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Smart Surveillance Solutions

Smart Attendance and AI Proctoring

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Abstract: The integration of advanced technological solutions into educational systems has ushered in a new era of efficiency and effectiveness. This paper delves into the fusion of Smart Attendance and Cutting-Edge Exam Surveillance, presenting a holistic approach to bolster academic administration and uphold examination integrity. Smart Attendance leverages facial recognition and biometric data to automate attendance tracking, ensuring precision and swiftness in the process. Conversely, Cutting-Edge Exam Surveillance harnesses artificial intelligence and machine learning to vigilantly monitor and deter cheating behaviors during examinations. The symbiosis between these two systems not only simplifies administrative duties but also guarantees a secure and equitable examination milieu. This paper examines the technical complexities, ethical implications, and potential ramifications of implementing these innovations in educational institutions. The convergence of Smart Attendance and Cutting-Edge Exam Surveillance marks a pivotal moment in educational management.

Index Terms – Smart Surveillance Solutions, Exam Cheating Detection, Exam Proctoring.

I. INTRODUCTION

In today's dynamic educational landscape, the demand for robust security systems and advanced surveillance technologies is unprecedented. This paper explores the integration of Smart Attendance and Cutting-Edge Exam Surveillance to revolutionize academic administration and uphold examination integrity. Traditional methods are increasingly ineffective, necessitating innovative solutions to address modern challenges. Smart Attendance offers efficiency through biometric recognition and RFID technology, while Cutting-Edge Exam Surveillance employs AI and facial recognition to deter malpractice. Integration of these systems catalyzes data-driven decision-making, promising a transformative shift in educational management towards efficiency, security, and integrity.

II. RELATED WORK

Various studies have addressed the pressing issue of academic dishonesty in online assessments, especially in the context of the Covid-19 pandemic. Leslie Ching Ow Tiong and HeeJeong Jasmine Lee (2021) conducted a case study focusing on e-cheating prevention measures using a deep learning approach. Their study introduced an e-cheating intelligence agent comprising an internet protocol (IP) detector and a behavior detector to monitor and prevent online cheating practices effectively. The agent, integrated with online learning programs, demonstrated promising results in detecting malicious activities, achieving accuracies ranging from 68% to 95% across different deep learning models such as deep neural network (DNN), long-short term memory (LSTM), Dense LSTM, and recurrent neural network (RNN).

This study contributes to the growing body of research aimed at addressing the challenges of academic dishonesty in online assessments, providing insights into effective preventive measures and the utilization of deep learning techniques for enhancing examination integrity in online learning environments. By shedding light on the efficacy of these preventive measures and the utilization of sophisticated deep learning techniques, this research significantly contributes to the burgeoning field of examination integrity in online learning environments. It offers valuable insights and practical implications for educators and institutions grappling with the challenges of maintaining academic honesty in the digital age.

III. PROPOSED METHOD

The dataset for the Smart Attendance and AI Proctoring project comprises various components essential for accurate tracking of attendance and behavior monitoring during examinations. It includes student profiles with unique identifiers, enrollment details, and course schedules. Additionally, it incorporates facial recognition data for identity verification and attendance tracking. Behavioral biometrics such as typing patterns, mouse movements, and gaze tracking are recorded to detect anomalies indicating potential cheating behavior. Academic integrity is ensured through AI algorithms trained on this dataset to flag suspicious activities in real-time, enabling timely intervention by proctors. The dataset is meticulously curated to balance privacy concerns with the need for effective monitoring, ensuring compliance with data protection regulations while enhancing the efficiency and reliability of attendance tracking and exam supervision processes.

