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Iris Detection for Attendance Monitoring in Educational Institutes Amidst a Pandemic: A Machine Learning Approach

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Abstract: Amid the COVID-19 pandemic, the imperative for alternative biometric attendance systems has arisen. Traditionally, fingerprint and facial recognition have been employed; however, these methods posed challenges in adherence to Standard Operational Procedures (SOPs) set during the pandemic. In response to these limitations, iris detection has been advanced as a superior alternative. This research introduces a novel machine learning approach to iris detection, tailored specifically for educational environments. Addressing the restrictions posed by COVID-19 SOPs, which permitted only 50% of student occupancy, an automated e-attendance mechanism has been proposed. The methodology comprises four distinct phases: initial registration of the student's iris, subsequent identity verification upon institutional entry, evaluation of individual attendance during examinations to assess exam eligibility, and the maintenance of a defaulter list. To validate the efficiency and accuracy of the proposed system, a series of experiments were conducted. Results indicate that the proposed system exhibits remarkable accuracy in comparison to conventional methods. Furthermore, a desktop application was developed to facilitate real-time iris detection.

Keywords: Pandemic; Iris recognition; Desktop application; Biometric; E-attendance

1 Introduction

Biometrics has long been recognized as an exceptional tool for identity verification due to its resilience and accuracy over traditional methods, such as file-based attendance systems [1]. Historically, maintaining attendance through files, characterized by calling out names and signing documents, was standard practice. Numerous drawbacks have been associated with this approach, notably concerns over the integrity, accuracy, and availability of attendance records. Thus, biometric recognition emerged as an innovative solution, identifying individuals based on their unique physical features like fingerprints or facial patterns. Nevertheless, with the rise of digital sophistication, concerns about the accuracy and potential forgery of biometrics have also escalated. Consequently, advanced identification techniques, notably retinal and iris recognition, have been explored. It has been observed that iris recognition has gained significant traction due to its reliability; it is understood that no two irises are identical and their forgery remains improbable.

However, the recent global spread of COVID-19 has necessitated a pivot from touch-based to contactless technology. Fingerprint biometrics and facial recognition have been deemed less effective under these conditions [2]. It has been noted that fingerprint identification typically necessitates human contact, thereby increasing virus transmission risks. Concurrently, prevalent use of face masks by individuals has added layers of complexity to facial recognition systems. In this context, iris detection has been presented as a more suitable alternative.

In efforts to mitigate the spread of COVID-19, global organizations adopted diverse strategies [3–5]. Initial responses were characterized by stringent lockdowns, resulting in widespread closure of educational institutions and workplaces [6, 7]. Restrictions extended to both large gatherings and smaller assemblies. Work-from-home and remote learning became commonplace, with students worldwide transitioning to online classes [8–11]. As infection rates declined, restrictions were gradually relaxed. Yet, attendance constraints persisted in places like educational institutions [12], leading to rotational student attendance. Distinct groups, often referred to as Group A and Group B, were created, with each group attending on alternate days [13, 14]. Prior to the pandemic, attendance was often managed manually or through rudimentary tools. Monitoring students to ensure an 80% attendance rate, especially for examination eligibility, posed challenges. The inadequacies of manual systems were amplified during the pandemic, underlining the need for more refined, digital approaches.

In response to these challenges, an iris detection system was developed to automate and refine student attendance processes. This system was designed to cater to the nuances of alternate-day attendance, ensuring that only the students from the designated group for the day are permitted entry. Furthermore, it was equipped to identify students attempting to falsify their identities during examinations. Notably, any student from Group B attempting to enter on a Group A designated day would be flagged, with their names being added to a defaulter list. The system was also programmed to bar any student with less than an 80% attendance record from examination participation.

The contributions of this study can be delineated as follows:

• Student Iris Registration: Students' irises, along with additional information such as name, age, gender, attendance, and group affiliation, are registered.

• Group Verification: Post-registration, iris verification is employed to ascertain group adherence. In instances where a student fails to attend on their designated day, a system notification is generated.

• Exam Eligibility: Attendance is rigorously monitored, and instances where a student, with attendance below 80%, attempts to participate in an examination are highlighted.

• Defaulter List: A comprehensive list is maintained, documenting students who either attend on the incorrect day or have insufficient attendance for examinations.

