Grenze International Journal of Engineering and Technology, June Issue

Smart-Vision: Automated System for Attendance Management and Uniform Detection

Rohit Gakhare[1], Chandravani Rokde[2], Vishal Kotnod[3], Adnan Sayyad[4], Shoyab Khan[5] and Kunal Rathod[6]
[1-6]Department of Information Technology, Yeshwantrao Chavan College of Engineering, Nagpur, India
Email: rohitgakhare2205@gmail.com, chandrayanirokde@gmail.com, vkotnod@gmail.com, adnanahemadsayyad@gmail.com, shoyabkhan910910@gmail.com, kunalrathod10101010@gmail.com

***Abstract*— This paper presents an automated attendance tracking system that integrates facial recognition with uniform detection to enhance reliability and efficiency in classroom attendance management. The system captures live video streams within a classroom environment and identifies students by matching detected faces with a pre-enrolled database using a deep learning–based face recognition framework. Simultaneously, a YOLOv8-based object detection model verifies whether the detected individual is wearing the prescribed uniform. Attendance is recorded only when both identity verification and uniform compliance are successfully confirmed. The system performs real-time processing using OpenCV with a Flask-based backend architecture, while a React.js web interface provides an intuitive platform for monitoring attendance records and system outputs. Experimental evaluations conducted in a real classroom environment demonstrate strong performance, achieving over 95% accuracy for face recognition and more than 90% accuracy for uniform detection. The proposed framework effectively handles challenges such as variations in lighting conditions, occlusions, and similarities in clothing patterns, thereby improving the reliability, security, and efficiency of automated attendance monitoring systems.**

***Keywords*— Facial recognition, attendance system, uniform detection, YOLOv8, computer vision, deep learning.**

I. INTRODUCTION

To address the inefficiencies of manual attendance systems and uniform compliance monitoring, this research explores the integration of facial recognition and object detection techniques for educational environments. Traditional attendance methods such as roll calls and RFID-based systems are often time-consuming, error-prone, and vulnerable to manipulation [1], [2]. Similarly, manual verification of uniform adherence requires significant human effort and lacks consistency. With advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV), it is now possible to automate these processes with high accuracy and reliability. Several works have demonstrated the effectiveness of deep neural networks in image recognition and real-time object detection [5], [6], [13], offering scalable and efficient solutions for automation in academic institutions.

The proposed system combines a facial recognition module based on the face_recognition library with a YOLOv8- based uniform detection model, ensuring that attendance is recorded only when both identity and dress code verification succeed.

Grenze ID: 01.GIJET.12.2.245_24

A Flask backend manages the real-time recognition pipeline, while a React.js interface provides administrator-tors with an intuitive dashboard for attendance visualization and management. By leveraging pre-trained models such as YOLOv8 [9] and FaceNet [3], the system achieves real- time, secure, and unbiased monitoring. This dual-verification approach minimizes human intervention, enhances operational efficiency, and promotes discipline and compliance within educational institutions.

II. Related Work

The automation of attendance management has gained considerable attention with the advancement of computer vision and deep learning technologies. Traditional attendance methods such as manual registers, RFID cards, and biometric fingerprint systems are widely used in educational institutions but often suffer from issues such as proxy attendance, maintenance costs, and human errors.

Early computer vision research laid the foundation for automated attendance systems through techniques such as the Viola–Jones face detection framework [1] and benchmark datasets like Labeled Faces in the Wild (LFW) for evaluating face recognition algorithms under unconstrained conditions [2]. These developments enabled the detection and identification of human faces from images and video streams, paving the way for intelligent attendance monitoring systems.

With the emergence of deep learning, facial recognition accuracy improved significantly. Approaches such as FaceNet introduced embedding-based methods that map facial images into high-dimensional feature spaces for reliable identity matching [3]. The success of convolutional neural networks in large-scale image classification tasks, such as those demonstrated through ImageNet-based architectures [5], further strengthened feature extraction capabilities for facial analysis. Several modern deep learning frameworks and architectures have been applied to face analysis and recognition tasks, enabling robust identification even in complex environments [14]. Consequently, a number of studies have proposed automated attendance systems based on facial recognition technologies, demonstrating improved efficiency and reduced manual intervention in academic environments [17] – [19].