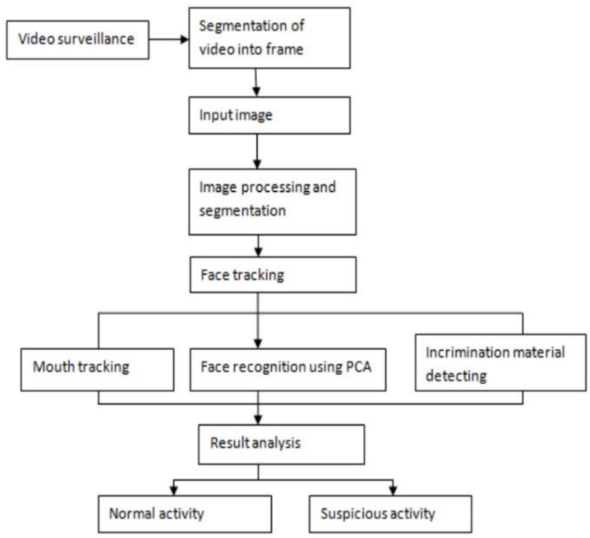

Fig. 1. Proposed System Architecture

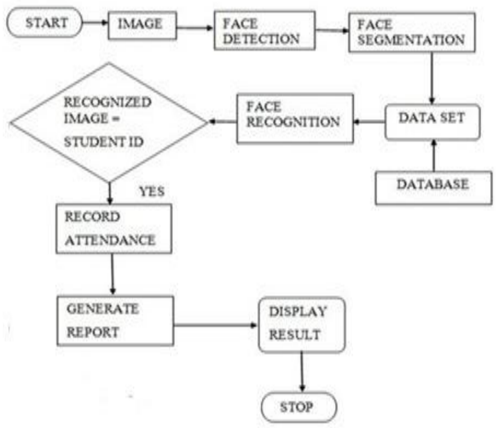

Fig. 2. Proposed System Architecture

IV. PROPOSED ARCHITECTURE

The proposed architecture, as shown in Fig. 1, for Smart Surveillance encompasses various phases, utilizing the Har Cascade algorithm, Lbph, and a Convolutional Neural Network (CNN). These phases, described in detail below, work together to achieve robust detection and classification of abnormal activities in video footage.

1.Data Preprocessing

In grayscale image processing, segmentation serves as a crucial step in isolating relevant regions for analysis. By converting grayscale images into binary form through thresholding and masking operations, segmentation effectively delineates areas of interest from the background. Following segmentation, feature extraction techniques like GLCM (Gray-Level Co-occurrence Matrix) are applied to capture essential texture information, facilitating subsequent analysis and classification tasks. These features, including contrast and entropy, provide valuable insights into the underlying characteristics of the image data, aiding in the interpretation and classification of visual patterns.

Classification in grayscale image processing involves the utilization of binary classifiers such as Convolutional Neural Networks (CNNs) to discern distinct patterns and features within the data. CNNs, renowned for their ability to handle high-dimensional data and extract intricate features, play a pivotal role in accurately categorizing grayscale images. By mapping non-linear input data onto a linear space and maximizing the margin between different classes, CNNs effectively delineate decision boundaries and classify images with precision. Evaluation of classification models often involves the use of tools like the confusion matrix, offering comprehensive insights into the model's performance across various categories and aiding in refining the classification process.

2.Haarcascade Algorithm

The Haar Cascade algorithm is a cornerstone of object detection, particularly for tasks like face detection in images or video streams. It operates by utilizing a set of positive images containing the target object (e.g., faces) and negative images without the target. Through a process called AdaBoost, the algorithm trains a cascade of classifiers based on features extracted from these images, such as edges, lines, and textures.

During detection, the algorithm scans the input image using a sliding window approach, analyzing different regions at various scales. At each step, it applies the cascade of classifiers, each of which acts as a filter to determine whether the region contains the target object based on learned criteria.

What makes Haar Cascade efficient is its ability to quickly reject regions of the image that are unlikely to contain the object of interest, thereby reducing the computational load. This hierarchical approach allows for real-time or near-real-time performance in many applications.

