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CHEAT DETECTION IN ONLINE EXAMINATIONS USING ARTIFICIAL INTELLIGENCE

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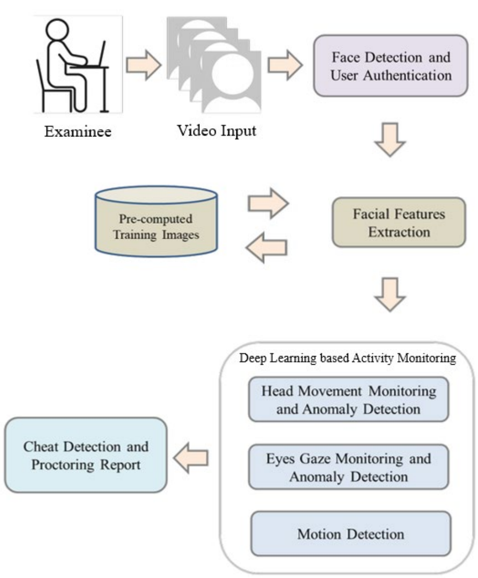
Graphical abstract



Abstract

With increasing use of ICT and technical advancements in the education sector, distant and online education as well as examinations are being carried out frequently. However, online examination, as a method of assessment offers the risk of an unmonitored setting where students have full access to external resources. Online-proctored exams are the most efficient way for educational institutions to ensure academic honesty and ethics to counteract this. Typically, proctoring requires human assistance in the form of online proctors who remotely monitor students' performance. Yet, due to the rising demand for personnel and the intrusive nature of human proctoring, it is imperative to explore other areas. To tackle this pressing issue, this research work aims to devise a novel architecture that, through the development of a robust and automated Artificial Intelligence system, enables students to take exams remotely and reduces proctor involvement. The method overcomes the shortcomings of the previous automated proctoring system by combining important components of online exam cheating detection with cost-effective and efficient hardware. By proposing a Hybrid of FaceNet Model, Lucas Kanade Algorithm, and Active Appearance Model for Face Detection and Activity Monitoring of the student, the proposed system extracts semantic indicators to evaluate whether an applicant is cheating in an online examination. The proposed Cheat Detection system's experimental results measured via an F-score of 0.94 demonstrate its efficacy, and promising performance compared to the standard baseline techniques.

Keywords: Artificial Intelligence, Computer Vision, Cheat Detection, Image Processing, Online Examinations

1.0 INTRODUCTION

In recent years, Information and Communication Technology has taken on a greater role in human existence, notably in the field of education. The same is supported by the National Qualification Framework (NQF) in many countries, which highlights vocational training in both in-person and distant modes. Emphasis is also put on making education available to a wider audience by catering to the required flexibility which some individuals might need. Online and Distance Education [1] have come up as a holistic solution to address this need. The rapid expansion of these approaches can be attributed to this push from the NEP 2020 [2] in addition to its ability to provide students with remote access to campus resources and other restricted resources like academic materials and learning opportunities. Learning at a distance through the use of the internet is becoming increasingly popular across the nations for several reasons, including the fact that it can be accessed at easily at any time of the day and the fact that it can be adapted to individual needs. With such benefits of online and distance, the trend of entirely online programs is only expected to rise.

When it comes to assessment of learners, examinations are the most vital component in any education mode, including online learning [3]. E-learning platforms are used to conduct online tests, which are then graded and scored without students and teachers needing to be physically present in the same room. However, the assessment and supervision of online examinations brings forth a new set of challenges to be tackled. Regarding e-learning, online examinations must be carried out in a dependable, level-playing field, and hassle-free manner.

Exams that are taken at a distance significantly enhance the risk that students will cheat. Exam cheating is an act of dishonesty that is committed to gain access to resources in a manner that is inconsistent with the standards of the testing procedure. According to the findings of a recent survey [4], 73% of students cheated during the entirety of the online exam. According to the results of a poll, 36% of undergraduate students and 24% of graduate students admit to paraphrasing information from the internet. A total of 38% of undergraduates and 25% of graduate students are responsible for paraphrasing textbook content. In addition, it was discovered that 7% of undergraduates and 4% of undergraduates reproduced practically word-for-word without providing a citation. In spite of the recent growth of online education, not a great deal of research has been done to determine whether or not online exams encourage students to cheat.

