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# DETECTING AUTISM OF EXAMINEE IN AUTOMATED ONLINE PROCTORING USING EYE-TRACKING

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**ABSTRACT**

The purpose of this study is to alert the proctor in the automated Online Proctoring about the autistic examinee to closely monitor them. The existing studies have detected the autistic behaviour using MRI scan reports. In our work, the autistic behavior is captured through eye-tracking by generating heatmaps using hourglass modules. Eye movements of the examinee are recorded by calculating pith, yaw and roll angles on heatmaps generated by hourglass. Eye movements were tracked while they look for the information on the web pages. Eye movements data is used to train machine learning classifiers to detect the condition.. The autistic behavior is detected by using different gaze based tasks like search task, browse task and synthesis task. Experiments have also shown that eye-tracking data can be used for automatic detection of autistic examinee with the accuracy of 0.73. Results have proven that automated online proctoring system performs better with detecting autistic behaviour by using eye tracking without using MRI images.
**Keywords:** *Autism Detection, Gaze Tracking, Web, Automated Online Proctoring*

## 1. INTRODUCTION

Automated Online Proctoring has been the prominent proctoring system for live monitoring of the students and secures tracking of the system and other necessary verification. Unlike human proctoring systems, automated online proctoring system is a remote monitoring system that uses advanced, secure, and reliable Artificial Intelligence (AI) techniques to examine the examinees. Automated Online Proctoring has been a long-standing research topic due to the latest pandemic situation of COVID-19. In the past decade, the study on Automated Online Proctoring has become popular with increased interest in online learning globally [1]. Many disorders like Autism Spectrum Disorder (ASD) affects the functionality of normal Proctoring system as people on the spectrum have a typical sensory processing and attention shifting patterns.

To overcome these type of issues, Automated Proctoring systems can detect the autistic people after examinee verification and alert the proctor so that proctor can closely monitor them. Basically, The ASD diagnostic procedure is highly subjective assessment process which is restricted to historical, behavioral, and parent-report information [2] [3]. It would be beneficial to develop a detection method for identifying high functioning autism based on the features extracted for the examinee verification.

In this paper, we present an Automated Online Proctoring System which captures autism behavior after the examinee verification and before detecting other malpractice behavior. This approach is based on the idea that the eye-gaze tracking system captures differences in the two sets while performing information searching tasks. Then, these differences are used to train a machine learning classifier to detect the autistic people to alert proctor.

In this work, our Automated Online Proctoring System is proposed with the following objectives:

- Examinee verification system using Inception-Resnet v1 blocks.
- Usage of Hour-Glass models to track the eye gaze movement.
- Classification of two cognitive profiles in performing information searching tasks.

Further sections of the paper include chapter 2 with literature survey of the Autism detection and Automated Proctoring Systems, chapter 3 with Methodology and chapter 4 with experimental and results discussion.

## 2. LITERATURE SURVEY

### 2.1 Automated Online Proctoring

Firstly, Proctoring System has been evolved from various stages like No Proctoring, Manual Proctoring, Semi Automated Proctoring and Fully Automated

Proctoring. Online exams were conducted using different control Procedures to avoid the mal practices in the No Proctoring system as said by Authors[4]. Well Trained Proctors were recruited to continuously monitor examinee and verify the exam status in Manual proctoring [5]. Whereas in Semi-Automated Proctoring systems, Robots [6] and $360^0$ Camera were used to get the complete view of the examinee surroundings which can be used by the proctor to monitor the exam. This method requires costly equipment which may not be affordable by all the institutions. Finally, in Fully Automated Proctoring Systems [7], AI techniques were used in Face Verification, Eye-Gaze Estimation, Head Pose Estimation, Gadget Detection and Mouth-Open Detection to alert the proctor in case of any malpractice behavior. Authors [8] have used the SVM Classifier over Speech detection, user verification, text detection and gadget detection. Whereas authors [9] used Mouth Open Detection instead of speech detection to reduce the resources cost. Also, Authors have implemented Head Pose estimation and gadget detection along with face detection. But these systems didn't implement face verification. Later, Authors [10] have implemented examinee verification using Proctor Net along with the other functionalities like Head Pose Estimation, Eye-gaze Estimation, Mouth Open Detection and Mobile Detection. But, in all these methodologies, authors did not consider any disorders and monitored all the groups of examinees in similar manner.