This research unfolds as follows: Section 2 offers a literature review on emergent techniques. Section 3 delineates the proposed iris detection system. Experimental analysis and findings are presented in Section 4. Section 5 contrasts the proposed approach with existing techniques, and conclusions are drawn in Section 6.

2 Related Work

The landscape of iris detection has been extensively mapped in recent years. Biswas et al. [15] integrated conventional methods of iris detection, encompassing segmentation and normalization. Within this framework, the Hough Transformation was employed for detecting the pupil center, and Daugman's Rubber Sheet was applied for normalization. Subsequent to encoding and extraction, the image was subjected to Support Vector Machine (SVM) testing, yielding a 92% accuracy rate with 216 minimized features. Such accuracy, however, was found to be suboptimal in comparison to alternative models [16].

Mustafa et al. [16] introduced a multimodal fusion technique which amalgamated iris and fingerprint biometrics. In this innovative approach, Gray-Level Co-occurrence Matrix (GLCM) was utilized for the extraction of features from both iris and fingerprint images. Classification of images was achieved using the K-Nearest Neighbor (KNN), and subsequent comparative evaluations were performed against a database. Despite attaining an impressive accuracy rate of 95%, a high computational time was observed, suggesting potential inefficiencies in real-time application.

A distinct method emphasizing pattern recognition combined with optics was proposed by Athinarayanan et al. [17]. Here, iris images were captured using the Daugman iris Perception System [18]. Following the delocalization process, a Modified multi-texton histogram (MMTH) facilitated feature extraction. This method, although efficient in its results, hinges on the Texton approach introduced by Julesz [19] two decades ago, which may now be perceived as outdated and potentially susceptible to errors.

Wang et al. [20] shifted the focus to multi-spectral characteristics of the human eye, aiming to distinguish authentic irises from forgeries. This approach relied on an integrated feature vector, which, when processed by the SVM classifier, proved proficient in distinguishing genuine from counterfeit irises within short detection times.

The approach adopted by Khotimah and Juniati [21] hinged on Daugman's rubber sheet model to capture eye patterns. Feature extraction in this method was executed using box-counting, followed by feature matching facilitated by KNN and k-fold cross-validation. However, the accuracy achieved was notably lower than that of some contemporary methods.

In recognizing the significance of edge estimation for iris localization, Kaudki and Bhurchandi [22] introduced a technique to enhance the resilience of iris detection. Through iris feature extraction and template matching, computational speed was augmented. This method, after being tested on various databases, highlighted the utility of watermarking, which, though adding additional data, led to perceptible distortions.

Emphasizing the merger of efficiency and speed, Alabdullah and Ibrahim [23] incorporated the k-means algorithm with neural networks. This dual approach not only pinpointed the iris within eye images with a high degree of accuracy but also achieved a marked reduction in computational time and effort. However, the technique primarily revolved around Gabor wavelet-based iris encoding and the application of correlation filters.

By harnessing the capabilities of deep learning (DL), Jayanthi et al. [24] formulated an integrated model dedicated to precise iris detection, segmentation, and recognition. The Hough Circle Transform model played a pivotal role in isolating the iris region of interest. Empirical validation was undertaken using the CASIA-Iris dataset, emphasizing the potential for affordable implementations that might revolutionize security frameworks.

Lastly, an iris-driven attendance system was outlined by Kadry and Smaili [25]. Contrary to online systems, an offline iris recognition system, which decreased computational demands, was used. Its mechanics comprised iris scanning, minutiae extraction, image storage, and subsequent matching. Implementation challenges were observed, particularly when accommodating challenging topographies. Saqlain et al. [26–28] proposed different theories in hypersoft structures and their application in the field of medical and other daily life issues.

A synthesized summary of these groundbreaking iris detection techniques is encapsulated in Table 1.