In parallel, advancements in object detection algorithms have enabled real-time monitoring and analysis in computer vision applications. Frameworks such as YOLO and its improved versions, including YOLOv4 and YOLOv7, have demonstrated high accuracy and real-time performance in object detection tasks [6] – [8]. Other architectures such as Fast R-CNN, Mask R-CNN, and Faster R-CNN have also contributed to the advancement of object detection techniques [11] – [13]. Recent research has extended these techniques to applications such as uniform detection and classroom monitoring, where deep learning models are used to verify dress code compliance and student presence [20], [21], [26]. However, most existing attendance systems rely on a single verification method. To address this limitation, the proposed work integrates facial recognition with YOLO-based uniform detection to create a reliable and real-time automated attendance system suitable for modern smart classroom environments.

Despite these advancements, many existing attendance systems rely primarily on facial recognition alone and do not incorporate additional verification mechanisms such as dress code compliance. To address this limitation, the proposed system integrates facial recognition with YOLO-based uniform detection within a unified architecture. The system captures live classroom video streams, identifies students through facial embeddings, and simultaneously verifies uniform compliance using a trained object detection model. This combined approach enhances the reliability and security of automated attendance systems while maintaining real-time performance suitable for deployment in modern smart classrooms.

III. Methodology

The proposed system employs a multi-stage pipeline integrating computer vision, deep learning, and web technologies to automate attendance management through real-time face recognition and uniform detection. The architecture ensures that attendance is recorded only when both identity and dress code verification succeed. The methodology consists of the following major components: data acquisition and preprocessing, face recognition, uniform detection, attendance logging, and web-based visualization. These components operate in a coordinated manner to process classroom video streams, analyze visual features, and validate student identity in real time. The integrated framework enables efficient detection, reliable attendance recording, and seamless interaction through a web-based interface. This design improves system accuracy while reducing manual intervention in the attendance process.

A. Data Creation and Validation

For data collection and preprocessing, two datasets were prepared: a face dataset and a uniform dataset. For the face dataset, individual student images were collected under controlled lighting conditions to ensure consistent facial features. Each image was encoded using Dlib's deep metric learning-based face recognition framework to generate unique facial embeddings that serve as identifiers for each registered student. In addition, a custom uniform dataset consisting of over 1000 images was created, containing samples of students wearing the prescribed uniform (sky-blue shirt and dark-blue pants) as well as images of students without proper attire. Each image was manually annotated using bounding boxes to mark the uniform regions, enabling the YOLOv8 model to effectively learn and detect clothing patterns.

B. Uniform Detection Using YOLOv8

The YOLOv8 object detection model is trained on the annotated uniform dataset to classify whether a detected individual complies with the prescribed dress code. The model processes real-time video streams captured through a webcam or CCTV feed, enabling the system to detect individuals and verify uniform compliance simultaneously.

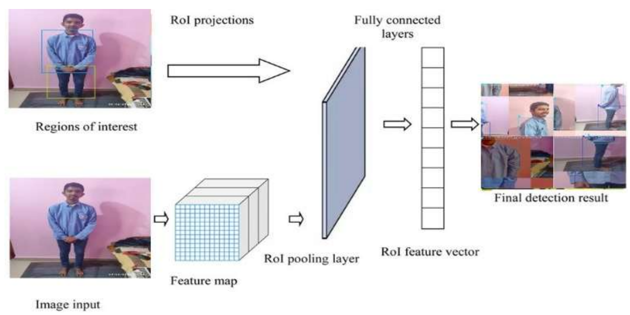

Fig. 1. RoI-based uniform detection pipeline from image input to final detection.

During inference, YOLOv8 identifies persons in the frame and generates bounding boxes along with confidence scores for detected uniform regions. These detection outputs are then transmitted to the Flask-based backend server for further analysis and integration with the attendance system. The overall pipeline, illustrated in Fig. 1, demonstrates the region-of-interest (RoI) based uniform detection process, which includes image input, feature extraction, RoI projection, fully connected layers, and final detection results.

C. Face Recognition for Student Identification

Facial recognition is performed using the face_recognition library built on Dlib's deep learning-based face recognition framework. When a student's face is detected in the video frame, the system extracts facial embeddings that represent distinctive facial features. These embeddings are then compared with stored facial encodings of registered students using the Euclidean distance metric. If the computed distance falls below a predefined threshold, the identity of the student is confirmed. This method allows reliable identification even under minor variations in pose and lighting conditions. To improve system reliability, facial recognition is combined with the uniform detection module. Attendance is marked only when both the face identity and uniform compliance are successfully verified.

D. Attendance Recording and Data Management

Once a student is verified, the system automatically records the attendance entry using Python's Pandas library for efficient data handling. Each record contains details such as student ID, name, date, time, and uniform status. The attendance data is stored in a structured CSV format, enabling easy management and retrieval of records. Before adding a new entry, the system checks for duplicate records to ensure that attendance is marked only once per session. The Flask backend manages secure communication between the detection modules and the database, ensuring reliable and consistent data storage.

