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Implementation of Invigilation System using Face Detection and Face Recognition Techniques. A Case Study

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Abstract

In recent years, face detection and face recognition techniques are improved sufficiently to make use in real-time applications and in crucial computer vision tasks. In this paper, the approaches that can use in real-time are discussed and implemented in a real-time application – Invigilation system. The web framework Django is used in designing the invigilation system and the database used is Mysql for storing the student and faculty data. The drawback of the traditional system is manual and failed to notify the wrong student attending the exam. This paper presents a method for automatic and optimised allotment into rooms and invigilators having face recognition for the student's correct prediction. Face detection is crucial for face recognition. To get the quick processing, an efficient, speed and accurate method was found by processing different images with various faces and found that the HOG method is best suited for processing a vast number of images. The face recognition model used in this paper has an accuracy of 99.38%, which is sufficient for proper identification. The cameras placed in the rooms can take the pictures and send them to the Django server. The server processes the images, the face detector extracts the faces from the image and the face recognizer compares them with the faces of the allotted from the database. The whole system can identify the wrong person and able to find the attendees list. In future, it can develop in identifying the malpractices by implementing the tracking algorithms.

Keywords: Computer vision, Face detection, Face Recognition, HoG, Haar Cascade, CNN, 128D embeddings extraction, Student allotment.

1. Introduction

Examinations are the traditional way to scrutinize the students. The three essential steps in Examination conduction are Allotment, Monitoring and Evaluation. The manual procedure of allotment takes more time, requires human resources, and the chance of faults is more. The automatic allotment[9] is very advantageous, which involves the proper distribution of students considering his/her year of study, branch etc., and easily feasible with present technology. The purpose of monitoring is authentication and supervision. The manual monitoring involves an invigilator for checking the student's hall ticket, id card etc. and paying continuous attentiveness for avoiding the malpractice. Computer vision developed a lot in recent days. The monitoring phase can be automated using computer vision techniques. Face detection and Face recognition can aid in successful authentication. But supervision involves many detection techniques like have a camera and active internet connection during the exam. It is not possible to observe the student's surroundings which makes it easier to commit malpractice. Hence, it is difficult to avoid cheating in webcam-based invigilation systems[8]. The last step of Examinations is Evaluation. Automatic evaluation is 100% success for the objective, but no best approach is found for subjective still. Some of the methods which use feature extraction[24] are achieved some success. The design of the software tool[13] for only a detecting the movement, whispering, face pose, abnormal behaviour, which are still under development. A candidate's movement can be detected by evaluating the difference between two successive frames and drawing contours. Open pose model can aid in detecting the pose. Abnormal behaviour can be estimated through emotion analysis. But the reliability of all these methods is not sufficient to use in the real-time. So avoiding an invigilator for monitoring is entirely not possible. But Remote proctoring can eliminate the invigilator's physical presence in the examination hall. Also, make it possible to conduct the examination for remote students which is unavoidable during situations like COVID. Online examinations are experienced by many threats. There were many possible ways of effectively confronting the attacks[15]. The usage of cryptographic technology[14] can aid in the security of online examinations. Invigilator, free fraudster detection system, is possible by the use of webcams [17]. The disadvantage of this system is every student must specific subject can aid in successful assessment. Overall the challenge of descriptive evaluation is still ON. Also eschewing invigilator during invigilations completely is not a good idea. But detecting the erroneous students is entirely possible with webcams through face recognition. The first step in face recognition is face detection. Many techniques were developed for efficient face detection. In knowledge-based face detection, certain rules like detection of eyes, nose at proper distances are framed and checked to identify a face. The practical implementation of such practices is difficult, and it gives many false positives. Compared to the knowledge-based method, the feature-based process is more successful, which is implemented by

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extracting the features of a face. Haar cascade method is an example of a feature-based method. Template matching method is the easiest way to implement. In this method, the frontal Face is predefined with a function but provides inadequate face detection results. Compared to all, the appearance-based method is the best-performed face detection method. It also used in face recognition. In this method, instead of defining a face template by experts, many training images are used for defining a face model and is achieved by applying Statistical analysis and Machine learning techniques. The popular methods for face detection are Haar Cascades[22], HoG and CNN[23].

2.1 Face detection using Haar cascades method

The face is said to be detected if the features of the face are found to be noticed. Haar cascade method perceives these features by Haar features or Haar wavelets. The face may be of any size and at any location in the image. Hence, the image is converted into different sized subwindows and all the Haar features are checked to match in the subwindow. One of the sub-window of Fig1 is shown in Fig 2. Since there were 1600+ Haar features, it takes more time for the detection process to complete. Hence, the most relevant features are checked first. To do this, all the Haar features are divided into different stages based on their priority. If it passes all the stages, then the face is found in that specific sub-window, illustrated in Fig 4. A single face would be detected by many subwindows as shown in Fig3. All the concentric subwindow detections are neglected and treated to be one face. All such subwindows are called neighbours. There will be false positives if only one such neighbour is considered. For example, in Fig 5, three false-positive faces are detected. For least minimum neighbours, the false positives are more, and for huge minimum neighbours, the face detection is not accurate. Hence the minimum neighbours selection is optimum to detect the exact faces present, which is illustrated in Figs 5,6 and 7.

2.2 Face detection using CNN

Dlib provides face detection using CNN, which is a deep neural network trained with millions of images. The stored, trained .dat model is loaded and used for face detection. This model can find even the odd faces that cannot detect with HoG and Haar cascades. But it is very slow with CPUs. Fig 8 illustrates the implementation of CNN based face detector.

Fig. 1. Full image

Fig. 2. Sub window

Fig. 3. All the sub windows which detects the face

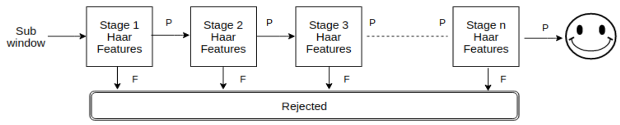


Fig. 4. Illustration of stages of Haar features for detecting the face in a subwindow

