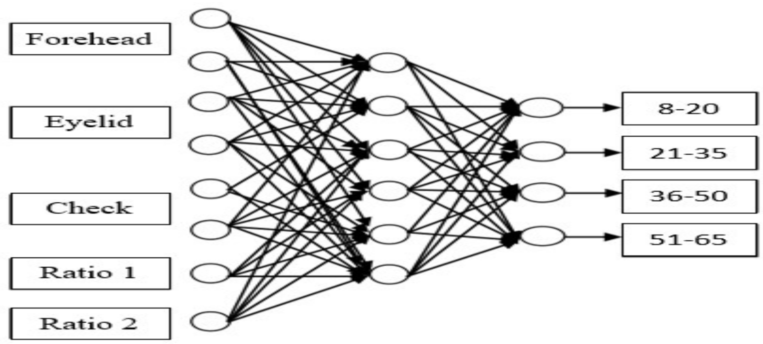


Figure-8**:** Neural network structure used for Age Classification [22]

• Develop real-time Interface: OpenCV has allowed us to pick up images from the webcam of our laptop. We then extracted the face as before, pre-processed the image for the CNN, and with the help of Visual Geometry Group and Keras model, we got a prediction and the results would be shown in my pc webcam.
• Dataset Development: The first step in the development of our emotion-detection system was to gather data to train our classifier. We sought to find the largest data set we could have, and with the help of FERET database [19], FGNET database [20] and UTKFace dataset [23].
This data set is composed of over 100 individuals portraying 6 different labeled emotions: angry (1), fear (2), happy (3), Neutral (4), sad (5) and surprise (6). One thing we really liked about this data set is that the directory includes 10 to 30 images for each person expressing an emotion, showing the progression of that individual from a neutral expression to the target emotion. Initially we chose to take the first two photos from each series and mark them as neutral, and the last three as the target emotion. Nonetheless, we found this significantly restricted the size of our training package, as we were left with less than 1000 training photos. To combat this, we looked at the images more closely and decided to take as the target emotion the last third of each sequence, as opposed to just the last three. Our emotion detection system follows the given model to express human emotion.

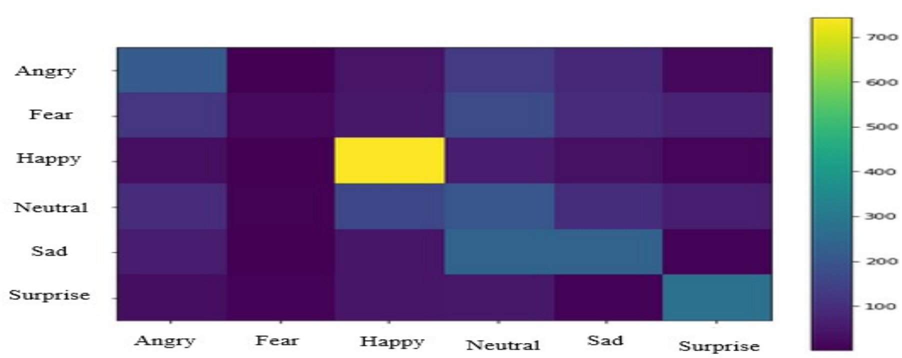


Figure-9: Trained model

Our system can detect all 6 classes emotion and we had good accuracy on Happy, Fear, Neutral, sad and Surprise but gives bad accuracy on angry emotion.

Data Collection: Data collection is divided into three consecutive phases as follows-

Data Collection for Training: To train our system, we used a total of 28000 data. Our intelligent system's training data was broken down into 6 categories. All of categories are described below with sample pictures:

a) Angry: some image samples are given below-

b) Fear: some image samples are given below-

c) Happy: some image samples are given below-

d) Neutral: some image samples are given below-

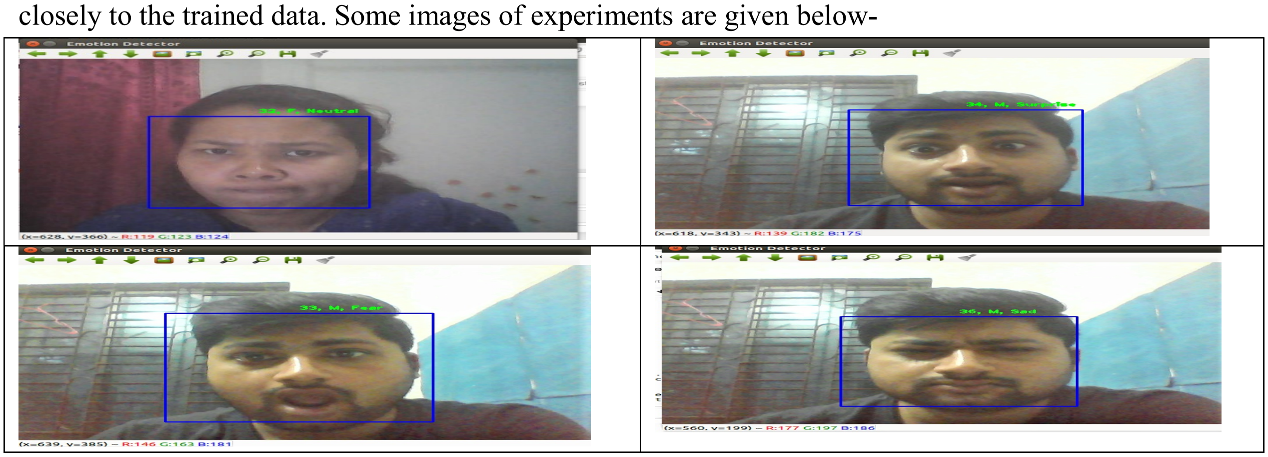
e) Sad: some image samples are given below-

f) Surprise: some image samples are given below-

Data Collection for Testing Age and Gender in Real Environment: Real data were collected from various locations in Bangladesh while our system was being tested. Both male and female engaged in the system's perfornance testing. The participants are aged 8 to 65 years old. The samples are given below:

Figure-10: Data Collection for testing age and gender

Data Collection for Testing Emotion Detection in Controlled Environment*:* For testing data in controlled environment, there were two participants. They were instruced to show different emotions which matches closely to the trained data. Some images of experiments are given below-



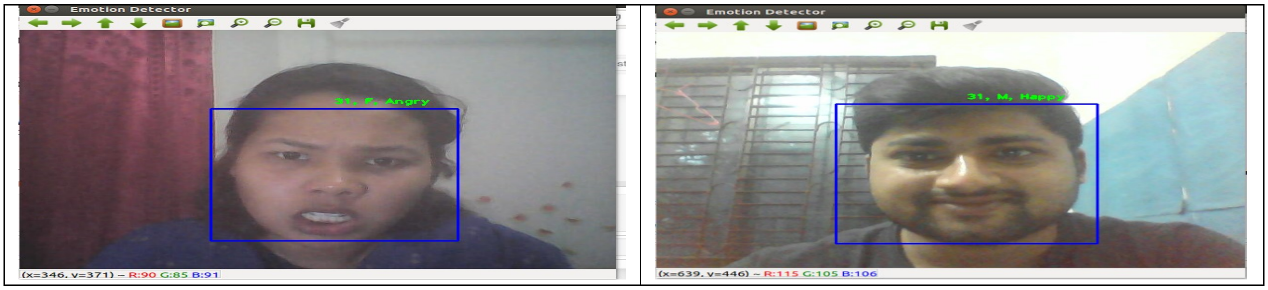


Figure-11: Data Collection for emotion detection

Result & Discussion: The formula to detect the suspicious body movement by means of canny edge detector is-

$$\textbf{Accuracy} = \frac{\text{Total number of body movement detected}}{\text{Total number of body movement occured}} \times 100\% \qquad (7)$$

Figure -12 explains the accuracy of canny edge detector for different times.

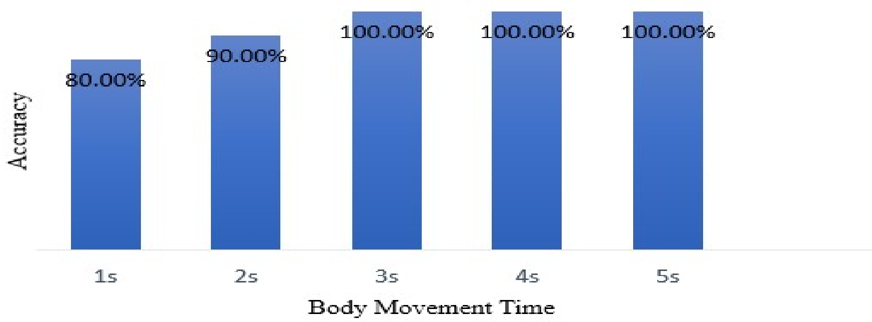


Figure -12: Accuracy of suspicious body movement detection (by canny edge detector)

We can say that our system can detect examinees' random movement with the help of canny edge detector with fair enough accuracy. Our intelligent system provides 100% accuracy, when the examinee takes 3, 4 and 5 seconds for a proper movement. It is seen that the accuracy of detection depends on the elapsed time. This is due to fact that, our low-cost camera needs some time for proper focusing if the object is in movement. Without proper focusing the captured frames results in improper data which degrades the overall performance.