The requirement for supervised methods to detect cheating in webcam-based online examinations is fundamental to validating this form of testing. Examiners and test supervisors can expand their reach beyond geographical borders and evaluate applicants from any location when using online exams because of the option to integrate remote supervision into the system [5]. It helps to maintain the reliability of online tests by stopping any instances of cheating that may occur and helps stimulate the efficient mechanisms of in-person examinations. Remote monitoring also helps maintain the politeness of code and behavior and encourages the authenticity of known information [6].

However, the practice of human remote proctoring is fraught with complications, to say the least [7, 8]. Proctors may acquire a variety of personal information from the student, including their names and addresses, as well as their driver's license numbers, and passwords, biometric records, to validate the student's identification. These kinds of details can be put to use in analyzing usage patterns as well as shared with third parties. In addition, a number of students have expressed that they found their experiences with remote proctoring to be "uncomfortable" and "dubious" due to the intrusive nature of such methods. To exacerbate the problem further, there is a significant gap between the number of available proctors and the number of students who need their exams to be proctored, which results in employees being stretched to their limits. So, making the changeover to real-time automated monitoring is vital to continuously secure student identities and preserve a code of conduct during the assessment period, all while ensuring minimal intrusion.

In recent years, the focus of computer applications has shifted dramatically away from simple data processing and towards machine learning. This is primarily due to the availability and accessibility of vast data obtained via sensors and the Internet. The ideas behind machine learning illustrate and spread the idea that computers might one day be able to improve their performance through experience. Machine learning and computer vision subfields have evolved into a close association with one another. The use of machine learning has helped to improve the capabilities of computer vision in terms of both recognition and tracking. It offers an effective method for the capture of computer vision, the processing of images, and the focusing of objects. The combination of the two fields is famously known as the “AI-Vision” [9]. The fact that the algorithms underlying machine learning and computer vision can be utilized in various contexts [10] demonstrates that the fields are quite expansive and may be amalgamated and extended to solve pressing issues. New educational use cases are being provided due to the significant development in AI-Vision technology. Implementing computer vision into the classroom can assist students in reaching their full academic potential. In comparison to traditional methods of instruction in the classroom, the evaluation process that is used with this technology in education is uncomplicated and unobtrusive. This is the fundamental advantage of using AI-Vision in education. In general, computer vision comprises three stages: the first is the acquisition of a video frame from a camera, the second is the processing of the image with an image processing algorithm, and the third stage is the comprehension of the image.

It is at the image processing stage of computer vision that machine learning really comes to aid. With recent advances in deep learning and newer iterations of models like Convolution Neural Nets (CNN), image processing is more efficient than ever. In online examinations, CNNs ensure integrity using models to verify and validate the student’s identity, an essential phase for online exams [11]. Such models may further be tuned to identify various aspects that indicate that the applicant is cheating or attempting to cheat. It is reflected in the facial expression as a reflection of the hidden intention to cheat. The combination of head movement tracker and eye / line-of-sight tracker helps determine the applicant's line-of-sight direction. Also, to avoid the still image scenario where the applicant puts the photo in front of the camera and tricks the supervision system, a motion detector may go into the frame and run the motion detection scan to confirm the input sequentially to identify the motions [12]. Similarly, many scenarios and aspects of cheating as a drawback of online examinations may be overcome using advanced technologies.

This next level of technological advancement, represented by computer and machine learning, are investigated in this study. An AI-vision approach is utilized by the proposed system to solve the issue of unobtrusive detection of cheating in online examinations. This AI-based computer vision solution can view its surroundings by identifying nearby objects and basing its conclusions on a set of predetermined guidelines. As a result, Artificial Intelligence helps with user identification and motion detection while monitoring online tests, whilst Computer Vision assists with video-based surveillance and monitoring of the process.

1.1 Contributions of this Work

The application area of the work is improvement and automation in the education sector. The work researches and integrates various activity monitoring features and functional modules to monitor the activity of applicants during online exams based on webcams with the following added benefits:

1. The work provides an efficient and automated system to track, monitor, and analyze the activity of students giving remote online examinations.
2. The work advances the research done on usage of Artificial Intelligence and Computer Vision in the Education sector and closes the gaps left by existing systems.