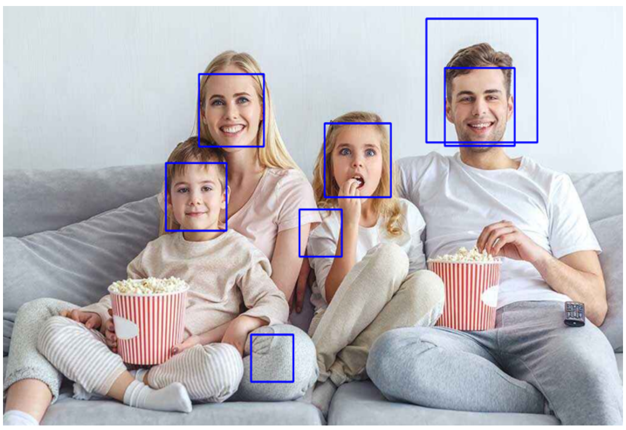


Fig .5. Minimum Neighbours – 1

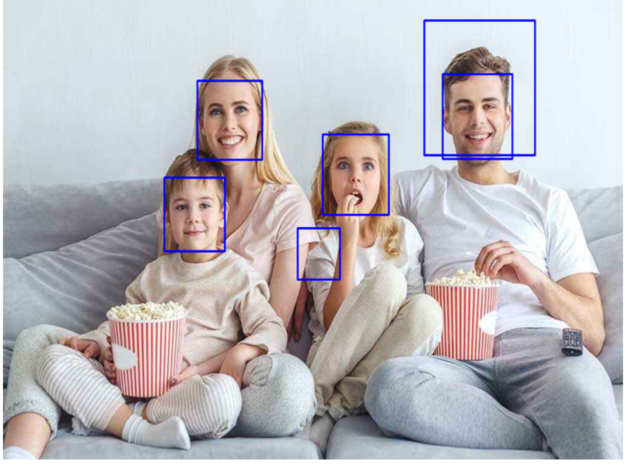


Fig. 6. Minimum Neighbours – 2

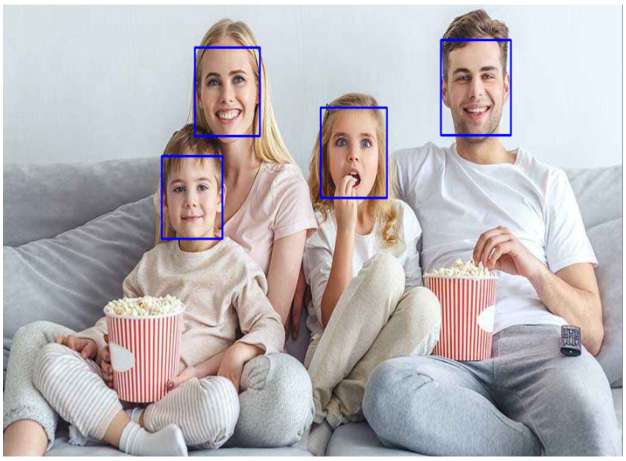


Fig. 7. Minimum Neighbours - 3

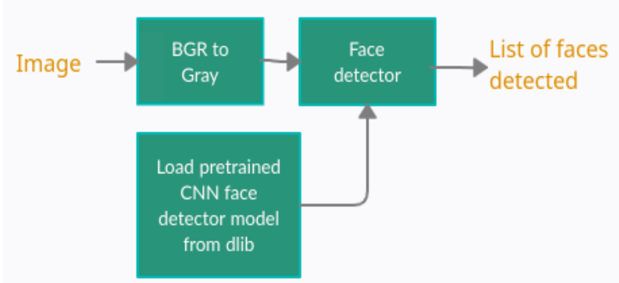


Fig. 8. Implementation of CNN face detector.

2.3 Face detection using Histogram of Oriented Gradients (HOG)

Gamma correction can enhance the image quality[25]. For gamma correction, the pixel intensities are scaled from [0 255] to [0 1].

The scaled output image is defined as (scaled input image)$^{1/g}$ and is rescaled in [0 255] to obtain the output image.

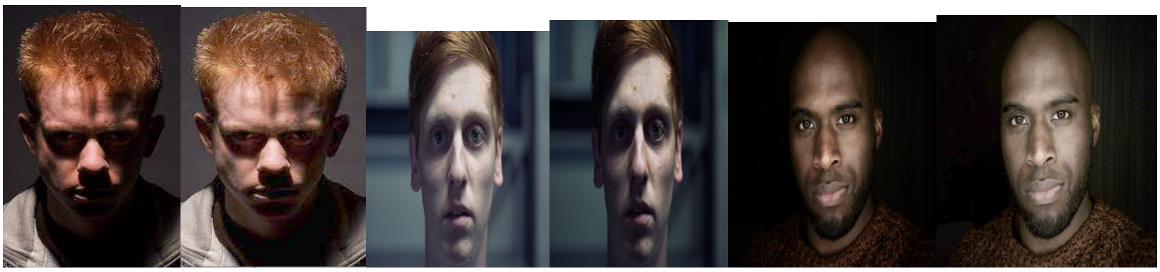
g= 1 ------> original
g<1 -------> Makes image darker
g>1 --------> Makes image lighter

The image at different values of g is illustrated in Fig 9. It is found that g=1.5 is good for most of the images. Fig10 illustrates the improvement in images when g=1.5.

Before proceeding with the HoG feature representation, the image is resized to 64x128 because the image is divided into 8x8 and 16x16 patches for extracting the features.

g=0.1 g=0.5 g=1(original)g=1.5 g=2 g=2.5 g=3

Fig. 9. Image enhancement at different gamma corrections



Before After Before After Before After

Fig. 10. Improvement in various images due to gamma correction (g=1.5)

HOG is a very useful image descriptor. HOG represents as a single vector for the entire image. It's computed by sliding window detector over an image and generate a HOG descriptor for each position in the image, and each position is combined with the single vector later on. The pyramiding technique is beneficial for generating this. HOG s are traditionally best used with SVM. By comparing the HOG patterns of the image with the HOG patterns from the trained data set, the faces in the image can be detected. The procedure of detecting the face is explained by using an algorithm ALG1.

ALG 1

1: Convert RGB to gray
2: Calculate the horizontal(HG) and vertical(VG) gradients.

3: Calculate the gradient magnitude $=\sqrt{VG^2 + HG^2}$ and gradient angle = $\tan^{-1}$(VG/HG)
4: Disintegrate the image into 16x16 pixels and replace the 16x16 pixels block with a gradient of resultant of gradient of each pixel of all the 16x16 pixels.
5: Plot the hog features of original image as in Fig 11, and compare it with the known HoG pattern (Fig 12) which is produced from the training images.

The face detector that uses HOG method detects the faces in the given image and extracts the images for identification as illustrated with the help of Fig 13 and 14.