Table 1. Summary of existing iris detection techniques

S/No	Author	Method	Remarks
1	Biswas et al. [15]	Application of SVM	Efficiency limited due to reliance on conventional methods.
2	Mustafa et al. [16]	Concurrent use of iris and fingerprint biometrics	Prolonged computational time impedes real-time processing.
3	Athinarayan et al. [17]	Feature extraction via Modified Multi Texton Histogram (MMTH)	Relies on Texton method, over two decades old, with potential for errors.
4	Wang et al. [20]	Feature extraction via SVM classifier	-
5	Khotimah and Juniati [21]	Feature extraction with box-counting. Matching via KNN and k-fold	Exhibits a 7.37% margin of error.
6	Kaudki and Bhurchandi [22]	Enhanced resilience in iris detection	Incorporates watermarking, introducing extra data, leading to potential distortions in biometric information.
7	Alabdullah and Ibrahim [23]	Combination of fast k-means algorithm and neural networks	-
8	Jayanthi et al. [24]	Integrated DL model for precise iris detection, segmentation, and recognition	Emphasis on affordability in equipment to set new security standards.
9	Kadry and Smaili [25]	Wireless iris-based attendance system using Daugman's method	Implementation hurdles in areas with challenging typography.

3 Proposed Methodology

Amid the challenges posed by the COVID-19 pandemic, educational institutions and enterprises experienced mandatory closures. To adapt, a government-led initiative—termed "smart lockout"—was introduced, stipulating a 50% attendance model. Under this structure, educational institutions bifurcated the attendees into two groups: Group A and Group B. Attendees in Group A were scheduled for Monday, Wednesday, and Friday, while Group B attendees were allocated Tuesday, Thursday, and Saturday.

To manage this attendance model, a system was proposed. This system, primarily driven by iris recognition, encompasses several modules, each fulfilling distinct roles in student management:

• Student Iris Registration: Herein, the iris of the student is registered, alongside pertinent details such as name, age, gender, group, and attendance record.

• Group Verification: Post-registration, students' group affiliations are verified via their iris scans upon institution entry. Any discrepancy in the group attendance results in system notifications.

• Exam Eligibility: This module assesses the eligibility of students for examinations based on attendance metrics. Students with attendance falling below the 80% threshold are flagged during examinations.

• Defaulter List: A consolidated list is maintained, pinpointing students who either attended on incorrect days or fell short in examination attendance.

A notable feature of the system's architecture, depicted in Figure 1, is its utilization of the ORB (Oriented FAST and Rotated BRIEF) detector for iris matching. High-definition image acquisition from the camera is vital for effective ORB-based iris matching. In cases where the image quality does not meet the standard, a prompt is displayed, indicating: "Image quality is low definition; verification is not possible." Nevertheless, a camera with a minimum resolution of 4 megapixels was deemed adequate for this purpose. It's worth noting that ORB, a fusion of the FAST keypoint detector and the BRIEF descriptor, is enhanced with multiple modifications to boost its efficiency.

For array manipulations and advanced mathematical computations, particularly in iris detection, NumPy is employed. This software facilitates efficient operations on vast datasets. Additionally, Pillow, an imaging library for Python, is utilized for its array of lightweight image processing tools. These tools enable image creation, editing, and storage. The Dlib toolkit, renowned for its capabilities in machine learning, especially in facial detection and facial landmark identification, further augments the system.