The paper is structured as follows: Section 2 describes the current state of the art in test monitoring and proctoring systems and Section 3 describes the various baseline algorithms used. Section 4 presents the suggested procedure for detecting and identifying the applicant's deceptive behavior during the test. Section 5 presents the implementation outcomes. Section 6 summarizes the work and suggests next research areas.process.

2.0 LITERATURE REVIEW

The related literature and review of the work are described in this section. The existing applications and methods used for cheat detection and their respective fallacies are discussed.

Automated proctoring is undoubtedly not a novel idea. An extensive amount of research has been done on online (webcam-based) monitoring or proctoring for exams due to the growing interest in this technology. Yet, the fact that each system has a few unresolved problems highlights the need for an improved strategy.

In [13], the author presents a more secure online exam management environment through the use of cryptography. The encryption allows for increased security control during the online test procedure, as well as authentication and integrity. To avoid cheating, e-monitoring gives a proctor function to distant examinees, removing the need for them to travel to a remote location. Unauthorized access to pre-exam question papers and safeguarding them using standard cryptographic methods are among the security concerns associated with online tests.

An autonomous online test proctoring system is built using a multimedia analytics system in [14] with the goal of maintaining academic integrity in remote learning through automated monitoring. The suggested approach entails the extraction of visual and acoustic information in order to continually assess the behavior of the applicant using one webcam, one wear-cam with a microphone. The six core components that continuously assess the important behaviour cues are user verification, text detection, voice detection, active window detection, gaze estimation, and phone detection. By combining the continuous estimation components and employing a temporal sliding window, the approach generates higher level features to classify whether the test taker is cheating at any point during the exam.

Micro-expressions are unintentional and delicate expressions that can disclose concealed human emotions. Authors in [15] proposed an automatic technique to identify facial motions in constant, lateral, and/or profile-view color face photos. The multi-detector technology is used to identify facial features to spatially sample profile contours and contours of facial components such as eyes and mouth.

The initial phase in the face recognition / validation pipeline is face identification, and a typical facial recognition pipeline comprises deep network training for target classification with soft-max loss, utilising the penultimate layer output as a feature descriptor, and a cosine similarity score. The suggested method employs a deep pyramid single shot face detector as well as CNN to locate critical spots on the face. All feature-based FR systems rely on feature extraction techniques to extract the most observable edge information from face photos and generate feature vectors to complete the recognition process. [16, 17].

The authors of [18] describe a distributed architecture for evaluating head motions to identify the visual attention of a driver, with an emphasis on the capacity to move robustly and continuously in big head movements. It records face characteristics, evaluates their geometric composition, and estimates head posture using 3D models. Two such techniques are shown in this research, which also take use of the limitations available in a driving context and video data to increase tracking accuracy and computation time. In addition, authors undertake a full comparison research with various camera combinations.

The authors of [19] developed a method to measure head movements and attention using global motion estimates and colour statistics to track head and face characteristics. The system detects rotation in all viewing directions, eye/mouth occlusion, eye blinking and eye closure, and recovers the eyes' three-dimensional gaze. Additionally, the system can track through occlusions caused by eye blinking and closing, as well as occlusions caused by rotation. Authors in [9] use an approach with Deep Fusion Convolution Neural Network for facial expression recognition. Expression prediction can be accomplished by learning linear SVM classifiers with 32D fused deep features or directly conducting SoftMax prediction with 6D expression likelihood vectors.

In [20], non-intrusive eye tracking technologies are used to assess eye gaze and pupil response. The average duration of the look is 0.3 to 0.4 seconds, with frequency ranging from every 2 seconds to many tens of seconds. The study developed a method for tracking and detecting gaze blinks via localization using a statistical appearance model trained on labeled photos. To monitor and identify eye blink, a statistical Active Appearance Model (AAM) is created. The model has been developed to be resistant to changes in head posture or sight [21]. It investigates and identifies the parameters of the model that reflect the changes induced by blinking. This global architecture is subsequently enhanced by a number of sub-models to allow separate modeling and tracking of the two eye regions [22].