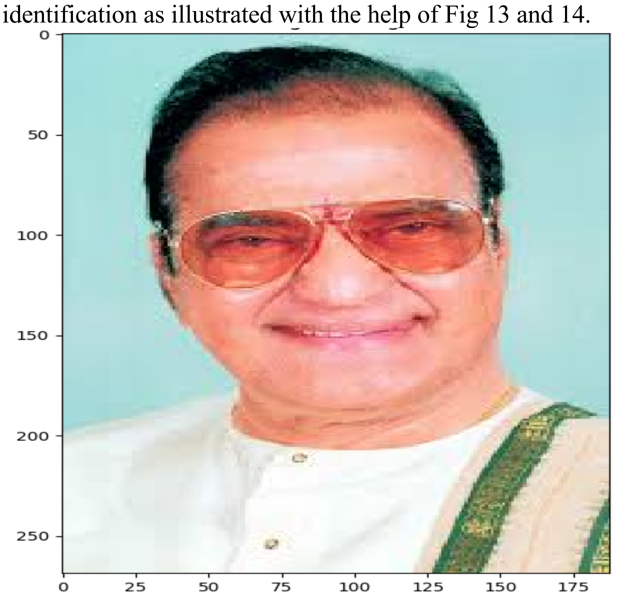
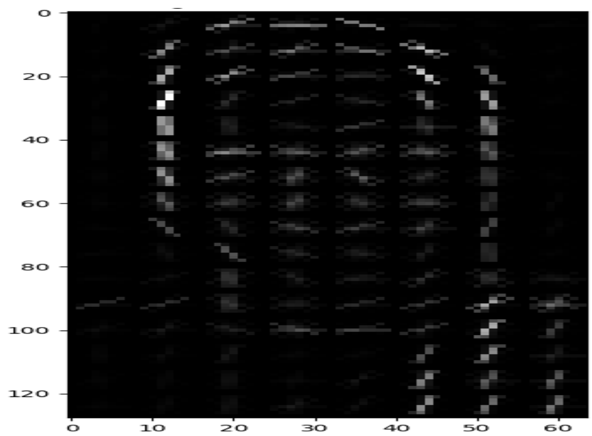


Fig. 11. Original Image and its HOG feature representation



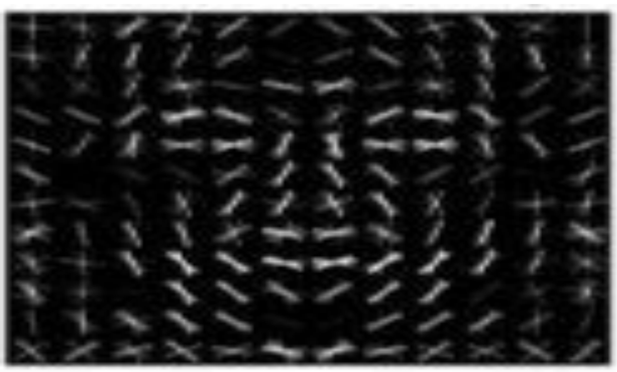


Fig. 12. HOG features extracted from training images

Fig. 13. Detection of faces using HOG method.

Fig. 14. Extracted faces of Fig 13 using HOG method.

3. Speed and Πerformance Comparison

The popular methods for face detection are Haar Cascades[22], HoG and CNN[23]. The speed of detecting the face is crucial as the images to be processed increases. To predict the faster method, Five categories of images having one, two, three, four and five faces are taken and calculated the speed of detection using these three methods which are illustrated in Figures 15-24. In Graphs CNN, HoG and Haar cascade methods' speeds are represented with yellow, Green, and Blue. From Figs 15 to 19, it is found that CNN is much slower compared to all. Since the time taken for CNN to detect face is very high compared to other methods, Figs 15 to 19 were not properly shown the speed differences of HOG and Haar Cascade methods. Hence, they were compared separately in Figs 20 to 24. The speeds are taken without considering the classifier loading time. The classifier loading time for Haar, HoG and CNN is 0.016, 0.317 and 0.075 seconds, respectively. For the given images the speeds without considering classifier loading times are between 0.007 and 0.19 for Haar, 0.069 and 3.14 for HoG and between 1.46 and 90.94 for CNN. Since classifier will be loaded only once, it only affects the first image's speed. Hence this effect is neglected. The fastest among all is Haar, followed by HoG and CNN. Haar and HoG methods don't use much CPU resources, but CNN affects speed of other running processes on the same CPU.

Even though Haar cascades method is faster, it requires the scale factor and minimum neighbours as inputs. For example, for Fig 24, the correct prediction of faces, the scale factor and minimum neighbours required is 1.2 and 3 (Table 1) but is not valid for all the cases. For example, for Fig 25, it is 1.11 and 3. So the chance of false detection is more in this method. Hence, interns of speed even though Haar is faster, HoG is best to use.

With the increase in faces in the image, the face detection time increases, which can't be shown with these graphs because of only 1 to 5 faces of image difference. To notice the difference, Consider Figs 25 and 26, the faces detected in Fig26 is 215 at 4.73 seconds and Fig 25 is 7 faces at 0.5 seconds by HoG method.

In order to predict the best performer in terms of accuracy and precision, 1015 images are considered. The TP, FN and accuracy values of these approaches are illustrated in Table2.It is found that CNN is best in terms of accuracy and sensitivity but consideration of speed makes it worse and It is found that HoG is best suited for real time applications when all the performance measures are take into the account.