E. Web Application for Data Visualization

A user-friendly web application is developed using React.js to provide easy access to attendance information. The platform offers separate dashboards for administrators, teachers, and students. Administrators can monitor attendance statistics and manage student data, while teachers can view and download attendance reports for selected date ranges. Students are able to access their daily attendance status through their accounts. Firebase is integrated to provide secure authentication and role-based access control, ensuring that system features are accessible only to authorized users.

F. System Integration and Real-Time Processing

The Flask server acts as the central component that coordinates communication between the frontend and backend modules. It processes requests from the web interface and manages responses from the computer vision models. OpenCV is used for video capture and frame-by-frame processing of live camera feeds. Each frame is analyzed for uniform detection using the YOLOv8 model and for student identification using facial recognition. The results are then sent to the backend for attendance verification and recording. This integrated pipeline enables near real-time processing with minimal delay, making the system suitable for practical classroom environments.

G. Testing and Evaluation

The system was tested in real classroom environments to assess accuracy, performance, and reliability under various lighting and distance conditions. The facial recognition mod- ule, implemented using the Dlib library, achieved an average accuracy above 95%, even with partial occlusions such as masks or glasses. The YOLOv8-based uniform detection model attained a mean Average Precision (mAP) of 0.92 at an IoU threshold of 0.5, with precision and recall rates of 96% and 94%, respectively.

Overall, the integrated system operated in real time at approximately 30 FPS, ensuring efficient and accurate automated attendance marking

IV. RESULT

A. Model Performance

To evaluate the performance of the proposed automated attendance system, experiments were conducted in a real classroom environment. The system was assessed using standard evaluation metrics, including precision, recall, and F1-score, to measure the effectiveness of both the face recognition and uniform detection modules. These metrics provide a quantitative understanding of how accurately the system identifies students and verifies uniform compliance during real-time operation.

TABLE I: PERFORMANCE METRICS OF SYSTEM MODULES

Module	Precision	Recall	F1-score / Accuracy
Face Recognition	0.98	0.997	0.988
Uniform Detection	0.91	0.92	0.915

Table I presents the performance results of the individual modules. The face recognition component achieved a precision of 0.98 and a recall of 0.997, indicating highly reliable identification of registered students with minimal false detections. Similarly, the uniform detection module demonstrated consistent performance, achieving precision and recall values above 0.90 despite variations in lighting conditions and camera perspectives. Overall, the integrated attendance framework achieved an end-to-end system accuracy ranging from 92% to 95%, highlighting its effectiveness and suitability for real-time deployment in academic environments.

B. User Interface Workflow

The proposed system incorporates an interactive user interface to facilitate secure access and efficient monitoring of attendance records. The workflow begins with the user accessing the application interface, where authentication is performed using Firebase-based login credentials. If a user is not registered, the system redirects them to the registration module; otherwise, successful authentication grants access to the main dashboard. This authentication mechanism ensures that only authorized users can interact with the attendance management system.

Once authenticated, users can access the system features through a centralized dashboard that provides real-time monitoring and control. The interface allows instructors or administrators to initiate the attendance detection process, view system status, and monitor detection results. Additionally, the dashboard provides quick access to attendance records and analytics, enabling efficient tracking and management of student attendance data.

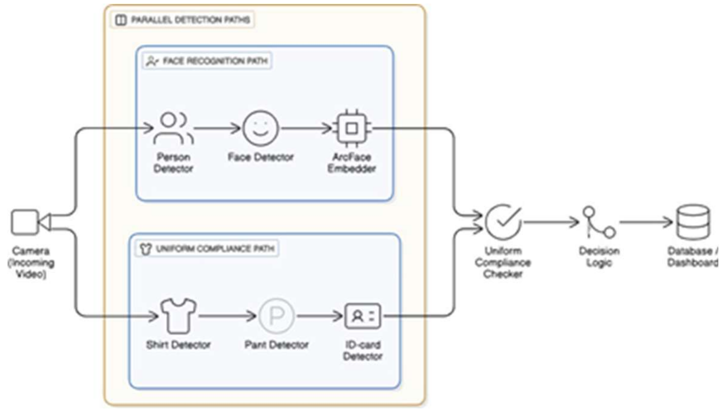

Fig. 2. Block diagram of the proposed attendance pipeline: camera → uniform detector → face recognizer → decision logic → database/dashboard