In [23], researchers present kinematics technique based on the assumption of a piecewise constant acceleration process is proposed and demonstrated to track head locations with a root mean square error of less than 2 degrees for head motions with accelerations less than 3000 degrees/sec. Real-time eye tracking systems from video analysis have the potential to open a new category of possibilities for consumer electronic devices. And in intelligent cars, driver gaze has been proved to be an excellent proxy for driver attentiveness. Severa other authors propose face detection approaches [24]. Authors of [25, 26], describe a generalized approach to have systems using Convolutional Neural Network by fine tuning popular architectures provided to ensure face monitoring be faster and efficient.

Despite the fact that each approach addressed in the pertinent literature addresses a different component of the detection and supervision of online proctored examinations using AI and computer vision, none of them offers a holistic solution to the issue or is accurate or time- or resource-efficient. The research presents an approach that makes use of Image Processing to detect any dishonest conduct demonstrated by the test-taker while they are being evaluated, using these insights gathered from the already accessible approaches. This strategy consists of a comprehensive system that may be implemented at a reasonable cost in order to address the issue.

The following section further discusses the several algorithms which have been tested for the proposed system and the advantages of the same.

3.0 BASELINE METHODS

The literature survey shows that many algorithms have been researched and tested for Cheat Detection, ranging from several types of object detection models to deep and advanced neural networks. To validate the proposed system's efficacy, its performance was compared to two frequently applied baseline methodologies from the literature review. The two baseline techniques are detailed in detail below:

a) *Baseline Method 1*: This technique employs three algorithms to identify cheating in online examinations - Viola Jones and CNN for the detection phase and the Lucas Kanade method for optical flow in a real-time video stream.

b) *Baseline* Method 2: This approach includes three algorithms that aid in detecting cheating in online exams - Kalman filter for real-time object tracking, DCNN for object detection, and Pixel displacement statistical model.

The description of the algorithms which are used in the above-discussed baseline methods and how they relate to the current system are presented below:

- Viola Jones [27]: The algorithm was first suggested by Paul Viola and Michael Jones in 2001. Although it was designed to focus on the issue of face detection, it can also be trained to identify various object classes. It is implemented as cvHaarDetectObjects in OpenCV(). It is preferred due to its durability and ability to quickly identify faces (full frontal upright faces) in real-world scenarios. It has four phases, starting with:

1. Haar Feature Selection.
2. Construct a complete picture.
3. Adaboost Education.
4. Amplifiers that cascade.

The features chosen by Haar are similar to those seen in human profiles. The integral image has an advantage over other sophisticated features in that it determines the rectangular features in fixed time.

- Lucas Kanade [28]**:** The Lucas-Kanade approach is a popular differential technique for computer vision and optical flow estimation. Using the least squares criterion, this technique resolves the fundamental optical flow equations for every pixel in that neighbourhood. It cannot provide flow information in the interior of uniform regions of the image, making it a strictly local method. Here, it is assumed that the flow is basically constant in the immediate area surrounding the pixel in question.
- Convolutional Neural Network [29]: Similar to conventional ANNs, convolutional neural networks (CNNs) are neurons that learn to optimize themselves. The fundamental building block of countless ANNs, each neuron will continue to take in data and carry out an action (such as a scalar product followed by a non-linear function). The complete network will still express a singular perceptive score function from the input raw picture vectors to the class score at the end (the weight). The final layer will include loss functions related to the classes, and all standard techniques created for conventional ANNs are still applicable.
- Kalman Filter [30]**:** The Kalman filter is a method that predicts unknown variables more precisely from a set of data that has been collected over time but includes noise and other imperfections. It was first put forth by R. E. Kalman in 1960 and has since become a widely accepted method for optimum prediction. The Kalman filter has been extensively used in the fields of digital image processing and in the presently popular study areas such as pattern recognition, image segmentation, and image edge detection due to its advantages of real-time, quick, efficiency, and strong anti-interference. Demonstrated

4.0 PROPOSED APPROACH

The study proposes a solution which is an AI-based continuous verification system that aims to provide reliable, low-cost, and highly accurate cheat detection in online examinations. The architecture of the proposed system is a webcam-based integration of various activity monitoring functional modules. The formulated approach of the system is represented in Figure 1 followed by its detailed description.