### 2.2 Face Verification

Face Verification is the key functionality of the Automated Online Proctoring system. Before system detects malpractices of the examinee, system must verify the examinee. Authors [11] integrated Scale-invariant feature transform (SIFT) and Speeded up Robust Features (SURF) descriptors to recognize the 2D – human faces. Authors have used two classifiers i.e., decision tree and random forest. But authors[12] have claimed more accuracy with few samples. Authors [13] have used Open CV for detecting and recognizing faces. The Open CV does not perform well for occluded faces and low-resolution faces. Massoli et al. [14] recognized faces using Cross-resolution learning. Authors of [15] used Deep Neural Network for Human Face Recognition. Authors [16] have addressed the open set face recognition where research is very weak and needs more attention. Multi-Task Cascade Neural Network (MTCNN) algorithm is used [17] for face detection in the field of crime detection. But, MTCNN is very robust and accurate when compared to other models but, it works slowly. As, the accuracy is more important to the Online Proctoring application, MTCNN is considered as the backbone for the Face detection and recognition model.

### 2.3 Eye-Gaze Tracking

Automated Online Proctoring System must locate the iris using the features extracted to track the eye-movement after examinee verification. A statistical approach for tracking the eye-movement is to find the correspondence between corneal motion and screen space motion which is further used to Gaussian Process Regression Models as proposed by authors [18]. Authors in [19] combined both supervised and un-supervised methods to track the eye-gaze. Supervised method is used to locate the eye- region and unsupervised method is used to compute the iris center. Whereas Authors [20] implemented dual coordinate system of deep learning to locate the face using first coordinate system and to estimate gaze using second coordinate. The second coordinate uses YOLO v3 package which doesn't predict absolute coordinates of the center of the bounding box. Authors [21] have implemented appearance-based methods for in the context of person-independent and gives detected landmarks as input to iterative-model fitting. Stacked Hourglass network which are like the auto-encoders are used in appearance-based methods. Hourglass module down samples the features first and up samples the features to generate heatmap. As appearance-based methods works efficiently for unconstrained settings, Hourglass module is used as base model for generating eye features using heat maps to track the eye-gaze.

### 2.4 Autism Detection

Autism detection in automated proctoring plays a key role as monitoring of autistic people is different from the other cognitive group. Authors [22] have used functional MRI data on which machine learning algorithms were implemented to detect the autistic people. Ibrahim et al [23] had used Discrete Wavelet Transform (DWT) for pre-processing the electroencephalography (EEG) signals for feature extraction and classification techniques. Two non-linear methods like Shannon entropy and largest Lyapunov exponent measures complexity and chaoticity of EEG recording are used. But EEG signals are not generated in our Online Proctoring System. Authors [24] used different machine learning classifiers on Rs-fMRI Scans to diagnose the autism spectrum disorder (ASD). As per authors, this method falls short of biomarker standards. So, Autism detection based on the gaze methods is considered as backbone for this work.

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## 3. PROPOSED METHODOLOGY

Prior to starting with autism detection, live video of the remote examinee is processed for the frame's extraction and examinee verification. The entire flow of the proposed model is as described in the Figure 1. From the Figure 1, it is observed that, all the frames of the live video of remote examinee are processed instead of the key frames. Processing of only key frames as in [25]–[27] may skip some of the malpractice behaviors which affects the performance the system. Further, in step 3, each frame is examined for verifying the examinee using Proctor Net which uses the inception-resnet v1 blocks as the backbone. If examinee identity is verified, then system moves forward to step 4 to detect the autistic examinee and alert proctor for special monitoring. Autistic behavior of the examinee can be detected by tracking the eye movement of the examinee for answering the specially framed questions visualized on the web pages. The Automated proctoring system continues with step 5 for detecting various mal practices using head pose estimation, eye-gaze tracking and mouth open detection using various AI methods. The working of each module is elaborated in further sections.