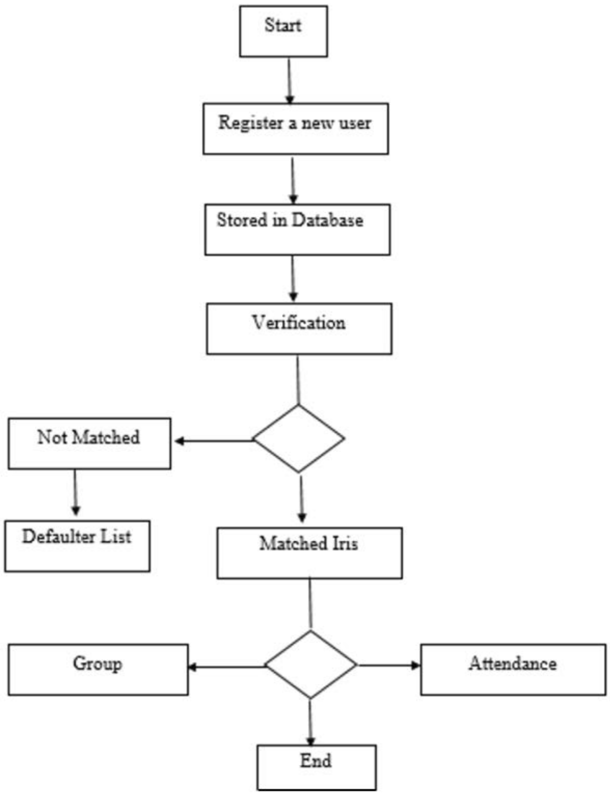

Figure 1. Architecture of the proposed system

3.1 Student Iris Registration

For the operationalization of the proposed system, the initiation process requires students to be cataloged within the institution's Iris database. During this procedure, fundamental attributes such as name, age, gender, and group affiliation are meticulously collated. Subsequently, the student's iris is captured using an appropriate imaging device and is subsequently archived in the database accompanied by the aforementioned personal details. Upon successful completion of this phase, a unique identifier is assigned to each registered iris. Thus, future validations or authentications are facilitated by juxtaposing live iris scans with the stored reference image and its associated data, especially when entry into the institution or participation in examinations is sought. Figure 2 delineates the intricacies of the iris registration module.

3.2 Group Verification

Upon the arrival of a student at the institution, an iris scan is conducted. The system then proceeds to cross-reference this scan against the existing student database. When a match is identified, a prompt indicating "match found" is generated, confirming the individual's affiliation with the institute. Subsequent to this iris validation, the system embarks on the process of group verification to ascertain if the student is aligned with the appropriate or an invalid group. Figure 3 provides a graphical representation of this verification against the database.

3.2.1 Correct group verification

When a congruence between both irises is detected, the subsequent step taken by the system is group verification. If the student's appearance corresponds with the designated group, a "correct group" prompt is displayed, permitting the student to gain access post-verification. Individuals with authenticated irises are thus denoted by the system as members of the valid group. Figure 4 visually captures the confirmation of a student's alignment with the correct group.

Figure 2. Iris registration module visualization

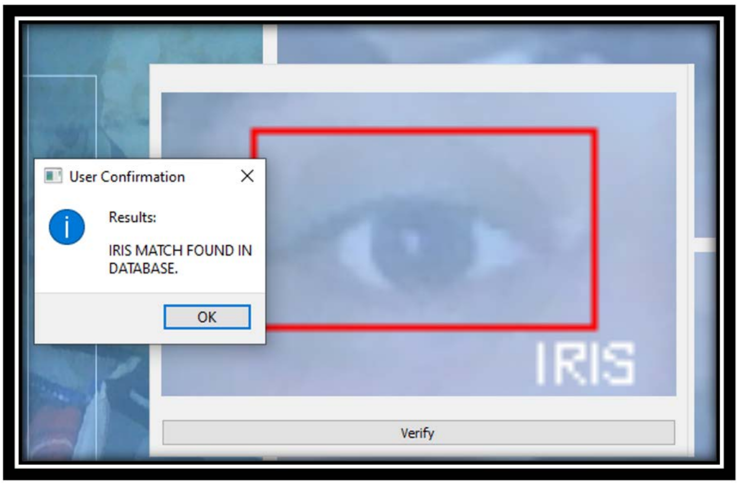

Figure 3. Iris verification process

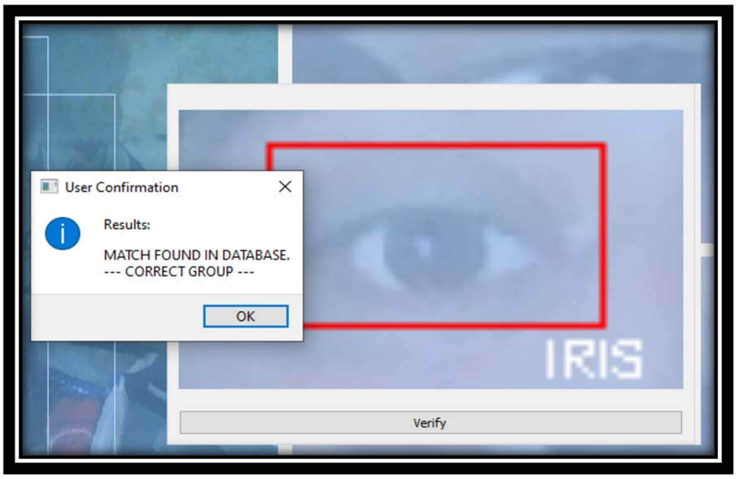

Figure 4. Confirmation of correct group alignment

3.2.2 Invalid group verification

Should an individual attempt access on a non-designated day, the iris fails to receive validation. Under such circumstances, an "invalid group" alert is manifested on the interface. Consequently, admittance is denied, with the system classifying them under the category of an invalid group until their scheduled day within the specified group arrives. Their designation is also appended to the defaulter's list. Figure 5 illustrates an instance of a student's alignment with an invalid group.

