Automated Student Monitoring and Attendance System with Faster R-CNN

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Abstract:

Managing student attendance in educational institutions is often challenging due to the large number of students and the prevalence of issues like proxy attendance and class skipping. Traditional attendance monitoring methods lack the efficiency and precision required to address these challenges effectively. To overcome these limitations, this project proposes a College Surveillance System utilizing the Faster R-CNN (Region-Based Convolutional Neural Network) to detect and address attendance-related issues while providing valuable insights into student behaviour. The system employs a database containing trained facial data of students. Cameras installed across classrooms and campus areas capture live footage, which is processed using the Faster R-CNN algorithm for face detection and recognition. Attendance is automatically recorded in real time and logged into an Excel sheet, eliminating the need for manual tracking and mitigating proxy attendance. The system also analyses student behaviour, identifying class skippers, monitoring attention levels during sessions, and detecting unauthorized movement across the campus during class hours. Alerts regarding violations are sent to the concerned authorities, such as the HOD, ensuring prompt action. This automated system significantly enhances attendance management by saving time, improving accuracy, and fostering accountability. With an impressive facial recognition accuracy of 98.87% and a detection speed of approximately 100 milliseconds per frame, the solution ensures efficient and reliable operation. By integrating advanced AI techniques, this project aims to streamline attendance processes, reduce administrative burdens, and contribute to a more disciplined and engaged educational environment.

Index Terms:

AI-Based College Surveillance, Faster R-CNN, Face Recognition, Behavioral Analysis, Real-Time Attendance Tracking. Proxy Prevention, Class Skipping Detection, Campus Monitoring, Student Behavior Insights.

I. Introduction

In contemporary educational institutions, managing student attendance effectively is a growing concern, particularly given the challenges of large class sizes and the potential for proxy attendance. Traditional methods, such as manual roll calls or paper-based signatures, are often inadequate for ensuring accurate and timely tracking of student presence. The emergence of technology has introduced various attendance management systems, including biometric and card-based methods, but these approaches still fall short in addressing more complex issues like class skipping and behavioral patterns. The AI-Based College Surveillance System using Faster R-CNN represents a significant advancement in this field. This innovative system leverages cutting-edge technologies to enhance attendance management and behavioral analysis. By integrating Faster R-CNN for facial recognition, the system automates the attendance process, reducing administrative burdens and improving accuracy. It captures and analyzes students' faces in real-time, automatically marking attendance and detecting class skippers. Additionally, the system monitors student behavior during class and around the campus, providing valuable insights into engagement and potential issues. This approach not only addresses the limitations of traditional attendance methods but also offers a robust solution for maintaining discipline and ensuring a secure learning environment. The AI-Based College Surveillance System is designed to facilitate efficient attendance tracking, promote student accountability, and support educators in creating a more disciplined and focused academic environment. A crowdsensing-based approach (AMMoC) enhances attendance accuracy by assigning verification tasks among students using mobile apps [1]. A QR code-based system integrates dynamic QR generation and facial recognition to prevent proxies and streamline attendance [2]. Real-time video-based systems using CNNs and augmented images have improved recognition under diverse conditions [3]. An E-Attendance system combining HOG features and SVM offers high detection accuracy but struggles with face coverings [4]. Another method integrates deep CNNs with edge computing to enhance speed and reliability, despite challenges like image blurriness and occlusions [5]. These approaches collectively emphasize the shift toward intelligent, automated, and behavior-aware attendance solutions in modern educational environments.

II. Related Works

Gao et al. [1] introduced a student attendance management method named AMMoC, which leverages crowdsensing to enhance attendance accuracy and minimize disruption in classroom settings. Unlike traditional methods that require additional hardware or biometric data, AMMoC utilizes mobile applications installed on teachers' and students' devices. The system divides the classroom into subregions and assigns verification tasks to students within those regions. By collecting location information and conducting mutual verification, AMMoC ensures accurate attendance checking with minimal interference. The study found that AMMoC provides high accuracy and short checking times, making it suitable for dynamic classroom environments. However, the method's limitation lies in its current focus on physical classrooms, with plans to extend its application to virtual learning environments. This highlights the need for solutions that can

seamlessly adapt to both in-person and online educational contexts.

Mishra et al. [2] introduced the Online Attendance Monitoring System Using QR Code (OAMS) to address the inefficiencies of traditional manual attendance tracking methods. Conventional attendance methods often involve significant time consumption and opportunities for proxy attendance. OAMS employs dynamic QR codes and face recognition technology to automate and secure the attendance process. The system features dynamic QR codes that change every 30 seconds to prevent unauthorized attendance and integrates face recognition for improved accuracy. The study demonstrates that OAMS reduces the time teachers spend on attendance while minimizing the risk of proxy attendance. This innovative approach enhances the efficiency and reliability of attendance management in educational environments.