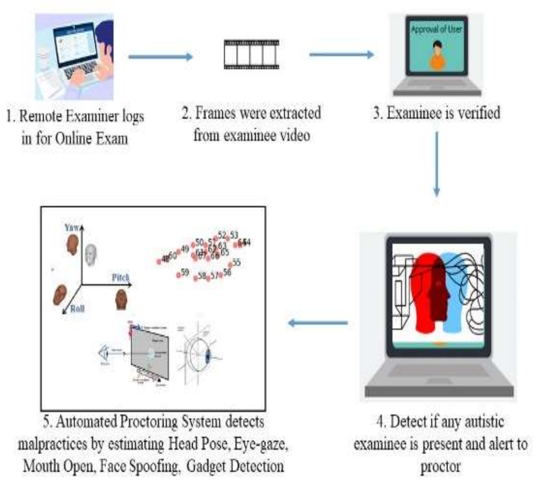


*Figure 1: Architecture of Proposed Methodology.*

### 3.1 Examinee Verification

Examinee verification is the process of matching the identity of the examinee in live video to the identity of the registered examinee. Each frame of the live video is processed to detect faces using a Multitask cascaded Convolution Neural Network (MTCNN) [28]. MTCNN passes image pyramid through three stages namely, Proposal Network (P-Net), Refine Network (R-Net) and Output Network (O-Net) as shown in Figure 2. Each stage feeds scaled images to gather outputs. Bounding boxes with low confidence were deleted in gathered outputs using non-maximum suppression. Further, all the bounding box and facial landmark coordinates were converted to unscaled image coordinates. The image pyramid employed by the MTCNN enhances detection of both small and big faces. MTCNN uses the stride 2 to reduce the number of operations to the quarter of the original. Each stage fine tunes the results of the previous stage.

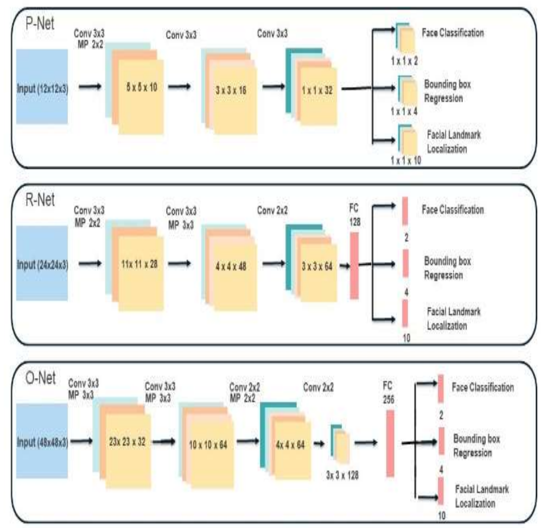


*Figure 2: Architecture of MTCNN*

Inception – Resnet based deep convolution network along with triplet loss is used for the examinee verification. 160 x 160 x 3 size face images detected by the MTCNN are given as input to the Proctor Net. Proctor Net maps these high dimensional faces to the low-dimensional 128 numbered embedded vector which represents different features of the face. The face embeddings generated are used to match the examinee face with registered face. The training of Proctor Net is done using triplet loss as shown in Figure. 3. Triplet Loss starts with selecting anchor image of a person. Along with anchor image, a positive example and negative example of the same person are selected. Considering these samples for training, parameters of the proctor Net are adjusted to make positive example closer to anchor than the negative example. This process is repeated till all the positive samples of same person are close to each other and far from others.

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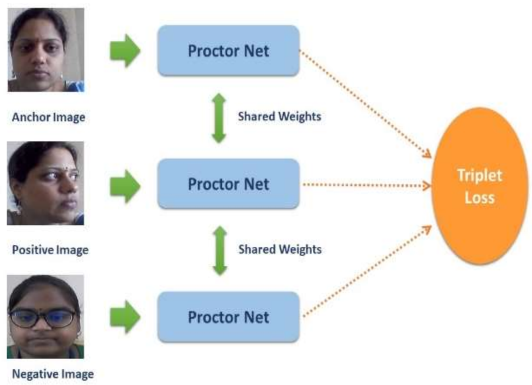


*Figure 3: Triplet Loss function of Proctor Net.*

All the verified faces are examined for detecting autistic behavior and alerts proctor as described in the following section.