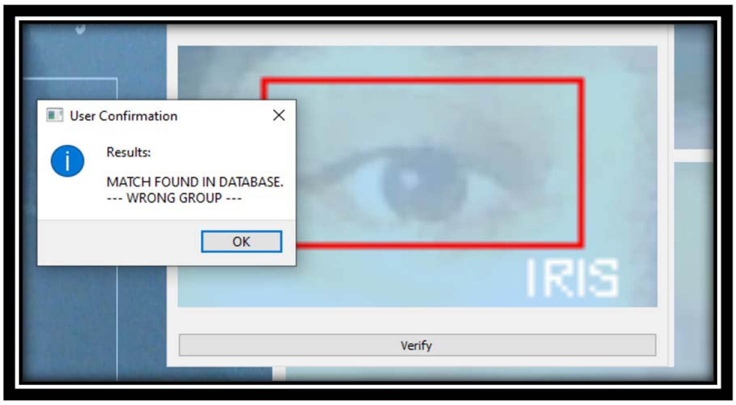

Figure 5. Depiction of invalid group alignment

3.2.3 Unregistered students

In the scenario where unregistered students attempt to leverage the system for attendance purposes, the system remains unresponsive and does not proceed with the scan, consequently producing an "unregistered student" alert. Figure 6 showcases the manifestation of an unregistered iris.

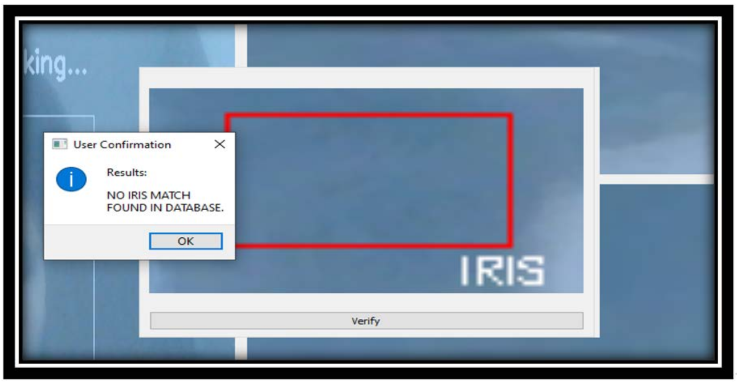

Figure 6. Illustration of unregistered iris

3.3 Exam Eligibility Verification

The efficacy of the proposed detection methodology is especially evident during examination periods. Upon a student's arrival at the examination hall, the iris is first scanned and cross-referenced with the database. Subsequently, the individual's profile, inclusive of attendance details, is displayed. This data facilitates the swift and accurate assessment of student attendance. As per institutional policy, eligibility for sitting the examination is contingent upon the student maintaining an attendance rate of 80% or above. Students falling short of this threshold are denied entry into the examination hall. By digitizing this verification process, potential errors inherent in manual assessments are circumvented, ensuring both accuracy and efficiency. Figure 7 illustrates the student's eligibility credentials, while Figure 8 portrays a scenario of insufficient attendance.

3.4 Defaulter List Compilation

The proposed system's database offers a robust mechanism for the monitoring and regulation of student attendance. In instances where a student attempts to gain entry into the university under an incorrect group or seeks to sit for an examination with attendance below the requisite 80%, such infringements are duly recorded. These individuals are subsequently cataloged in the "defaulter list" within the database. Upon subsequent detections by the biometric system, these students are immediately flagged as defaulters. This defaulter designation not only impedes unauthorized or unregistered entries into the institution but also serves as a verifiable record in the event of disputes regarding attendance percentages.