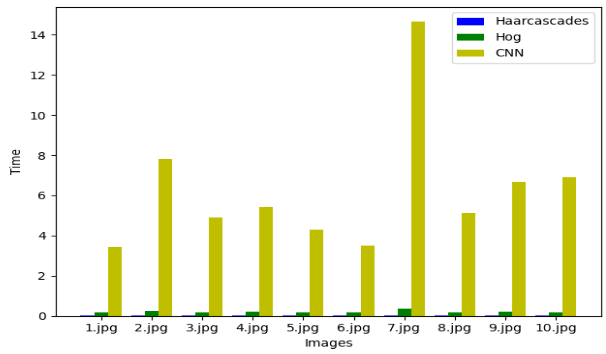


Fig. 15. Single face image comparison of all the methods

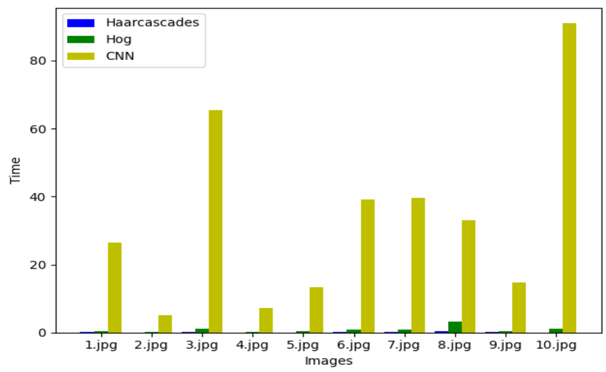


Fig. 16. Two face image comparison of all the methods

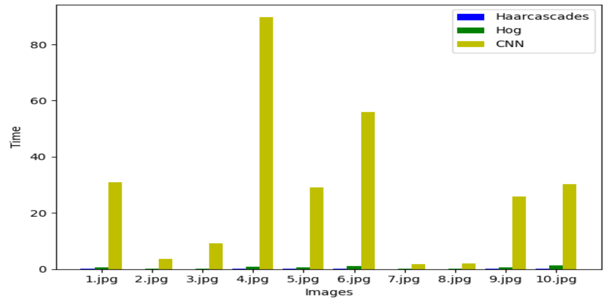


Fig. 17. Three Face image comparison of all the methods

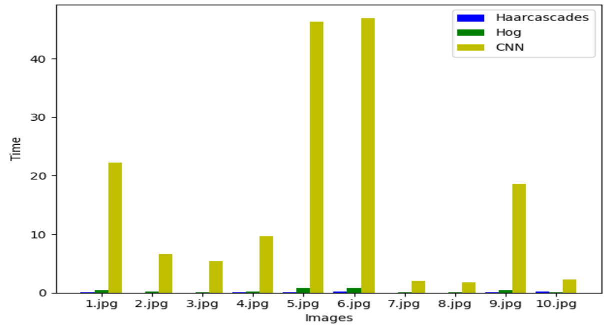


Fig. 18. Four Face image comparison of all the methods

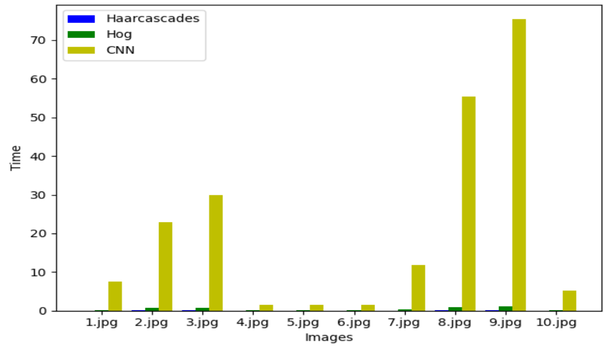


Fig. 19. Five Face image comparison of all the methods

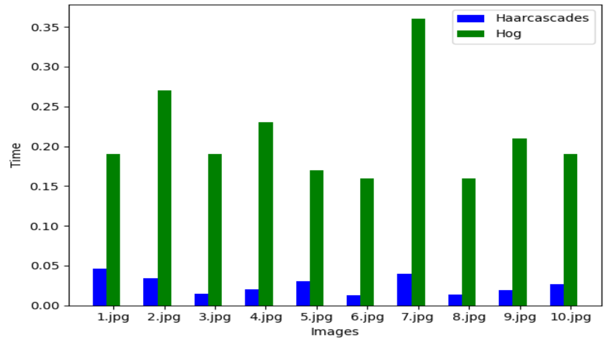


Fig. 20. Single face image comparison of Haar and Hog methods

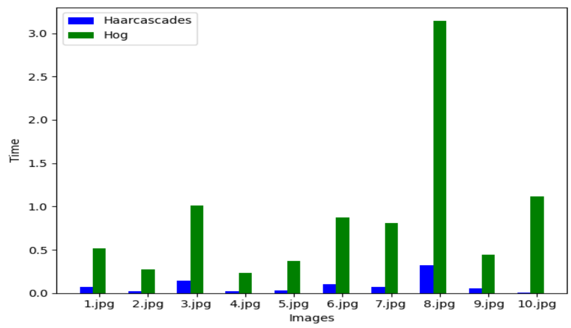


Fig. 21. Two face image comparison of Haar and Hog

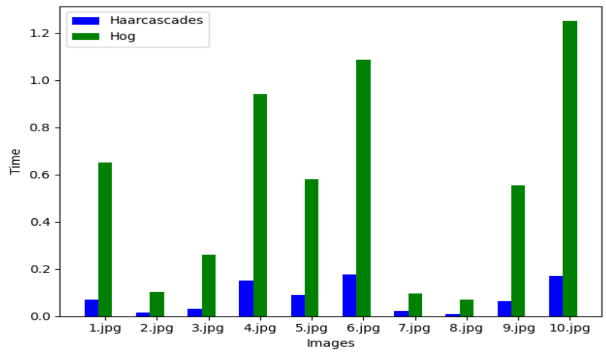


Fig. 22. Three face image comparison of Haar methods and Hog methods

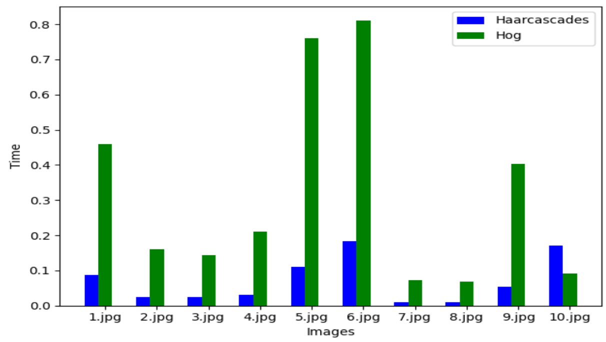


Fig. 23. Four Face image comparison of Haar and Hog

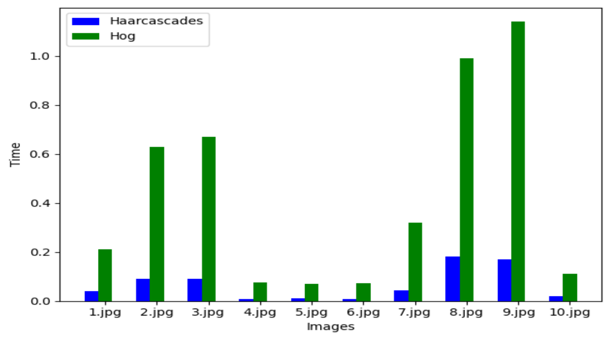


Fig. 24 .Five Face image comparison of Haar methods and Hog methods

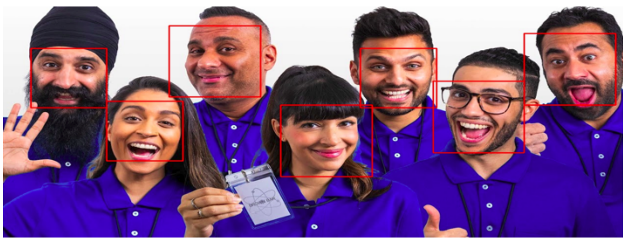


Fig. 25. Face detection for less images

Fig. 26. Face detection for huge number of images

Fig. 27. Image 1

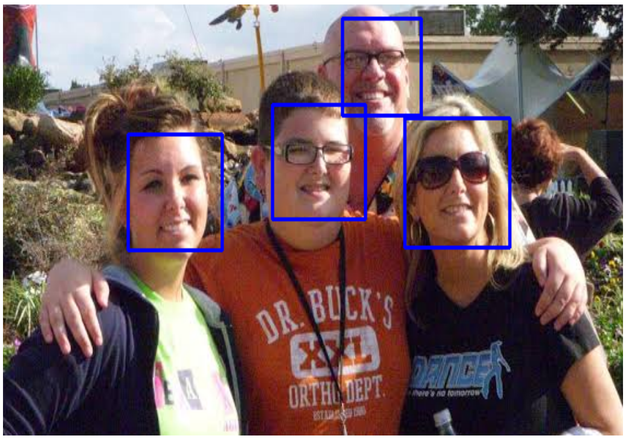


Fig. 28. Image 2

Table 1. Scale factor and Minimum Neighbours selection

Scale Factor	Minimum Neighbours	Faces detected for Fig 27	Faces detected for Fig 28
1.1	1	7	5
1.1	2	6	3
1.1	3	4	3
1.11	3	4	4
1.2	3	3	3

.