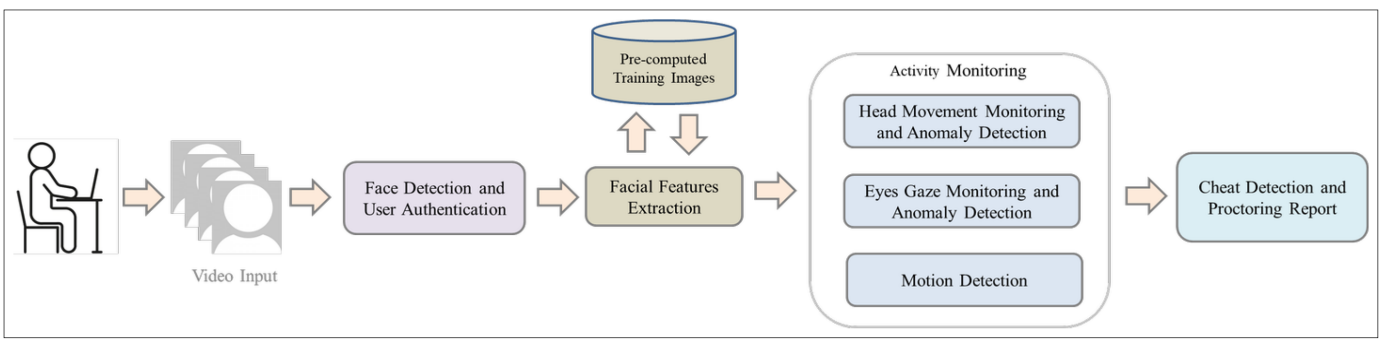


Figure 1. Proposed Approach for Online Examination Cheat Detection

As depicted in Figure 1, the system is divided into three major modules each of which is explained in detail as follows:

4.1 Face Detection and User Authentication

The proposed system's first module is Face Verification and User Authentication. In the instance of facial recognition authentication, the input device takes the video input of the candidate, converts it to image format which is further fed to FaceNet Model [17]. The FaceNet model maps the face image to a compact Euclidean space, where distances correspond to the similarity of the image. It then performs the task of face recognition and verification. The identification model is trained on the triplet loss function to accomplish this. This function takes three images, which are positive, anchor, and negative. Vectors of images with the same identity are likely to be more similar than vectors of images with various IDs.

4.2 Activity Monitoring

The part of activity tracking phase on identifying illegal activities such as mischievous, odd motions and viewing direction throughout the test. The primary goal of the Activity monitoring module is to keep scholastic integrity. This proposed solution methodology includes micro-expression identification, such as detection of laughing expressions, eye trailing to anticipate applicant's viewing direction, eyes blinking, and eyes closure duration, as well as head activity / movement detection and motion estimation to predict fraudulent activity.

As the monitoring phase is the proposed architecture's second phase, it also includes three sub-processes that contribute to decision making which are explained below.

4.2.1 Head Movement Tracking and Anomaly Detection

One of the most important elements in identifying cheating is monitoring the repeated range motion during an online or offline test. Analyzing online exam applicants' actions, particularly their head and behavior, is an important factor for cheat detection systems, as it indicates exam applicants' focus and concentration. Frequent directional movement throughout the online or offline test suggests that the applicant is looking for illegal and immoral behavior. After determining the location and alignment of the face, it can determine the identification of the lips, eyes, and watch head motions and tilts recorded throughout the online test.

For tracking head movement, the suggested technique employs the Lucas Kanade method [18]. The programme performs detection and tracking based on fixed musculature such as the septum, eyelids, and mount outlines.The method used is linked with studying and monitoring facial movement. The relocation of the recorded image of the candidate's frame contents within a point's vicinity between two adjacent vectors is limited and virtually unaltered.

4.2.2 Eyes Gaze Monitoring and Anomaly Detection

Eye gaze recognition and movements, as distinguishing features of a person's face, play an important part in the cheat detection system throughout the online test. The eyes are primarily a biological sensor for receiving optical information. The gaze orientation that indicates the place in which the test candidate concentrates their attention also conveys context successfully.

Once a test candidate's eyes are detected, predicting his or her gaze direction is straightforward. The proposed method correlates a forecast approach of an object's shape and feature to a newly taken image using the AAM (Active Appearance Model) [19] method. It also recognises eye motions and gaze orientation by finding the optic centre and eye contours and aligning the model with the feature points.

