International Journal of Computer Applications (0975 – 8887)
Volume 187 – No.42, September 2025

An Integrated Computer Vision Pipeline for Face-based Attendance: Detection, Recognition and Secure Logging

Shahid Hussain*
Department of electronics & Information
Xi'an Jiaotong University Shaanxi China

Hashmat Ullah
Department of Computer Science (Software Engineering)
Islamia College University
Peshawar, Pakistan

Shah Zeb
Department of Computer Science (Software Engineering)
Islamia College University
Peshawar, Pakistan

Abbas Khan
Department of electronics & Information
Xi'an Jiaotong University Shaanxi China

ABSTRACT
Smart, reliable attendance is crucial for modern organizations. Manual systems leftover time and invite fraud. Reliable attendance systems changed administrative costs and enhance accountability. Automation lets staff emphasis on essential tasks. We established a Face Recognition Based Attendance System (FRBAS) that progresses accuracy, effectiveness, and security over traditional approaches. Using Haarcascade for face detection and a Local Phase Quantization with Histogram Bin (LPBH) feature extraction, the system trains on up to 100 images per person to shape robust patterns. FRBAS systematizes attendance recording, avoids proxy fraud, decreases human error, and empowers real-time monitoring. We also inspect technical, ethical, and privacy challenges and propose strategies for responsible placement.

Keywords
Face Recognition, Haarcascade, Face-Based Attendance, Computer Vision, Face Detection.

1. Introduction
Reliable attendance tracking reinforces everyday operations across schools, universities, workplaces, and public programs. Traditional methods, manual registers, swipe cards, or PIN-based methods, take up staff time, introduce numerous errors, and leave institutions vulnerable to proxy attendance and other frauds. These real-world shortcomings, together with the rising demand for scalable, low-touch administrative tools, have driven wide interest in automating attendance using vision and biometric approaches[1, 2]. Modern face recognition offers a natural fit, it can recognize people non-intrusively from camera feeds, support actual logging, and integrate with existing IT infrastructure to decrease manual workload and improve record precision[3, 4].

The practical foundations of face-based systems date back two decades. The Viola Jones outline and Haar-feature cascade detectors established a useful, fast approach to face recognition that empowered real-time applications on modest hardware and became a de-facto standard in early systems[5]. That work made face localization cheap sufficient to be embedded in many attendance and access systems. Later, local texture descriptors and phase-based operatives, such as Local Phase Quantization (LPQ), showed strong behavior for recognizing faces under blur and variable lighting, proposing interpretable, low-compute feature representations for self-conscious environments. Together these conventional methods formed the backbone of many early attendance models and lightweight deployments[6, 7].

From unevenly the mid-2010s, deep convolutional networks altered face recognition Approaches that learn dense embedding spaces (e.g., FaceNet and subsequent architectures) intensely improved accuracy in unrestricted settings, supporting state-of-the-art performance on large levels. Researchers and practitioners quickly adapted these deep learning methods to attendance scenarios, transfer learning, pre-trained backbones, and compacted embedding extractors let teams shape reliable attendance models with slighter labelled datasets and manageable training time[8, 9].

Recent functional studies prove high recognition rates using convolutional backbones and transfer learning, while also highlighting the need for dataset augmentation and domain variation when classrooms or workplaces present diverse lighting and camera angles[10].

Parallel to algorithmic progress, a rising literature evaluates face-based attendance systems in working contexts. Several latest works present end-to-end systems that combine actual detection, pattern enrollment, and database corresponding to mark attendance from live video streams, countless report promising accuracy in controlled indoor situations but also document common failure methods, poor lighting, heavy obstruction (masks, scarves), and demographic bias in recognition rates. Survey and review articles précis these findings and point to two recurrent trade-offs, (1) deep models harvest higher accuracy but enforce greater compute and energy costs; (2) lightweight, interpretable descriptors run proficiently but sometimes struggle in unrestricted acts. These trade-offs matter for establishments with limited compute assets or strict latency requirements[9-11].