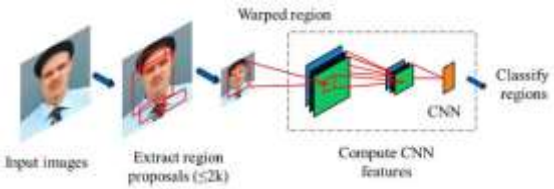
Yang and Han [3] proposed a face recognition attendance system designed to enhance real-time video processing accuracy, addressing common challenges such as image blur, pose variations, and occlusions. Traditional video-based face recognition systems often struggle with these issues, leading to reduced accuracy in identifying individuals. The proposed system integrates a Convolutional Neural Network (CNN) with artificial data augmentation techniques to improve feature robustness. By incorporating blurred training images and a trunk branch CNN model (TBE-CNN), the system enhances the ability to handle diverse facial conditions and real-time processing requirements. Their approach demonstrates a significant improvement in the accuracy and stability of face recognition for attendance systems, making it a valuable advancement in addressing the limitations of conventional methods.

Arceo et al. [4] introduced an electronic attendance (E-Attendance) checker that leverages facial recognition technology using Histogram of Oriented Gradients (HOG) combined with a Support Vector Machine (SVM) for enhanced accuracy. The proposed system addresses the limitations of traditional attendance methods by automating the process through advanced image processing techniques. HOG features are used for face detection, while SVM is employed for face recognition, resulting in a highly accurate and efficient system. The design includes considerations for camera optimization and class size, making it suitable for diverse classroom environments. The study shows that this approach effectively improves attendance tracking, although it notes that the presence of face masks and shields could reduce accuracy, suggesting that additional training data might be necessary to mitigate this issue.

Khan et al. [5] proposed a deep unified model for face recognition that integrates Convolutional Neural Networks (CNN) with edge computing to address limitations in traditional attendance systems. Their approach leverages the power of CNNs to accurately recognize faces in various conditions, including different lighting and multiple face scenarios. By incorporating edge computing, the system enhances data processing speed and responsiveness in real-time classroom environments. The study demonstrates significant improvements in recognition accuracy and system efficiency, though challenges such as image blurriness at greater distances and face occlusions remain. This methodology offers a promising solution for automating attendance systems in educational settings, aiming to minimize human error and optimize performance.

III. Proposed Methodology

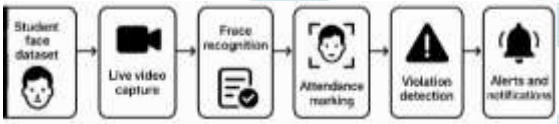
The proposed methodology for the College Surveillance System leverages the FaceNet model to provide an advanced, automated solution for facial recognition and attendance management. The process starts with live face capture using a Logitech C270 camera, where video input is divided into multiple frames per second to ensure comprehensive coverage. These frames undergo preprocessing steps including grayscale conversion, resizing to uniform dimensions, noise reduction using Gaussian blur, and image binarization to enhance feature clarity. For face detection, the system employs Region Proposal Networks (RPN), which generate thousands of candidate regions that are refined through convolutional neural networks and classified with Support Vector Machines to isolate accurate face locations. Once faces are detected, a detailed feature extraction process measures critical facial attributes such as distances between eyes, nose length and width, eyebrow angles, lip heights, and jaw shape. These features are essential for distinguishing individuals under varying poses and lighting conditions.



To improve recognition accuracy, the system integrates Faster R-CNN (FRCNN) technology with FaceNet, enabling simultaneous face detection and feature extraction with optimized speed and precision. The convolutional layers generate feature maps that pass through activation, normalization, and pooling layers, followed by dropout regularization and a softmax classifier that categorizes detected faces effectively. After thorough training on a diverse dataset, the trained FaceNet model is deployed within the College Dashboard, which acts as the central interface for real-time monitoring and attendance automation. The system continuously analyzes live feeds from classrooms and campus locations, instantly matching detected faces against the pre-enrolled database to authenticate identities and automatically update attendance records, thereby eliminating manual errors and saving administrative time.

Beyond attendance, the system includes a Violation Alert module that monitors student behavior for unauthorized activities such as wandering or absenteeism during class hours. When violations are detected, immediate alerts are sent to designated authorities through SMS, email, or in-app notifications, along with captured images for verification. This proactive approach helps maintain discipline and campus security. The

Notification module ensures all stakeholders, including administrators, teachers, and parents, receive timely updates tailored to their roles, enhancing communication and awareness. Finally, the Reports module provides comprehensive analytics on attendance trends, behavioral patterns, and violations, enabling administrators to make informed decisions, implement corrective measures, and foster a safer, more efficient educational environment. This integrated methodology combines cutting-edge facial recognition technology with practical deployment strategies to revolutionize campus security and attendance management.