4.2.3 Motion Detection

The motion detection phase's major goal is to make sure the exam candidate is moving around during the online exam and isn't trying to cheat by putting a static image in front of the webcam and breaking the rules of conduct. When the pixel displacement of two subsequent captured images is negligible for a longer period of time, static frames are indicated.

4.3 Cheating Detection and Proctoring Report

This phase assesses the penalty imposed following the activity monitoring phase and produces a report in PDF format outlining the actions taken by the applicant throughout the test. At the conclusion of the test, a cheat report will be generated. It may contain images of all unethical behavior by the candidate, including instances where they were out of frame, more than two faces were discovered during the detection process, there were too many head movements, or their viewing direction was outside the screen for an extended period. It may also include the number of penalties the test taker has received.

This proposed solution is an entirely autonomous system for detecting cheating in online tests that uses a webcam for video input and several sub-processes that incorporates information processing from various perspectives in order to guarantee academic integrity. The testing, effectiveness comparisons, and subsequent outcomes are covered in the next section.

5.0 IMPLEMENTATION AND RESULTS

The proposed architecture for Cheat Detection is trained, tested and validated on a comprehensive dataset using the various Machine Learning algorithms as described in section 3 of Baseline Methods. The implementation is conducted using Keras, an open-source high-level deep learning framework written in Python. The dataset consists of video data collected from over 1000 online examinations conducted at the institute where the proposed study is based. Consent of the exam candidates were taken prior to the recording. The following subsections details about the algorithmic parameters of these algorithms, evaluation of various baseline methods as discussed previously and their performance comparison with the Proposed Method and the derived results of this study.

5.1 Algorithmic Parameters

Table 1 shows the Parameters and Key Inputs defined for the tested model. These hyperparameters are tuned using Grid Search Cross-Validation technique provided by the scikit-learn library in Python. This technique performs automated search to find the best combination of hyperparameters for the models.

Table 1. Algorithmic Parameters used in Proposed System

Algorithm	Parameters/Key Inputs	Values
FaceNet	Learning Rate	0.08
	Optimizer	Adaptive Moment Estimation
	Images per Person	25
	Classifier	Support Vector Classifier (SVC)
	Type of SVC Kernel	Linear
Lucas Kanade	Window Size at Pyramid Level	(20,20)
	Facial Point's Data Type	Array of float32 integers
	Input Frame Size	384 Pixels
	Output Frame Size	384 Pixels
	Number of Input & Output Channel	3
DLib Motion Detection	Noise filter	Gaussian
	Dilation iterations	3

Viola Jones	Type of Haar-like Feature	Edge Features and Line Features
	Integral Image Size	24x24
	Classifier	Cascading Classifier
Convolutional Neural Network	Learning Rate	0.3
	Activation Function	LeakyReLU
	Pooling Layer	Max Pooling (4)
	Loss Function	Binary Cross Entropy
	Input Frame Size	128 Pixels
	Output Frame Size	128 Pixels
	Optimizer	SGD
	Sampling Method	Stratified K Fold

5.2 Evaluation Parameters

To evaluate the performance and efficiency of the said algorithms, a segment-based metric to evaluate the performance of the online exams monitoring system is defined. It is represented by *Precision* and *Recall*.

For Face Detection and User Authentication, the parameters considered are:

- T_P - True Positive: Face Region correctly classified as Face Region
- F_P - False Positive: Non-Face Region incorrectly classified as Face Region
- T_N - True Negative: Non-Face Region correctly classified as Non-Face Region
- F_N - False Negative: Face Region incorrectly classified as Non-Face Region

For Cheat Detection, the parameters considered are:

- T_P - True Positive: Student Cheating classified as Cheating
- F_P - False Positive: Student Not Cheating incorrectly classified as Cheating
- T_D - True Negative: Student Not Cheating classified as Not Cheating
- F_D - False Negative: Student Cheating incorrectly classified as Not Cheating

The Precision value indicates the proportion of True Positive Predictions out of Total Positive Predictions as defined in Eq. (1).

$$Precision = \frac{T_P}{T_P + F_P} \qquad \text{... (1)}$$

The Recall value indicates the proportion of True Positive Predictions out of the Total Actual Positive instances as defined in Eq. (2).

$$Recall = \frac{T_P}{T_P + F_N} \qquad \text{... (2)}$$

To evaluate the model's performance, we compare its F-score, which is a standard measure of harmonic mean of *Precision* and *Recall*, and yields a value in the range 0 to 1. It is defined in Eq. (3).

$$F - score = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad \text{... (3)}$$

A higher *F-score* indicates successful performance of the detection method.