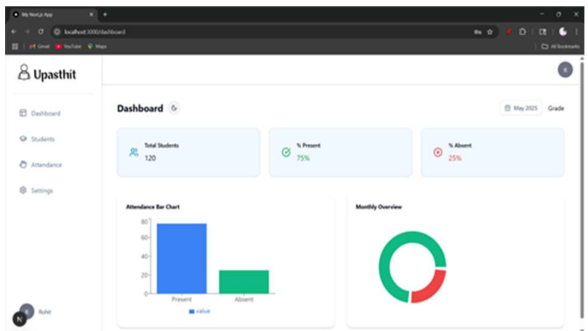

Fig. 3. Dashboard with logs and overlays for detected students

Fig. 2 illustrates the overall workflow of the proposed system, beginning with user authentication and concluding with automated attendance logging. After a successful login, the system activates the camera to continuously capture classroom frames for real-time analysis. Each captured frame is processed simultaneously by the face recognition and uniform detection modules. The face recognition component identifies students by comparing detected facial embeddings with those stored in the enrolled database, while the uniform detection module verifies whether the detected individual is wearing the prescribed uniform.

C. Validation Performance Evaluation and Comparison

To evaluate the performance of the proposed attendance system, experiments were conducted using a held-out test dataset. The evaluation focused on standard performance metrics such as precision and recall to assess the reliability of the individual system modules. The face recognition component achieved a precision of approximately 0.98 and a recall of 0.997, indicating highly accurate identification of registered students. Similarly, the uniform detection module, trained on examples of correct and incorrect attire, demonstrated robust performance with precision and recall values exceeding 0.90 even under challenging lighting conditions.

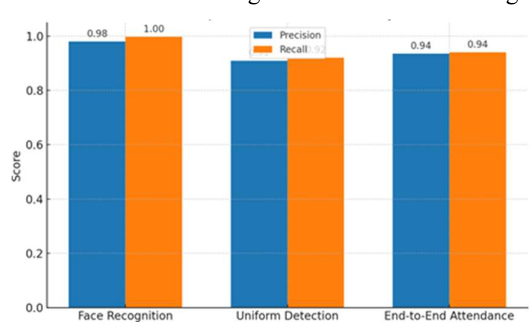

Fig. 4. Performance comparison of attendance system modules

Fig. 4 illustrates the comparative performance of the face recognition and uniform detection modules, along with the overall system accuracy. The overall system accuracy, defined as the proportion of correctly recorded attendance entries, ranged between 92% and 95% during real-world deployment. When compared with earlier attendance systems based on traditional convolutional neural networks or classical approaches such as Haar Cascade and Local Binary Pattern Histogram (LBPH), which typically reported accuracies in the range of 85–95%, the proposed approach demonstrates improved reliability and efficiency. The use of the YOLOv8 architecture, which incorporates advanced feature extraction and optimized detection mechanisms, contributes to higher accuracy and faster inference.

V. CONCLUSION

This study proposed a comprehensive automated attendance system that integrates facial recognition and uniform detection to enhance reliability, transparency, and compliance in academic environments. By combining the strengths of the YOLOv8 object detection framework and the Dlib-based facial recognition module, the system ensures that attendance is recorded only when both identity and uniform compliance are verified. This dual verification mechanism significantly reduces proxy attendance and manual intervention, making the process more secure and efficient. Experimental evaluations conducted in real classroom conditions demonstrated that the system achieves high accuracy and real-time performance, with an average facial recognition accuracy exceeding 95% and a uniform detection mAP of 0.92. The framework also showed strong resilience under varying lighting, camera angles, and partial occlusions, ensuring robustness for real-world deployment. The web-based interface developed using Flask and React.js further simplifies attendance visualization, record management, and report generation. Overall, the proposed system represents a reliable, intelligent, and practical approach toward digitizing attendance monitoring in modern smart classrooms.

FUTURE SCOPE

The proposed system can be further enhanced by expanding the dataset to include a wider variety of student images and environmental conditions, which would improve model robustness and detection accuracy. Future work may also focus on optimizing the system for deployment on edge devices to enable faster processing and reduced hardware requirements. In addition, the cloud-based database can be extended to support large-scale institutional deployments, enabling centralized attendance monitoring across multiple classrooms or campuses. Further improvements may include integrating advanced deep learning models to enhance facial recognition performance, as well as adding features such as mask detection, anomaly detection, and automated alerts. These enhancements would make the system more scalable, intelligent, and suitable for smart campus environments. The system can be improved by adding real-time emotion and behavior analysis so that students are evaluated not only on diagnostic accuracy but also on communication skills such as empathy, tone, and patient interaction. Features like voice tone analysis, response patterns, and facial expression recognition can help assess patient-centered communication more effectively. The system can also include adaptive learning, where personalized patient cases are generated based on each student's past performance and conversation history to identify weaknesses and improve learning. Additionally, the platform can be expanded by adding specialized medical modules such as psychiatry, pediatrics, cardiology, and emergency medicine, allowing students to practice with a wider range of clinical cases and gain more comprehensive training.