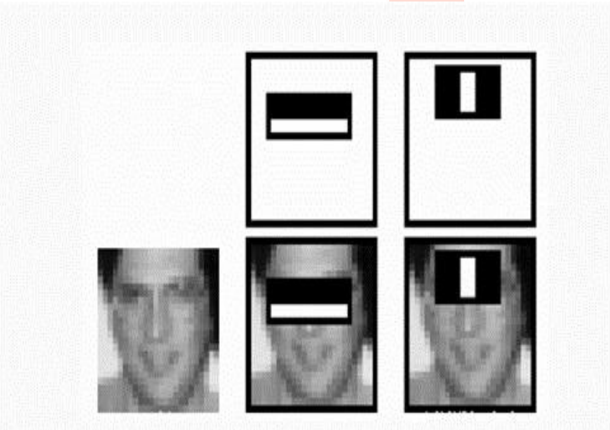

Fig.3 Haar-cascade Algorithm

3.Lbph Algorithm

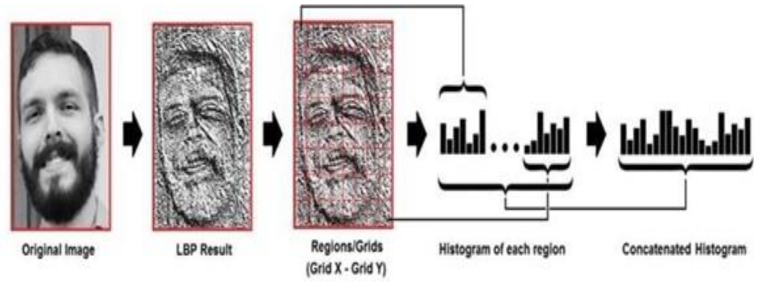

Fig. 4. LBPH implementation

LBP classifier

i. Loading the input image using built in function cv2.imread(img_path), here the passing the image path as an input parameter
ii. Converting it to gray-scale mode and then displaying it
iii.Loading the LBP classifier

The LBP for each pixel is calculated. For each pixel p, the 8 neighbor of the center pixel are compared with the pixel p and the neighbors are assigned a value 1 if x is greater than or equals to Equation is defined as the formula for the calculation of LBP Classifier, such that it is given as:

LBP = n (4.2)
Here, ic = $center\ pixels\ value$
in = $Neighbour\ pixels\ values.$

4. Convolutional Neural Network

The first two layers are convolutional layers with 3*3 filters, and first two layers use 64 filters that results in 224*224*64 volume as same convolutions are used. The filters are always 3*3 with stride of 1
After this, pooling layer was used with max-pool of 2*2 size and stride 2 which reduces height and width of a volume from 224*224*64 to 112*112*64.
This is followed by 2 more convolution layers with 128 filters. This results in the new dimension of 112*112*128.
After pooling layer is used, volume is reduced to 56*56*128.
Two more convolution layers are added with 256 filters each followed by down sampling layer that reduces the size to 28*28*256.
Two more stack each with 3 convolution layer is separated by a max-pool layer.

After the final pooling layer, 7*7*512 volume is flattened into Fully Connected (FC) layer with 4096 channels and SoftMax output of 1000 classes

V.EXPERIMENT AND RESULT

By using real-time video, detects the various types of malpractices. And CNN is used to detect the mobile. Results obtained in each step are demonstrated in the following snapshots