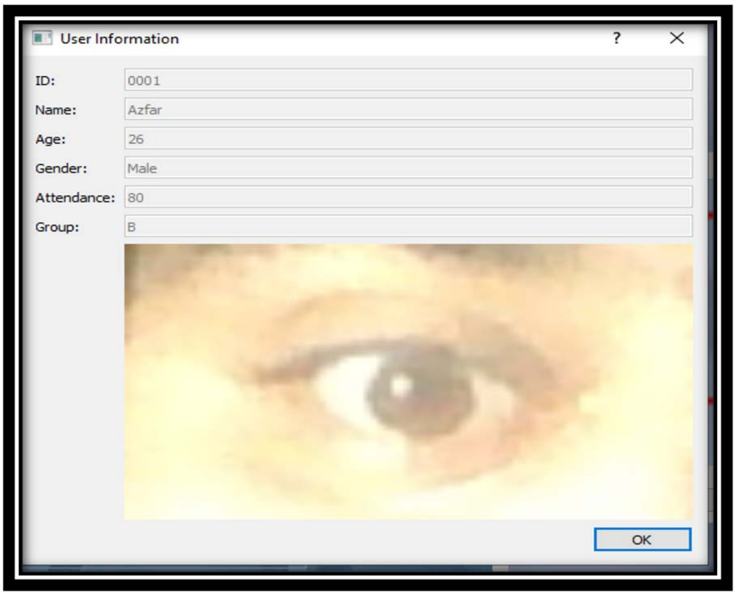

Figure 7. Display of student's exam eligibility credentials

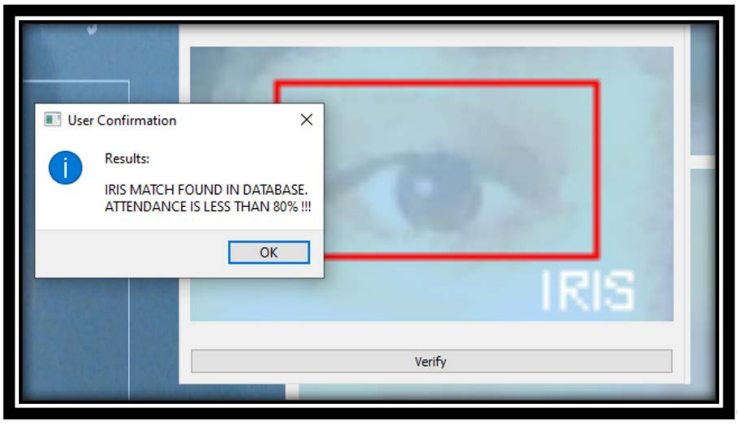

Figure 8. Representation of insufficient attendance

4 Experimental Analysis and Results

Experiments were conducted on a system equipped with an Intel Core i5-6200U processor, operating at 2.4 GHz, complemented by 8 GigaBytes (GB) of RAM. Python served as the programming language of choice. The primary objective of these experimental analyses was to assess and validate the accuracy of the proposed system, with an overarching aim of mitigating COVID-19 transmission risks. Notably, the proposed system's capabilities extend beyond mere iris detection. It encompasses a suite of functionalities, including student group monitoring as stipulated by the institution, the evaluation of student exam eligibility based on attendance metrics, and the presentation of a defaulter list.

Performance metrics were rigorously evaluated based on parameters such as precision, recall, F1-score, and overall accuracy. The following mathematical expressions elucidate these evaluation parameters:

$$Precision\ (P) = TPTP + FP$$

$$Recall\ (R) = TPTP + FN$$

$$F1 -\ score\ = 2 \times P \times RP + R$$

$$Accuracy\ = TP + TNTP + FP + TN + FN$$

For these analyses, iris samples of university students were amassed and categorized by gender and age to gauge the efficacy of the proposed system. The dataset comprised 100 iris samples from male subjects and an equal number from female subjects, encapsulating a spectrum of age variations. Table 2 delineates the age- and gender-specific details of the datasets, while Figure 9 presents select images from the dataset.