Table 2. TP, FN, Accuracy and Sensitivity values of face detection techniques.

Method	TP	FN	Accuracy	Sensitivity	Sensitivity
HoG	994	21	97.93	97.93	97.93
CNN	1013	2	99.8	99.8	99.8
Haar Cascade	874	141	86.1	86.1	86.1

4 Rotation of face

In order to identify the face recognizer more accurately. The extracted faces are rotated so that the eyes are in a straight line with mouth centred. The rotation of face is applied by identifying the 68 landmark points in the face, which is illustrated in Fig 29. The points 37 to 40 represents a right eye, 34 to 48 represents a left eye, and 49 to 61 represents the mouth. The centre of the image coordinates is half of extreme x and y coordinates of the image. The mouth is centred by shifting the average of 53 and 57 coordinates to centre coordinates and the eyes are straightened by making the y coordinates of 37,40,43 and 46 as same.

5 Face Recognition

There were different methods for face recognition[10]. [3] proposes a new descriptor for face recognition, [19] introduces IPCA-ICA algorithm for face recognition. Infrared based face recognition is best suited compared to the visible spectrum[4]. [16] proposes a method of face recognition based on Infrared. It isn't easy to recognize the face if the whole frontal face is not observed. By projecting 3D shape in a 2D plane, the face contour can be detected, which can help recognise the faces at different poses[6]. Even though the whole frontal face is not seen, the face can be recognized through the gait[21]. But expensive in 3D discourages in embedded applications. It is possible to detect the face at different poses without using 3D. The developments are made in the face technology under various illumination conditions[1] for indoor[2] too. [5] proposes a method for recognising the face at different ages. [20] proposes a method for face, with the addition of the tracking algorithm[11] can use in humanoid robots. One of the accurate methods for recognizing the face is by finding the 128D embeddings in a face using deep neural network and calculating the euclidean distance between them which is illustrated in Fig 30, and the same is used in this paper. presentation attack detection. After recognizing the

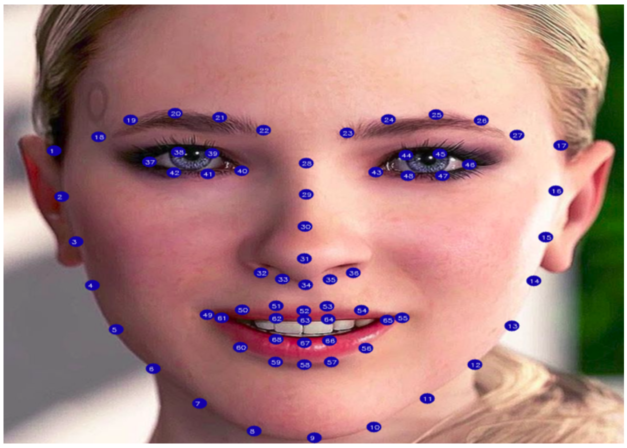


Fig 29. Representation of 68 landmarks on face.

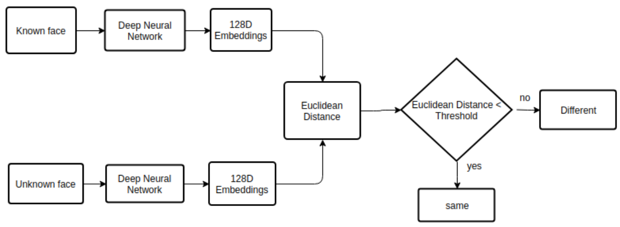


Fig. 30. Face Recognizer.

The deep neural network outputs a feature vector instead of the single label from the inputted image. The feature vector is 128 D embeddings which are illustrated in Fig 31. The neural network used is based on RESNET-34. Approximately 3,000,000 images are used for training the network. The training image sets consists of three image per set. Two are of the same face and the third is of a different face. The network is trained such that the embeddings are nearer for identical faces and far for the negative face. 99.38% is the accuracy achieved on the standard Label faces in the wild (LFW) benchmark. In LFW, a total of 1680 people having distinct images are present which are used for testing purposes. The Euclidean distance between the known and unknown images = $\sqrt{\sum_{i=1}^{128}(a_i-b_i)^2}$ and is compared with the given threshold and if the Euclidean distance is found to be less than the threshold. The face is said to be matched.

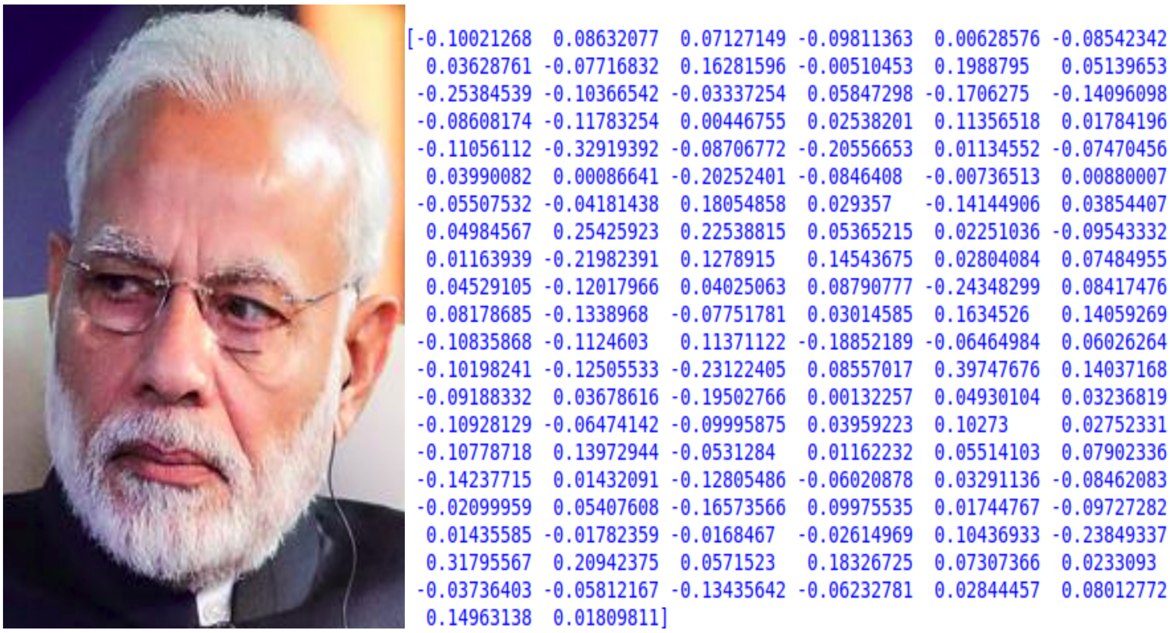


Fig. 31. 128D embeddings(RHS) of the image(LHS)