REFERENCES

[1] P. Viola and M. J. Jones, "Robust real-time face detection," International Journal of Computer Vision, vol. 57, no. 2, pp. 137–154, 2004.

[2] G. B. Huang, M. Mattar, T. Berg, and E. Learned-Miller, "Labeled Faces in the Wild: A database for studying face recognition in unconstrained environments," University of Massachusetts, Amherst, Technical Report 07–49, 2008.

[3] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2015, pp. 815–823.

[4] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, "Joint face detection and alignment using multitask cascaded convolutional networks," IEEE Signal Processing Letters, vol. 23, no. 10, pp. 1499–1503, 2016.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in Proc. Neural Information Processing Systems (NIPS), Lake Tahoe, NV, USA, 2012, pp. 1097–1105.

[6] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779–788.

[7] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, “YOLOv4: Optimal speed and accuracy of object detection,” arXiv:2004.10934, 2020.

[8] C. Y. Wang, A. Bochkovskiy, and H. Y. M. Liao, “YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors,” arXiv:2207.02696, 2022.

[9] M. Everingham et al., “The PASCAL Visual Object Classes Challenge (VOC),” International Journal of Computer Vision, vol. 88, no. 2, pp. 303–338, 2010.

[10] A. Dosovitskiy et al., “An image is worth 16×16 words: Transformers for image recognition at scale,” arXiv:2010.11929, 2020.

[11] R. Girshick, “Fast R-CNN,” in Proc. IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, 2015, pp. 1440–1448.

[12] K. He, G. Gkioxari, P. Dollár, and R. Girshick, “Mask R-CNN,” in Proc. IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 2961–2969.

[13] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

[14] R. Ranjan, S. Sankaranarayanan, and R. Chellappa, “An all-in-one convolutional neural network for face analysis,” in Proc. IEEE International Conference on Automatic Face and Gesture Recognition, Washington, DC, USA, 2017, pp. 17–24.

[15] T. Mita, T. Kaneko, B. Stenger, and O. Hori, “Discriminative feature co-occurrence selection for object detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 7, pp. 1257–1269, 2008.

[16] N. Otsu, “A threshold selection method from gray-level histograms,” IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62–66, 1979.

[17] M. S. Raut and P. R. Dakhole, “Automated attendance system using face recognition with OpenCV,” International Journal of Engineering Research and Technology, vol. 8, no. 5, pp. 1056–1060, 2020.

[18] R. Mehta and A. Mehta, “Smart attendance management system using face recognition,” International Journal of Computer Applications, vol. 169, no. 5, pp. 36–40, 2017.

[19] M. K. Jain and S. K. Singh, “An IoT-based face recognition attendance monitoring system using deep learning,” IEEE Access, vol. 8, pp. 134563–134573, 2020.

[20] P. S. Pawar et al., “Uniform detection for school surveillance using deep learning,” International Journal of Innovative Research in Computer and Communication Engineering, vol. 8, no. 5, pp. 10456–10463, 2020.

[21] S. R. Tripathi and A. N. Jha, “Real-time uniform detection using YOLO for school attendance automation,” in Proc. IEEE International Conference on Image Information Processing (ICIIP), Shimla, India, 2021, pp. 112–118.

[22] H. Zhou et al., “Deep learning-based object recognition for surveillance systems,” IEEE Access, vol. 7, pp. 124779–124788, 2019.

[23] A. S. Al-Ali, M. A. Zualkernan, and F. Aloul, “A mobile-based attendance management system using face recognition,” IEEE Transactions on Learning Technologies, vol. 13, no. 4, pp. 761–773, 2020.

[24] S. J. Park et al., “Real-time student identification using YOLO and deep learning,” Sensors, vol. 21, no. 18, p. 6024, 2021.

[25] D. S. Patil and S. K. Deore, “AI-powered automated attendance system for academic institutions,” IEEE Access, vol. 9, pp. 116392–116402, 2021.

[26] R. Sharma, M. Gupta, and P. Arora, “Real-time human uniform verification using convolutional neural networks,” International Journal of Computer Science and Engineering, vol. 10, no. 6, pp. 255–262, 2022.