### 3.2 Autism Detection

Web pages are key stimuli for investigating the use of visual processing differences for detecting autistic behavior. As per [29] Browse task, search task and synthesis task designed based on web pages are used to detect the autistic behavior of the examinee. Four web pages of instructions for exam before starting the exam are hypothesized to be particularly suitable to perform these tasks. Interactions with the web pages like scrolling, clicking, or typing were not involved in our detection procedure. The tasks given to examinee are as follows:

**Browse Task:** Examinee were instructed to read the instructions and were free to focus on any element of their choice for any time. Each page changes after every 40 seconds passed. The time limit to complete this task is 160 seconds.

**Search Task:** Examinee were asked to locate a specific element to answer the question. For example, the question can be like "Can *you see the Question paper code and retype in the box given."* The time limit for this question can be 30 seconds for two questions per page.

**Synthesis Task:** Synthesis task is like the search task but, examinee must locate at least two elements from the captcha and compare them. The example of the task can be like "*How many bikes are there and how many are of red color among them.*" To answer this question, examinee have to locate the bikes in captcha and later have to count the red bikes among them. The time limit for this task is 120 seconds per page and examinee can move earlier if they complete the task fast.

All the live recordings of the these tasks are examined for eye-gaze tracking to extract the features of the autistic behavior. The eye-gaze tracking was implemented using the hourglass modules as shown in the Figure 4. The eye-region detected by the MTCNN is given as input to the hourglass module. Feature maps generated using hourglass module were down sampled by a factor of N using pooling operations as shown in equation 1.

$$\{D_{P,N}\}_{ij} = \$\ N\,(\delta[i-j]) = \delta[Ni-j] \qquad [1]$$

Before every down sampling operation, single route is separated to retain the information in current size. Later, it was up sampled using binary interpolation by a factor of Q as shown in the equation 2.

$$\{U_{K,L}\}_{ij} = \uparrow Q(\delta[i-j] = \delta\left[\frac{i}{Q}-j\right] = \delta[i-Qj] \qquad [2]$$

The task relevant features at every scale are preserved by the residual module during training. The probabilities of eye-landmarks are represented using heat maps by Hourglass module. 18 heatmaps i.e., 8 in limbus region, 8 on the iris edge, 1 at the iris center and 1 at the eye-ball center are generated using 2D Gaussian probability density function as represented in equation 3.

$$f(X) = \frac{1}{\sqrt{2\pi Co}} \times e^{-\frac{1}{2}(X-\mu)^T C^{-1}(X-\mu)} \qquad [3]$$

Finally, heatmaps are processed by a soft-argmax layer to extract the sub pixel coordinates of these landmarks. These landmarks are used to train a support vector regressor (SVR) to estimate the gaze in 3D $(\theta, \emptyset)$. The pitch, yaw and roll estimated are used to visualize the eye-gaze marking gaze direction.

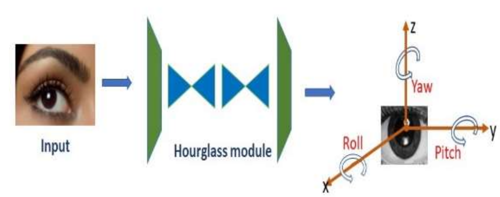


*Figure 4: Eye-Gaze tracking by calculating Pitch, Yaw and Roll on the heatmaps generated by HourGlass module.*

The recorded eye-movements are given as input to the logistic regression classification algorithm. Eye-gaze marking is used investigate behavior of the autistic people. Our Automated Proctoring system alerts the proctor if autistic behavior is detected which helps proctor to closely monitor autistic

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examinee. Later the proctoring system detects various malpractices of non-autistic examinee like speaking to others, using other resources by estimating head pose and detecting mouth open.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

Authors trained the Proctor Net on Labelled Faces in the Wild (LFW) dataset [30]. The dataset contains more than 13,000 images of distinct faces collected from the web and each face has its label on it. Examinee faces are verified before Autism detection using proctor-Net as shown in the figure 5.