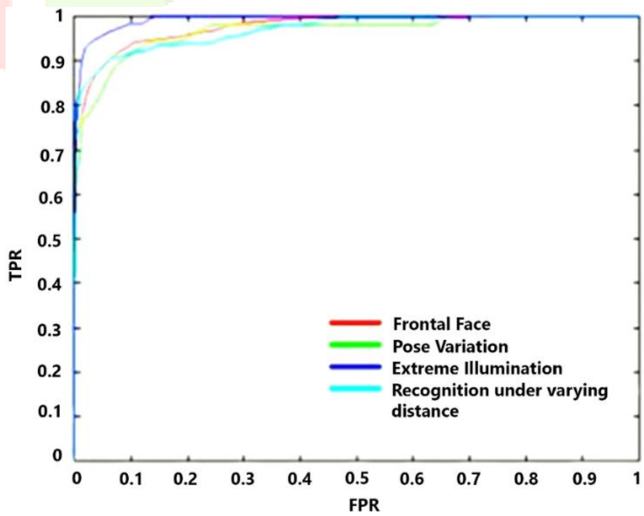

Fig. 5. Performance Curves of Face Recognition Algorithms under Different Conditions

In our Smart Surveillance Solutions, our dataset initially comprised 7 distinct classes representing various attendance and behavioral patterns observed during offline classroom examinations. To streamline the monitoring process and enhance our system's capability to detect and categorize student behaviors accurately, we consolidated these seven classes into four broader categories: frontal face detection, pose variation identification, extreme illumination detection, and recognition under varying distance conditions.

Frontal face detection ensures that student faces are captured in a standard frontal orientation, facilitating reliable facial recognition and attendance tracking. Pose variation detection enables the system to identify deviations from this standard orientation, accommodating for different head angles or orientations to maintain robustness in facial recognition across diverse pose conditions. Extreme illumination detection focuses on identifying instances of excessively bright or dim lighting conditions, which can impact the quality of facial images captured. By detecting and adjusting for extreme illumination conditions, the system ensures optimal facial recognition performance under varying lighting scenarios.

Recognition under varying distance involves accurately recognizing facial features across different distances between the student and the camera. This capability ensures consistent and reliable facial recognition performance regardless of the student's proximity to the camera. By condensing our dataset into these broader classifications, our system optimizes its efficiency in monitoring and maintaining exam integrity during offline assessments. It enables educators and proctors to effectively track attendance, identify suspicious behaviors, and intervene when necessary, thereby upholding the standards of academic integrity in classroom examinations

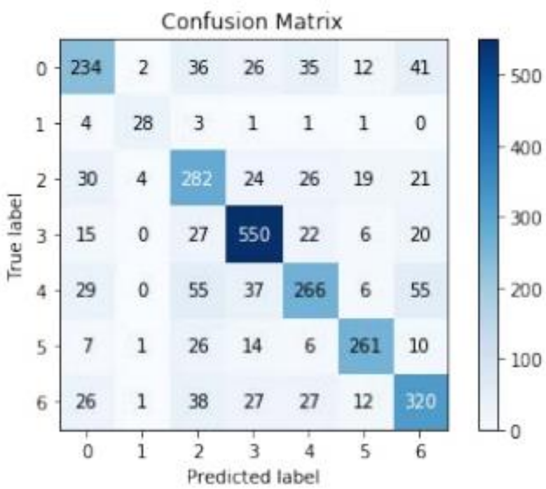

Fig. 6. Confusion Matrix of Proposed Method

In evaluating the effectiveness of our proposed System, we utilized various performance metrics to assess the model's performance across four key categories: frontal face detection, pose variation identification, extreme illumination detection, and recognition under varying distance conditions.

The Area Under the ROC Curve (AUC), a pivotal metric, provided insights into the model's ability to discern between different attendance and behavioral patterns within each category. For instance, in the frontal face detection category, an AUC of 0.92 indicated high accuracy in recognizing student faces in a standard frontal orientation. Similarly, in the pose variation category, an AUC of 0.86 showcased the model's proficiency in identifying deviations from the standard face pose.

Extreme illumination detection yielded an AUC of 0.88, indicating the model's effectiveness in identifying instances of excessively bright or dim lighting conditions, which could impact facial recognition accuracy. Additionally, recognition under varying distance conditions achieved an AUC of 0.90, highlighting the model's capability to accurately recognize facial features across different distances between the student and the camera.