The performance measures that are used in [26] are used in estimating the performance of the face recognition technique. The confusion matrix is illustrated in Table 3 and the performance parameters used are:

Accuracy = (TP+TN)/Total
Sensitivity or Recall or True positive rate= TP/actual correctperson = TP/(FN+TP)
specificity or selectivity or True negative rate = TN/actual wrong person = TN/(TN+FP)
Precision= TP/predicted correct person = TP/(FP+TP)
f-score=2x(precisionxsensitivity)/(precision+sensitivi ty)

Total five celebrities(Emma Watson, Bill Gates, Obama, Shakira and Tom cruise) each of 100 images is used in analysing the performance. TP and TN values of each subject at different thresholds is illustrated in Table 4. The suffix letter (E-Emma Watson. B-Billgates, O-Obama, S-Shakira, T-TomCruise) represents the subject name. The values of FP and FN are Total-TP and Total-TN respectively.

The performance measures of each subject are illustrated with the help of Table 5,6,7,8 and 9. It is found that the f score and maximum accuracy achieved is at threshold 0.7 in the range of 97 to 99.5. The sensitivity increases and specificity decreases with an increase in the threshold. But at 0.7, the measure of positives identified correctly(sensitivity) and negatives identified correctly (specificity) is between 96 and 100 which is the best performance. Hence the threshold of 0.7 is used for face recognition.

Table 3. Confusion matrix of face recognition technique

Cofusion Matrix		**Predicted**	
		Wrong person	**Correct person**
Actual	Wrong person	TN	FP
	Correct person	FN	TP

TP–True Negative, TP–True Positive, FP-False Positive, FN–False Negative

Table 4. TP and TN at different thresholds.

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
TPE	0	0	0	0	8	56	91	99	100	100	100
TNE	100	100	100	100	100	100	100	96	85	37	3
TPB	0	1	6	6	11	65	96	100	100	100	100
TNB	100	100	100	100	100	100	100	97	81	53	16
TPO	1	1	1	5	39	79	97	99	100	100	100
TNO	100	100	100	100	100	100	100	100	86	46	6
TPS	0	0	0	0	26	78	97	100	100	100	100
TNS	100	100	100	100	100	99	99	96	80	43	5
TPT	0	0	0	1	10	53	95	100	100	100	100
TNT	100	100	100	100	100	100	100	99	75	46	15

Table 5. Emma Watson

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Accuracy	50	50	50	50	54	78	95.5	97.5	92.5	68.5	51.5
Sensitivity	0	0	0	0	8	56	91	99	100	100	100
Specificity	100	100	100	100	100	100	100	96	85	37	3
Precision	x	x	x	x	100	100	100	96	86	61	50
F Score	x	x	x	x	14	71	95	97	93	76	67

Table 6. Bill Gates

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Accuracy	50	50.5	53	53	55.5	82.5	98	98.5	90.5	76.5	58
Sensitivity	0	1	6	6	11	35	96	100	100	100	100
Specificity	100	100	100	100	100	100	100	97	81	53	16
Precision	x	100	100	100	100	100	100	97	84	68	54
F Score	x	1	11	11	19	78	97	98	91	80	70

Table 7. Obama

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Accuracy	50.5	50.5	50.5	52.5	69.5	89.5	98.5	99.5	93	73	53
Sensitivity	1	1	1	5	39	79	97	99	100	100	100
Specificity	100	100	100	100	100	100	100	100	86	46	6
Precision	100	100	100	100	100	100	100	100	87	64	51
F Score	1	1	1	9	56	89	98	99	93	78	68

Table 8. Shakira

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Accuracy	50	50	50	50	63	89	98	98	98	71.5	52.5
Sensitivity	0	0	0	0	26	78	97	100	100	100	100
Specificity	100	100	100	100	100	99	99	96	80	43	5
Precision	x	x	x	x	100	98	98	96	83	63	51
F Score	x	x	x	x	41	87	97	98	90	77	67

Table 9. Tom Cruise

Threshold	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Accuracy	50	50	50	50.5	55	76.5	97.5	99.5	87.5	73	57.5
Sensitivity	0	0	0	1	10	53	95	100	100	100	100
Specificity	100	100	100	100	100	100	100	99	75	46	15
Precision	x	x	x	100	100	100	100	99	80	64	54
F Score	x	x	x	1	18	69	97	99	89	78	70

6. Procedure of Allotment

Django is used for storing the students and faculty data and for the procedure of allotment. It is an open-source web application framework which can even run in single board computers for applications like bicycle care[12]. In [7], the database data is communicated with SQL. It is difficult for the programmer to learn one language for website maintenance and other for database related queries. Hence Django is used, in which database queries can be managed with python instead of using SQL. Also, it is easy to change from one database to other without any code changes. Some of the databases that are supported by Django are sqlite, mysql, postgress etc.,. The Rooms data is stored in the database as rows and columns with the Room Name. Students data as student name, Roll number, branch, year, section and photo. Similarly, the faculty data is stored in the database with his name, designation and branch with an image.

Students are allotted into the exam halls following the algorithm ALG2. For efficient allocation, the sections having the highest students is allocated first. Care is taken to prevent students belong to the same section come back to back or side by side or diagonal.

ALG2

Step1: Total seats count $k = \Sigma_{i=1}^{n} (R_i \text{ X } C_i)$. Where, n is the total number of rooms, R_i and C_i are the number of rows and columns of the i^{th} room respectively. Check whether students count>k . if true, print error message and exit, else proceed with step2.

Step2: s be the students data as the combination of year and branch in descending order of the combination count. Let the combination be c. s1,s2,s3 and s4 ∈ s are the selectors. And each selector consists of one of c's list which is not allotted. An offset say o is maintained for s to find upto which combination, the allocation is completed.

Step3: Select the first room.