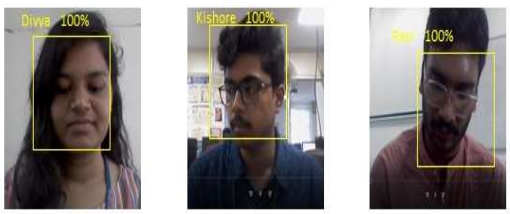


*Figure 5: Face Verification using Proctor Net*

Eye-gaze estimation module is trained on Unity Eyes image dataset which consists of one million eye images with a large degree of appearance variation. The gaze tracking using Hourglass module is visualized in the figure 6.

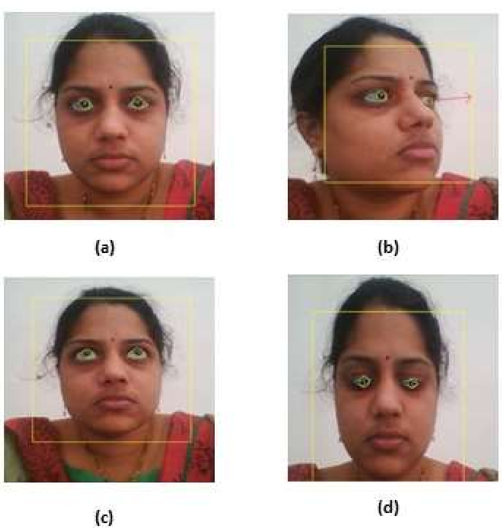


*Figure 6: Results of Eye-gaze Tracking. (a) Examinee seeing towards screen. (b) Exmainee seeing towards right of sscreen (c) Examinee seeing upwards (d) Examinee seeing towards down*

The list of the features considered for detecting autistic behavior are listed in the table 1. The features like Time to first view, Time viewed, Fixations and Revisits are gaze based features which can be calculated using the gaze tracking module.

*Table 1: Features and their explanation.*

| Feature | Explanation |
|---|---|
| Time to first view | The time in seconds when Area of Interest was first seen measured from the moment the instructions page was presented on screen. |
| Time viewed(sec) | The sum of the total durations of all activities |
| Fixations | The number of gaze fixations per each examinee |
| Revisits | The number of times examinee went back to same Area of interest visited previously |

The results for above mentioned features for various tasks are as shown in the Table 2. Three different tasks as mentioned in previous section were tested on Autistic examinee and Normal Examinee at two levels of difficulty as Low(L) and High(H). The results were examined using 95% confidence intervals. It is analysed that Autitic examinee spent more time compared to Normal exmainee in Browse task with 0.72 in low difficulty level and 0.76 in high difficulty level where as it is o.65 and 0.68 respectiely for normal examinee. The best result is achieved for the Search task with 0.75 and 0.78 at low level and high level respectively. Similar to previous results, autistic examinee has 0.73 and 0.77 at two levels for synthesis task.

*Table 2: Evaluation results of all tasks in two difficulty levels- Low(L) and High (H).(95% confidence intervals were considered)*

| Task | Autistic Examinee | | Normal Examinee | |
|---|---|---|---|---|
| | L | H | L | H |
| Browse Task | 0.72 | 0.76 | 0.65 | 0.68 |
| Search Task | 0.75 | 0.78 | 0.70 | 0.73 |
| Synthesis Task | 0.73 | 0.77 | 0.66 | 0.70 |

Best results were achieved with Search task followed by Synthesis task and then Browse task. Overall these results confirm that detecting autistic behaviour using eye-tracking gives better results. From the table 3, the performance of the autism detection is analysed in different scenarios. It is observed that system performs better with all three tasks like Search task, Browse task and Synthesis task with an accuracy of 78%, whereas it varies from

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73% to 76 % in other scenarios like browse, search and synthesis alone and it other combinations.