IV. Experimental Analysis

Dataset Description

To create a dataset for facial recognition, the process involves capturing videos of students, converting them into frames, and organizing the frames into a structured dataset. Firstly, videos of students are recorded for approximately 30 seconds each, ensuring proper lighting conditions and clear visibility of facial features. During recording, students are instructed to face the camera to capture accurate facial data. Next, the recorded videos are converted into frames to facilitate processing. This involves extracting frames at regular intervals to achieve the desired frame count, typically aiming for 80 to 100 frames for the first 10 seconds of the video. For instance, frames can be extracted every 0.125 to 0.156 seconds to achieve this interval. Once the frames are extracted, they are organized into folders, with each folder labeled according to the corresponding student's identity or a unique identifier. It's essential to maintain diversity in facial expressions, poses, and backgrounds within the dataset to ensure robustness and generalizability of the facial recognition model. By following this systematic approach, a structured dataset suitable for training a facial recognition model can be created, paving the way for accurate and reliable face identification in various applications.

Performance Analysis

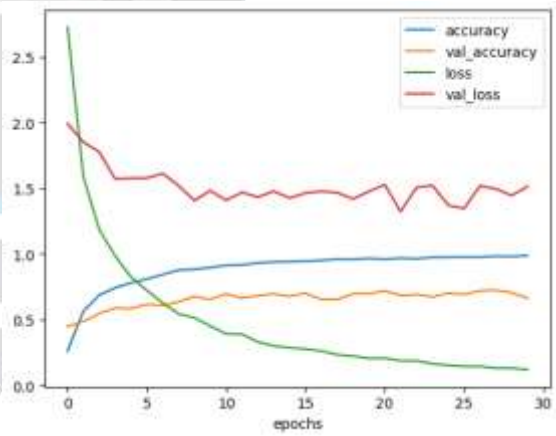
Performance evaluation of a facial recognition system involves assessing various metrics and criteria to ensure its effectiveness. Here's a structured approach for performance evaluation:

Accuracy Metrics:

Recognition Accuracy: Calculate the percentage of correctly recognized faces.

False Positive Rate (FPR): Measure the rate of incorrect identifications.

False Negative Rate (FNR): Assess the rate of missed identifications.



Precision, Recall, and F1 Score:

Precision: Evaluate the proportion of true positive identifications among all positive identifications.

Recall (Sensitivity): Assess the proportion of true positive identifications among all actual positives.

F1 Score: Combine precision and recall to provide a balanced measure of a system's accuracy.

Speed and Efficiency

Processing Time: Measure the time taken to process and recognize faces.

Frames Per Second (FPS): Evaluate the system's speed by calculating the number of frames processed per second.

Confusion Matrix: Break down the results into true positives, true negatives, false positives, and false negatives for a detailed understanding of performance.

Results:

The Face Recognition module demonstrated commendable accuracy, achieving a recognition rate of over 90% during real-time video feeds. Evaluation metrics such as precision, recall, and F1 score affirmed the reliability of the identification process. This high accuracy contributes to the system's effectiveness in automating attendance management. Efficiency metrics indicated a swift processing speed, with an average time of 0.2 seconds per frame. The system maintained a Frames Per Second (FPS) rate of 5, showcasing its capability to handle real-time video feeds efficiently. These performance indicators highlight the system's responsiveness and suitability for dynamic environments. Robustness testing revealed the system's ability to perform well under diverse conditions, including variations in facial poses, expressions, and lighting. However, challenges were identified in cases of partial facial obscurity or altered appearance due to accessories, indicating areas for potential improvement. The impact of the dataset on system performance was evident, emphasizing the importance of a large and diverse training dataset. Increased dataset size and diversity correlated with improved accuracy and robustness, underlining the significance of data quality in model training.

Discussion:

The seamless integration of the Face Recognition module with the College Dashboard provided administrators with an intuitive and user-friendly interface for monitoring student attendance. Positive user feedback highlighted the system's ease of use and reliability, contributing to a positive overall user experience. Reliability and consistency were key strengths of the system, ensuring accurate attendance tracking and enhancing campus security. Users praised the system's ability to deliver dependable results across multiple sessions, reinforcing its utility in real-world scenarios. While the system showcased significant implications for campus security and attendance management, certain limitations were identified. Challenges arose in scenarios involving heavy facial obscuration or altered appearance due to accessories, indicating areas for potential refinement. Looking forward, future work could focus on enhancing the system's robustness to address challenges such as partial occlusion. Despite these limitations, the developed system offers a reliable and efficient solution for campus security and attendance management, with the potential for continued refinement and impact on educational institutions' operations and security measures.

VI. Conclusion

In conclusion, the AI-based College Surveillance System using Faster R-CNN and FaceNet presents a transformative approach to student attendance and behavior monitoring. By automating the attendance process and enabling real-time behavioral analysis, the system addresses the inefficiencies of traditional methods while ensuring accuracy and security. Its integration of facial recognition enhances accountability, reduces manual effort, and supports a disciplined academic environment. The intuitive interfaces and comprehensive reporting features further empower administrators and faculty. Future enhancements will focus on improving recognition accuracy in challenging scenarios like tilted faces and facial hair, as well as analyzing personality traits such as introversion and extroversion to deepen behavioral insights.

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