Step4: If the selected room's rows are the multiples of three then fill the rows and columns of room with students in selectors as

if $R_{(i-1)(jmax)} = s_p$ then

$R_{ij} = s_p$ if j=4n where n=1,2,3, ---

s_{p+1} (for p+1<5) or s_{p-3} if j=4n-3

s_{p+2} (for p+1<5) or s_{p-2} if j=4n-2

s_{p+3} (for p+1<5) or s_{p-1} if j=4n-1

else if not the multiples of three, follow the below combination by taking three selectors

if $R_{(i-1)(jmax)} = s_p$ then

$R_{ij} = s_p$ if j=3n where n=1,2,3, ---

s_{p+1} (for p+1<5) or s_{p-2} if j=3n-2

s_{p+2} (for p+1<5) or s_{p-1} if j=3n-1

where p is 1 or 2 or 3 or 4, jmax is the maximum number of columns in the room.

The student data is removed from a selector once it was allotted. If a selector is empty, it is filled with c's list from s and o is improved by 1.

Step 5: If at least one student ∈ s is not allotted by the end of total seats filled in the room. Select the next Room and repeat step 4. Store all the room names which are used for allotment in a list say r and exit if all the students are allotted.

Similarly, invigilators are allotted for the students occupied rooms as per the algorithm ALG3.

ALG 3

Step 1 : Total number of invigilators needed is $T_i = \frac{1}{30}\Sigma_{i=1}^{n} (R_i \text{ X } C_i)$. Check $T_i < T$ where T is the total faculty. If true proceed with step 2 else exit with an error message.

Step 2 : Initialize an offset say fi to track the faculty and select the first room from r.

Step 3 : Number of faculty needed for a room $rf = \frac{1}{30}(RxC)$. Allot the faculty of T from fi to fi+rf and update fi value with fi+rf .

Step 4 : Check whether all the rooms are allotted. If yes, exit. Else select next room and repeat from step 3.

7 Results and discussion

The students data that used is Mechanical the third year from Roll no. 171FME101 to 171FME167, EEE third year from Roll no. 171FME101 to 171FME159, CSE third year from Roll no. 171FCS101 to 171FCS160, CSE second year from Roll no. 181FCS201 to 181FCS253, ECE first year from Roll no. 191FEC101 to 191FEC162,ECE second year from Roll no. 181FEC201 to 181FEC260,ECE third year from Roll no. 171FEC301 to 171FEC359 and the rooms taken are RM1 of 5x4 where 5 is rows and 4 is columns whose total strength is 5x4=20, RM2 of 6x7, RM3 of 9x9, RM4 of 7x7, RM5 of 6x4, RM6 of 7x9, RM of 6x4, RM8 of 9x8, RM9 of 7x9. The Rooms allotment as per the specified algorithm, seating allotment and the invigilator allotment are presented in Fig 32,33 and 34 respectively. The camera placed inside each room takes pics continuously and send to the server. The server detects the faces using the face detector and separates all the faces separately. The last step is the identification, each face separated is compared with the each of roll number's photo that is allotted in that room. If matches then that person is marked as present and this process continues for the first hour of the examination and stores the final attendance after half an hour.

Rooms Allotment

Room Name :Rm1

171FME101	181FEC202	191FEC104	171FME106
191FEC101	171FME103	181FEC204	191FEC106
181FEC201	191FEC103	171FME105	181FEC206
171FME102	181FEC203	191FEC105	171FME107
191FEC102	171FME104	181FEC205	191FEC107

Room Name :Rm2

181FEC207	171FME109	181FEC210	171FME112	181FEC213	171FME115	181FEC216
171FCS101	191FEC109	171FCS104	191FEC112	171FCS107	191FEC115	171FCS110
171FME108	181FEC209	171FME111	181FEC212	171FME114	181FEC215	171FME117
191FEC108	171FCS103	191FEC111	171FCS106	191FEC114	171FCS109	191FEC117
181FEC208	171FME110	181FEC211	171FME113	181FEC214	171FME116	181FEC217
171FCS102	191FEC110	171FCS105	191FEC113	171FCS108	191FEC116	171FCS111

Room Name :Rm3

171FME118	191FEC120	181FEC222	171FCS118	171FME127	191FEC129	181FEC231	171FCS127	171FME136
191FEC118	181FEC220	171FCS116	171FME125	191FEC127	181FEC229	171FCS125	171FME134	191FEC136
181FEC218	171FCS114	171FME123	191FEC125	181FEC227	171FCS123	171FME132	191FEC134	181FEC236
171FCS112	171FME121	191FEC123	181FEC225	171FCS121	171FME130	191FEC132	181FEC234	171FCS130
171FME119	191FEC121	181FEC223	171FCS119	171FME128	191FEC130	181FEC232	171FCS128	171FME137
191FEC119	181FEC221	171FCS117	171FME126	191FEC128	181FEC230	171FCS126	171FME135	191FEC137
181FEC219	171FCS115	171FME124	191FEC126	181FEC228	171FCS124	171FME133	191FEC135	181FEC237
171FCS113	171FME122	191FEC124	181FEC226	171FCS122	171FME131	191FEC133	181FEC235	171FCS131
171FME120	191FEC122	181FEC224	171FCS120	171FME129	191FEC131	181FEC233	171FCS129	171FME138

Room Name :Rm4

191FEC138	181FEC240	171FME143	191FEC145	181FEC247	171FME150	191FEC152
181FEC238	171FME141	191FEC143	181FEC245	171FME148	191FEC150	181FEC252
171FME139	191FEC141	181FEC243	171FME146	191FEC148	181FEC250	171FME153
191FEC139	181FEC241	171FME144	191FEC146	181FEC248	171FME151	191FEC153
181FEC239	171FME142	191FEC144	181FEC246	171FME149	191FEC151	181FEC253
171FME140	191FEC142	181FEC244	171FME147	191FEC149	181FEC251	171FME154
191FEC140	181FEC242	171FME145	191FEC147	181FEC249	171FME152	191FEC154

Room Name :Rm5

181FEC254	171FME156	181FEC257	171FME159
171FCS132	191FEC156	171FCS135	191FEC159
171FME155	181FEC256	171FME158	181FEC259
191FEC155	171FCS134	191FEC158	171FCS137
181FEC255	171FME157	181FEC258	171FME160
171FCS133	191FEC157	171FCS136	191FEC160

Room Name :Rm6

181FEC260	171FME163	171FEC303	171FEC305	181FCS203	171FCS141	171FEE112	171FEC312	181FCS210
171FME161	171FEC301	171FEE105	171FEE107	171FEC307	181FCS205	171FCS143	171FEE114	171FEC314
191FEC161	171FEE103	171FME166	171FCS138	171FEE109	171FEC309	181FCS207	171FCS145	171FEE116
171FEE101	171FME164	171FEC304	181FCS202	171FCS140	171FEE111	171FEC311	181FCS209	171FCS147
171FME162	171FEC302	171FEE106	171FEC306	181FCS204	171FCS142	171FEE113	171FEC313	181FCS211
191FEC162	171FEE104	171FME167	171FEE108	171FEC308	181FCS206	171FCS144	171FEE115	171FEC315
171FEE102	171FME165	181FCS201	171FCS139	171FEE110	171FEC310	181FCS208	171FCS146	171FEE117