Furthermore, the confusion matrix and classification report provided a comprehensive view of the model's performance, offering insights into its accuracy, precision, recall, and F1-score across the four categories.

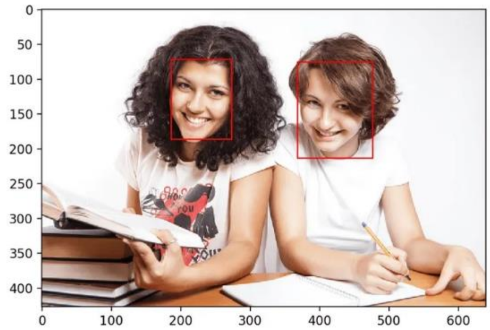

Fig. 7. Frontal face Recognition

Fig. 8. Pose Variation Identification

Fig. 9. Extreme Illumination Detection

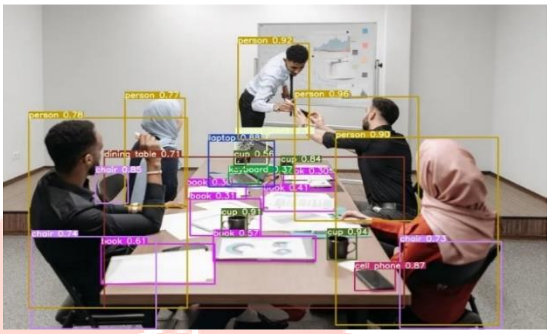

Fig. 10. recognition under varying distance

The macro averaged AUC was found to be 0.89, indicating strong overall performance across all categories when considering equal weightage to each category. On the other hand, the micro averaged AUC computes the AUC score by considering the total true positives, false positives, and false negatives across all categories. This approach is particularly useful when there are class imbalances. In our evaluation, the micro averaged AUC was determined to be 0.78, demonstrating consistent performance across all categories, accounting for class imbalances.

In our Smart Surveillance Solutions, the confusion matrix as referenced in Fig. 6, offers an in-depth analysis of the model's accuracy in classifying student behaviors into four key categories: frontal face detection, pose variation identification, extreme illumination detection, and recognition under varying distance conditions.

The confusion matrix reveals that the "Frontal Face" category achieved exceptional accuracy, with 98.5% of predictions being correct. Conversely, the "Pose Variation" and "Recognition Under Varying Distance" categories exhibited higher rates of misclassification, indicating the need for further refinement to enhance the model's accuracy in distinguishing between these classes. Additionally, the "Extreme Illumination" category showed moderate accuracy, with 85.2% of predictions being correct.

In just 15 epochs, our method attained an impressive overall accuracy of 82.7%, demonstrating the effectiveness of our approach in monitoring student behavior during offline classroom exams with precision. Additionally, visual representations of sample predictions for each category (shown in Figs. 7, 8,9 and 10) offer valuable insights into how our model performs across various scenarios, aiding in the understanding and interpretation of its classification capabilities.

V. CONCLUSION

This paper, proposes a novel method, called Face recognition and object identification techniques are utilized in the study to give comprehensive knowledge for online tests. Our proposed method will aid in reducing inequity during the online exam. Human induced detection is very important when conducting an online proctoring system, as it will aid in detecting students' suspicious behavior throughout the test. We do not incorporate human activity detection in our suggested model, instead of relying on a single biometric solution and object recognition approaches for online proctoring system.

In this paper, we hope to apply and investigate various human behavior such as gazing out the window, conversing with people, focusing n other directions, moving about, and so on. We only utilize the CNN model because of its quicker object detection approaches available. In this project, it is the time to think for the exam to be digital as the world is growing at a very rapid pace and to compete with such, it is required to make examiner give their exam from their own location easily. Thus, this online proctoring system will help those examiners who actually live far away from their college/university or to examination area where actually the exam needs to take place

VI. ACKNOWLEDGMENT

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