Table 2. Details of the iris dataset

Sr. No	Age	Gender (Male/Female)	Group (A/B)	Attendance ($>$80 / $<$80)
1	20-21	20 / 20	12 / 8	15 / 5
2	22-23	30 / 30	15 / 15	28 / 2
3	24-25	30 / 30	15 / 15	20 / 10
4	26-27	20 / 20	10 / 10	20 / 0
		Total=100/100	52 / 48	83 / 17

Figure 9. Representative images from the iris dataset

Figure 10 vividly illustrates the prowess of the proposed system, where all irises were accurately identified, irrespective of age or gender distinctions, eschewing any erroneous detections. Further, the system demonstrated adeptness in student group identification, discerning between correct and incorrect groups, and proficiently monitoring exam eligibility. Figures 10 and 11 elucidate the system's outcomes vis-à-vis group classification and student attendance monitoring for examinations.

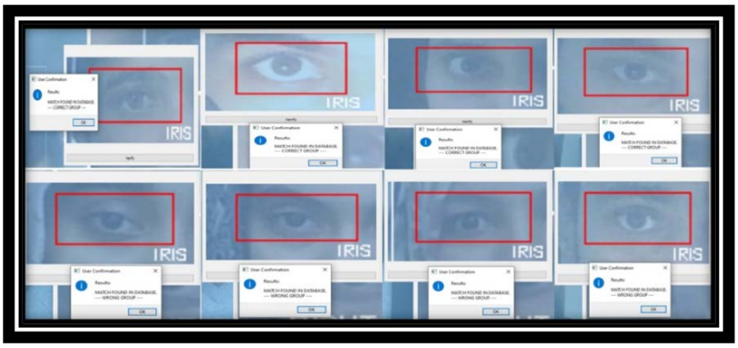

Figure 10. Iris-based group recognition (correct vs. incorrect group)

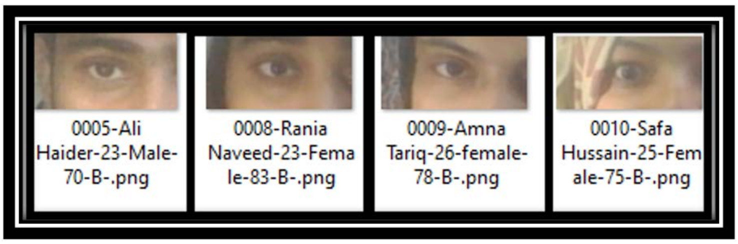

Figure 11. Defaulter list based on group classification

Figure 11 portrays the system's adeptness in recognizing students' group affiliations, thereby determining their eligibility for class attendance per scheduled protocols. In instances of incongruities, student details were systematically cataloged in a dedicated defaulter directory.

Figure 12 showcases the system's capabilities in monitoring examination attendance based on iris recognition. As delineated, students with attendance below the stipulated 80% threshold were deemed ineligible for examinations. However, it is noteworthy that this criterion is mutable, subject to institutional preferences. Pertinent details of students falling short of the attendance benchmark were archived in the defaulter directory. Figure 13 presents specifics of students with sub-80% attendance.

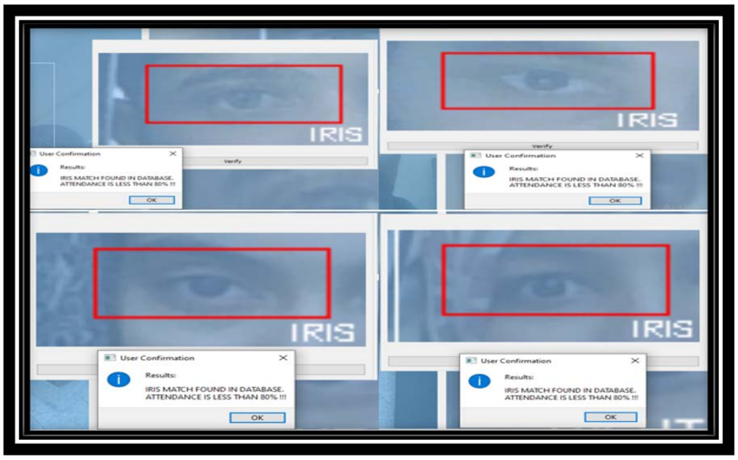

Figure 12. Exam attendance monitoring for students with attendance below the 80% threshold

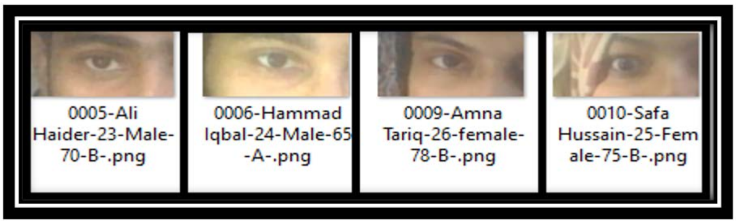

Figure 13. Defaulters with attendance less than the 80% benchmark

The system's confusion matrix, represented in Figure 14, corroborates the impeccable accuracy in iris recognition, instrumental in both student group categorization and attendance monitoring.