The standard deviation, σ measures the spread of the data about the mean value. To measure the performance of gender detection, we have used bar diagram of standard deviation for each of the age classes which is described below-

Our intelligent system provides better detection accuracy for 21 to 35 and 36 to 50 age groups in real environments. The fact is that, a neural network requires a huge data set to be trained (in our case 28,000 data) properly. Collection of this huge dataset from the native Bangladeshi people is a tremendous hard job. So, we have trained the network with image mostly taken from foreigners and tested the effectiveness of the network with the locally taken images. Hence, we have obtained a degraded performance for the age group 8-20 and 51-65.

The confusion matrix is a useful visualization tool that provides analysis on the true negative, false positive, false negative and true positive made by our model. Beyond a simple accuracy metric, we should also look at the confusion matrix to show the accuracy of gender detection. Confusion matrix result is given below which clearly indicates the higher accuracy for detecting male:

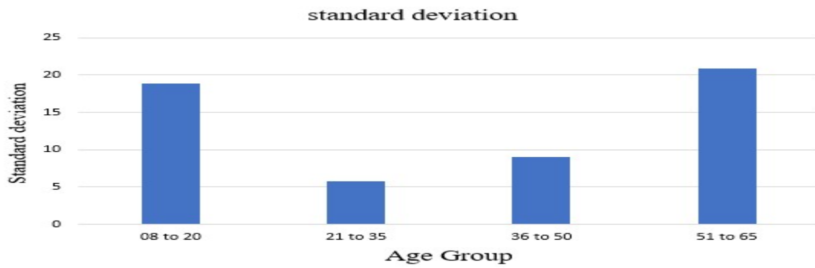


Figure-13: Standard deviation, σ for different age groups.

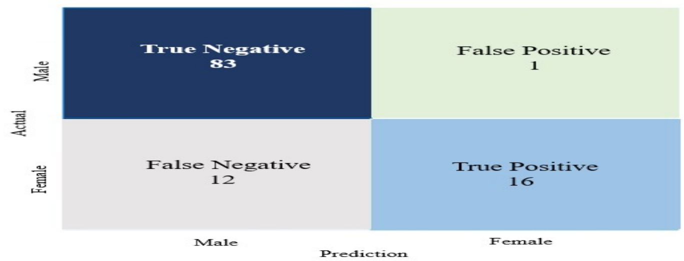


Figure-14: Performance of gender detection using Confusion Matrix

The accuracy for emotion detection is defined as follows-

$$\textbf{Accuracy} = \frac{\text{Total number of actual predection}}{\text{Total number of trial for a particular emotion}} \times 100\% \qquad (8)$$

Figure-15 describes the emotion detection accuracy of our intelligent system-

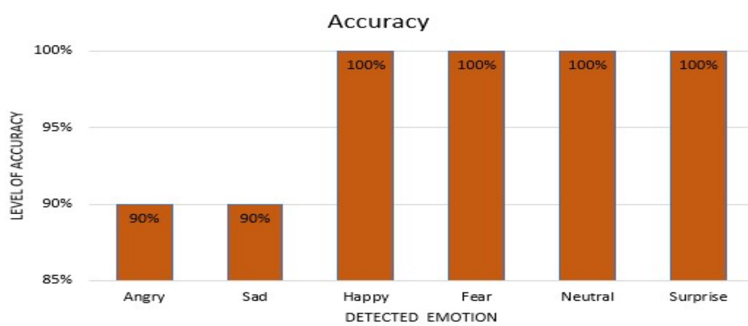


Figure-15: Emotion detection accuracy

While performing tests for emotion detection in controlled environment, our intelligent system can detect happy, fear, neutral and surprise perfectly and provide 100% accuracy. For the rest (angry, sad) the detection accuracy is 90%. The problem lies here is that, sometimes it becomes harder to distinguish among these emotion levels, even for a well-trained network because human emotion expression is not always well defined and it varies with man to man depending on his age, culture, customs, education, social status, economic backgrounds.

Conclusion: In this paper, an intelligent system has been proposed to detect examinees' suspicious behavior in smart class room. In this work, we considered moving edges to track examinee's suspicious movement detection for slow and fast movement and data extracted from face images to detect age, gender and emotion of the target student. We tested our proposed intelligent system effectiveness under controlled environments and as well as in real environments. In future, we would like to reduce the limitation of our intelligent system like focusing problem, data collection problem and also try to conduct experiment in real smart examination hall.

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