*Table 3: Performance Analysis of Autism detection.*

| Scenario | Accuracy |
|---|---|
| Browse Task | 0.74 |
| Search Task | 0.76 |
| Synthesis Task | 0.75 |
| Browse + Search Task | 0.74 |
| Browse + Synthesis Task | 0.75 |
| Search + Synthesis Task | 0.73 |
| All three tasks | 0.78 |

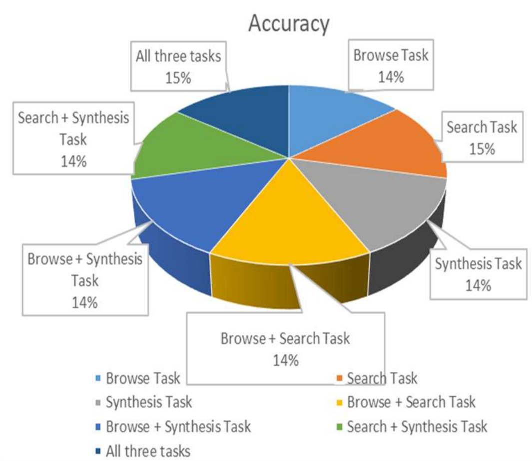


*Figure 7:Performance Analysis of Autism Detection*

Detecting Autistic examinee also improves the performance of the Automated Proctoring system as discussed in the figure 7. It is observed that the Automated Online Proctoring systems designed only with Proctor Net for Face Recognition, head pose estimation using affine transformation , mouth opening detection using mouth aspect ratio performs with 0.91 accuracy and 0.10 error rate as showcased in figure 7. With the inclusion of disorders detction like Autistic Spectrum Disorder Detection to the Automated Online Proctoring system, accuracy is improved to 0.93 and error rate is reduced by 0.02.

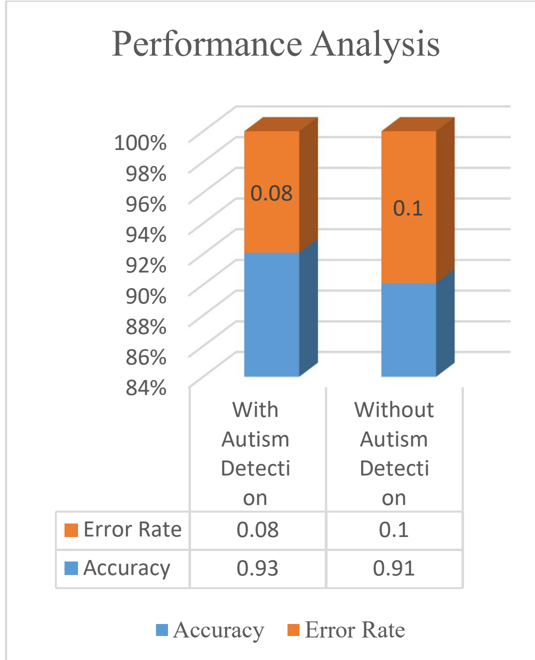


*Figure 8: Performance analysis of Automated Online Proctoring system in terms of Accuracy and Error Rate.*

With the inclusion of Autism Detection with Automated Online Proctoring system, cons also exist along with pros. There is no special hardware or algorithm required for autism detection as the eye-gaze tracking module of the Proctoring system can be used for estimating the visual behavior of the autistic examinee. The inclusion of autism detection improves the overall accuracy of the system and also provides provision to closely monitor examinee with ASD. The cons of the system is the overall time required for the proctoring increases as the web pages with instuctions are used to estimate the visual behavior using eye-movement tracking. The responsibility of the proctor is increased in terms of closely monitoring the examinee with ASD. The challenge of this system is the accuracy of the Autism detection module is only 0.73 which is to be improved further which in turn effects the performance Autmated Proctoring system.

## 5. CONCLUSIONS

This paper presented a way to embed the Autistic Spectrum Disorder Detection into the Automated Online Proctoring systems. Autism is detected by analyzing gaze-based features using heatmaps generated by hourglass module over which Pitch, Yaw and Roll are calculated using Soft-argmax, whereas existing models uses MRI images which increases complexity. As per results it is shown that

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the proposed proctoring system including detection of autistic behavior increases performance. The experiments showed that the autism detection module performs with 0.73 accuracy and Automated Online Proctoring with autism detection performs with 0.93 accuracy.

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