5.3 Results

The proposed algorithms have been verified using the performance metrics to compare their efficacy. Comparative analysis of the proposed architecture with different baseline methods using F-score has been performed as shown in Figure 2 and Figure 3.

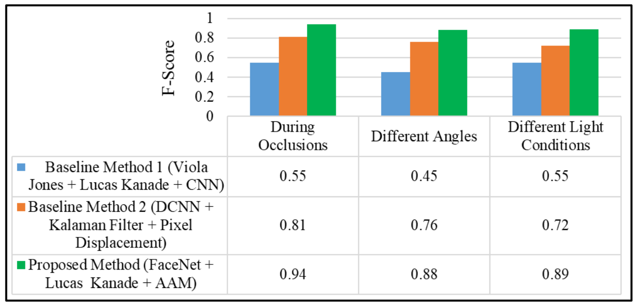


Figure 2. F-score Comparison of Different Face Detection Architectures in Various Scenarios

Figure 2 represents F-scores of the different baseline method architectures for Face Detection and User Authentication in different scenarios. The proposed method shows a significant improvement in the F-score as compared to the baseline methods. Specifically, in presence of occlusions, the proposed method performs face detection with F-score as 0.94. Also, the detection from different angles has F-Score of 0.88, whereas with different light conditions, the proposed approach retains its performance to F-score of 0.89. It indicates that despite different scenarios, the proposed method implies that means the algorithm is successfully detecting faces of students while minimizing false detections.

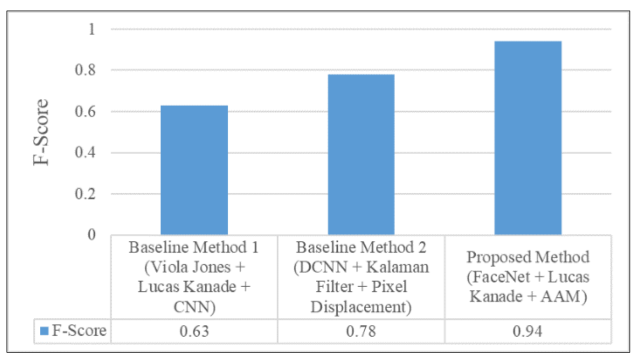


Figure 3. F-score Comparison of Different Algorithms for Cheat Detection

Figure 3 represents the F-score comparison of the baseline methods with the proposed architecture for classifying the cheating activities. Cheat detection is majorly performed based on the actions the student is performing during the web camera-based exam. The Baseline 1 and 2 methods have demonstrated high error in detecting the cheating cases, majorly due to the occlusions and changing angles. This has been addressed by the proposed approach by implementation of AAM along with the FaceNet and Lucas Kanade algorithm. As shown in Figure 3, the proposed approach yields F-score value of 0.94 for Cheat Detection, which is promising and significant.

6.0 CONCLUSION AND FUTURE SCOPE

The application of the study links to a remote learning model's online education to minimize and identify the cheating or illegal activities conducted by a candidate during the examination. The proposed work suggests an efficient, low-cost, and non-intrusive cheat detection system for online examinations that is based on a single camera that would serve as a useful testing instrument. For the same, different baseline methods were studied, tested and compared. On experimentation, it is found that AAM contributes for face point mapping once the face is detected and Lucas Kanade outperforms other object motion detection methodology along with help of a high performing detection algorithm FaceNet. Hence, a combination of these three works as the best approach for the cheat detection, yielding a high F-score of 0.94.

The suggested technique for spotting cheating, however, is completely reliant on webcam-captured video streams. As a future scope, the proposed framework can be enhanced by the inclusion of auditory input monitoring which could potentially increase the likelihood of cheat detection. Additionally, there are possibilities of mining the data to find patterns in anomalous actions performed by a candidate during examination to improve the efficiency of the proposed method for cheat detection.

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