Room Name :Rm7

171FCS148	171FEC317	171FCS151	171FEC320
181FCS212	171FEE119	181FCS215	171FEE122
171FEC316	171FCS150	171FEC319	171FCS153
171FEE118	181FCS214	171FEE121	181FCS217
171FCS149	171FEC318	171FCS152	171FEC321
181FCS213	171FEE120	181FCS216	171FEE123

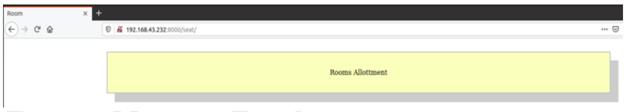
Room Name :Rm8

171FCS154	181FCS220	171FEC326	171FEE130	171FEE133	171FEE136	171FEE139	171FEE142
181FCS218	171FEC324	171FEE128	181FCS225	181FCS228	181FCS231	181FCS234	181FCS237
171FEC322	171FEE126	171FCS159	171FEC329	171FEC332	171FEC335	171FEC338	171FEC341
171FEE124	171FCS157	181FCS223	171FEE131	171FEE134	171FEE137	171FEE140	171FEE143
171FCS155	181FCS221	171FEC327	181FCS226	181FCS229	181FCS232	181FCS235	181FCS238
181FCS219	171FEC325	171FEE129	171FEC330	171FEC333	171FEC336	171FEC339	171FEC342
171FEC323	171FEE127	171FCS160	171FEE132	171FEE135	171FEE138	171FEE141	171FEE144
171FEE125	171FCS158	181FCS224	181FCS227	181FCS230	181FCS233	181FCS236	181FCS239
171FCS156	181FCS222	171FEC328	171FEC331	171FEC334	171FEC337	171FEC340	171FEC343

Room Name :Rm9

171FEE145	181FCS242	171FEC348	171FEE152	181FCS249	171FEC355	171FEE159
181FCS240	171FEC346	171FEE150	181FCS247	171FEC353	171FEE157	171FEC358
171FEC344	171FEE148	181FCS245	171FEC351	171FEE155	181FCS252	171FEC359
171FEE146	181FCS243	171FEC349	171FEE153	181FCS250	171FEC356	
181FCS241	171FEC347	171FEE151	181FCS248	171FEC354	171FEE158	
171FEC345	171FEE149	181FCS246	171FEC352	171FEE156	181FCS253	
171FEE147	181FCS244	171FEC350	171FEE154	181FCS251	171FEC357	

Fig 32. Rooms Allotment



Room Name :Rm1

171FME101 - 171FME107
191FEC101 - 191FEC107
181FEC201 - 181FEC206

Room Name :Rm2

171FME108 - 171FME117
191FEC108 - 191FEC117
181FEC207 - 181FEC217
171FCS101 - 171FCS111

Room Name :Rm3

171FME118 - 171FME138
191FEC118 - 191FEC137
181FEC218 - 181FEC237
171FCS112 - 171FCS131

Room Name :Rm4

171FME139 - 171FME154
191FEC138 - 191FEC154
181FEC238 - 181FEC253

Room Name :Rm5

171FME155 - 171FME160
191FEC155 - 191FEC160
181FEC254 - 181FEC259
171FCS132 - 171FCS137

Room Name :Rm6

171FME161 - 171FME167
191FEC161 - 191FEC162
181FEC260 - 181FEC260
171FEE101 - 171FEE117
171FEC301 - 171FEC315
181FCS201 - 181FCS211
171FCS138 - 171FCS147

Room Name :Rm7

171FEE118 - 171FEE123
171FEC316 - 171FEC321
181FCS212 - 181FCS217
171FCS148 - 171FCS153

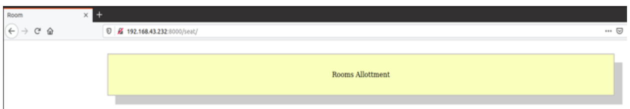
Room Name :Rm8

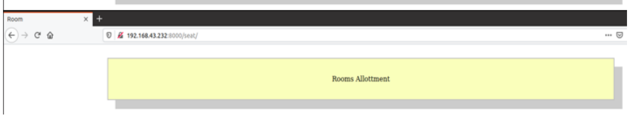
171FEE124 - 171FEE144
171FEC322 - 171FEC343
181FCS218 - 181FCS239
171FCS154 - 171FCS160

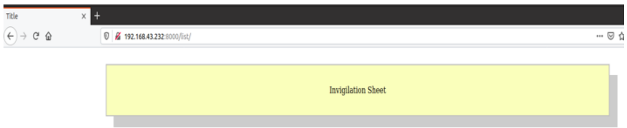
Room Name :Rm9

171FEE145 - 171FEE159
171FEC344 - 171FEC359
181FCS240 - 181FCS253

Fig. 33. Seating plan







Room Name	Name of the Invigilator	Signature
Rm1	Mounika	
Rm2	Manju	
	Munith	
Rm3	Mahesh	
	Hamsamuni	
	Susmita	
Rm4	Muneesh	
	Rajesh	
Rm5	Karthik	
Rm6	Jeevan	
	Soundarya	
	Aswini	
Rm7	Neelambari	
Rm8	Jyothi	
	Siva	
	Eswar	
Rm9	Priya	
	Feroz	
	Syed	

Fig 34. Invigilator Allotment

8. Conclusion

All the academic seminaries are appraising the mastery of students through tests or Examinations. Devising the students and invigilators into the examination halls are the part of proper conduction of Examinations. The number of invigilators in the examination hall depends on the number of students. The number of students depends on the seating capacity of the room. Available rooms are presented for a few section students having different examinations. The algorithm automatically picks the rooms and students and successfully allot so that no student of the same section are side by side or back to back or diagonal in all cases except for the last room. The camera placed inside the rooms take the pictures and sent to the server continuously. The Django server identifies the images of the specific room. The next step is to process the images for validation of students. The best face detector is needed for finding the faces. The face detector must have the capability to find the faces at speed and have very good accuracy. The three best-performed face detectors are chosen, which are Haar Cascade, HoG and CNN. It is found from speed analysis that CNN is too slow to use with CPUs. In terms of speed, Haar method is best, but it gives more false positives. Hence the HoG method is chosen for face detection. For recognising the faces, the faces from face detector are matched with stored faces in the database. The face recognizer matches the face by finding the Euclidean distance of their 128D embeddings and comparing with the threshold. The face recognizer can recognize the faces with 99.38% accuracy. Hence, achieved great success in predicting the right student for the right room.

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