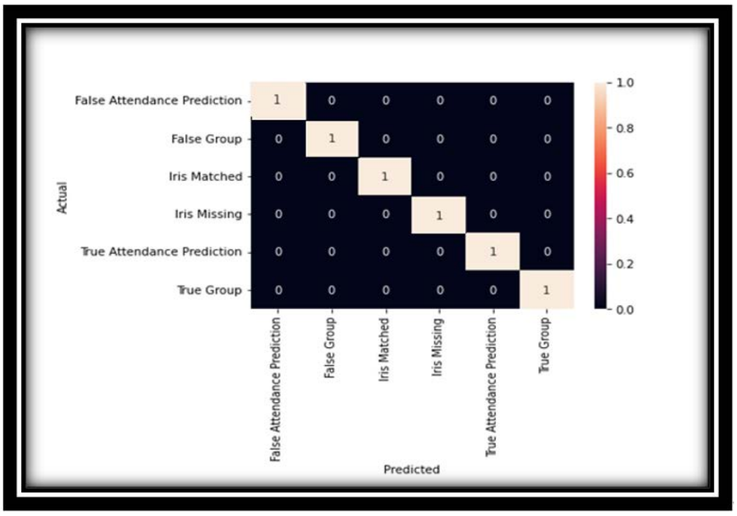

Figure 14. Confusion matrix of the proposed system

5 Comparison with Existing Techniques

Iris-based biometric methodologies have been extensively explored across various disciplines. Significant contributions by numerous researchers have led to the development of diverse techniques, each aiming to optimize accuracy and applicability. Yet, the integration of iris-based biometrics in the context of the COVID-19 pandemic remains unprecedented prior to this innovative endeavor. The distinctiveness of this method lies in its capacity to ascertain students' eligibility for institutional entry and exam attendance. Such precision was exhibited when iris-based detection was implemented on 50% of students segmented into groups (A, B). A detailed comparative analysis between the proposed iris detection system and contemporary state-of-the-art techniques is presented in Table 3.

Table 3. Comparative analysis of the proposed iris detection method with prevalent techniques

Name	Iris Biometric	Grouping System	Attendance Monitoring System	Accuracy
Biswas et al. [15]	√	×	×	92%
Mustafa et al. [16]	√	×	×	95%
Athinarayanan et al. [17]	√	×	×	95%
Wang et al. [20]	√	×	×	-
Khotimah and Juniati [21]	√	×	×	92.62%
Kaudki and Bhurchandi [22]	√	×	×	97%
Alabdullah and Ibrahim [23]	√	×	×	-
Jayanthi et al. [24]	√	×	×	99.14%
Kadry and Smaili [25]	√	×	√	-
Proposed System	√	√	√	100%

6 Conclusion

In response to the pervasive impacts of COVID-19, a transition has been observed from traditional biometrics towards more advanced identification methodologies, notably iris recognition. A government-initiated "smart lockout" was implemented, facilitating 50% attendance in educational and corporate establishments. Institutions permitted alternating attendance, allowing half of the total enrolment on one day, followed by the remaining half on the subsequent day. In this context, an innovative iris-based attendance system was introduced. Upon detecting the iris, student groups are identified by the proposed system. Furthermore, attendance during examinations is meticulously monitored, and in instances of invalid group appearance or insufficient attendance, defaulters are systematically documented. Comparative evaluations have indicated the superior efficiency, optimality, and speed of the proposed system over other iris detection techniques. Validation was undertaken using real-time datasets, comprising both male and female subjects spanning various age groups, with a recorded accuracy of 100%. A user-friendly desktop application was also developed, enhancing usability and understanding for end-users.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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