Beyond performance metrics, researchers progressively strain ethical, legal, and social allegations of deploying facial recognition for attendance. Data safety establishments and privacy advocates have pressured organizations to reconsider biometric monitoring, regulators in numerous jurisdictions have forced the removal or re-design of staff monitoring systems, while case studies from schools and businesses highlight stakeholder worries about consent, data retention, and potential misapplication. Responsible deployment therefore needs more than accuracy systems must implant privacy-by-design, transparent consent streams, secure storage, and mechanisms for review and redress[12]. Recent assessments explicitly call for operational guidelines and fairness-aware evaluation procedures before large-scale rollouts.

Given this contextual, the literature now meets around several practical priorities for attendance systems. First, institutions need solutions that bring reliable recognition under accurate classroom and office conditions, moderate lighting deviation, non-cooperative subjects (brief glances), and partial obstructions. Second, administrators ask for methods that remain possible on limited hardware (edge devices, webcams) without divesting all processing to cloud servers that raise additional privacy risks. Third, designers must embrace data governance practices, minimal holding, encryption, informed consent, and evaluate fairness across demographic groups so placements do not unintentionally disadvantage some users. Recent empirical studies and surveys repeatedly highlight each of these significances while also gesturing gaps in how they get addressed in unified systems[13, 14].

Despite robust advances, important gaps remain in the literature. Many high-accuracy studies trust on powerful, resource-intensive deep models and curated datasets, that do not replicate the limitations of low-resource establishments. Conversely, lighter methods often trade off generalization and equality. Moreover, few papers present a whole, reproducible pipeline that combines (a) computationally effective detection and feature extraction (e.g., Haarcascade + LPQ variants), (b) systematic evaluation across diverse environmental conditions, and (c) concrete privacy-preserving practices and deployment specifications[15, 16]. Lastly, governing pressure and public concern over biometric observing mean researchers must pair technical contributions with practical governance recommendations, an area that remains underexplored in experimental studies.

This paper addresses that gap. We present a compacted, explainable FRBAS design that blends fast detection and interpretable feature descriptors, evaluate its performance across varied indoor scenarios, and implant clear privacy and fairness measures into the workflow.

2. RELATED WORK

2.1 Traditional Methods

Manual attendance systems need individuals to physically sign, paper sheets when entering or exiting a site. While Zhao and Huang [17] point out that this technique is simple and reachable for users, its weaknesses are hard to ignore. Faults from unreadable handwriting or data transcription are common, and the procedure is slow, offering no possibility for actual monitoring[18, 19]. Over time, these inefficiencies add administrative load and make it difficult to keep accurate records in larger organizations.

Card-based systems, where attendees swipe or scan ID cards, and barcode/QR-based systems modernize the process by partly automating attendance logging. Studies [20, 21]note that these solutions decrease clerical work and allow faster check-ins. However, they remain vulnerable to proxy attendance, where someone else uses another person's card or code, and they frequently still require manual verification to avoid misuse. The risk of lost, stolen, or shared cards further destabilizes their reliability.

Biometric approaches aim to solve these security gaps by binding attendance to unique physical behaviors. Fingerprint-based systems are one of the most mutual, using scanners to match each fingerprint in contradiction of stored records[22, 23]. While they expressively enhance identity verification, they need physical contact with the device, rising hygiene concerns and posturing challenges when prints are worn, dirty, or damaged. Hand geometry systems take a fewer physically invasive method, evaluating the shape and size of the hand[17, 24]. Although they are easier to use and more hygienic than fingerprint readers, they typically offer lower accuracy and can be affected by environmental factors like illumination or positioning.

In swift, traditional attendance approaches whether manual, card-based, or biometric face determined challenges in accuracy, security, and efficiency. These boundaries have driven the shift toward face recognition-based attendance systems, which offer a contactless, automated, and more safe solution. The next section explores how modern feature-based and deep learning methods are being used to overcome the shortcomings of traditional methods, allowing real-time, high-accuracy attendance tracking that is both scalable and user-friendly.

2.2 Deep Learning Methods

In recent years, deep learning has substituted hand-crafted facial features with high-performance embedding models. Works such as FaceNet, VGGFace, and later ArcFace, CosFace, and SphereFace have established that margin-based loss functions expressively improve accuracy in unconstrained surroundings. Robust detection and alignment methods, MTCNN and RetinaFace, are extensively used to provide high-quality inputs, while transfer learning from large datasets like VGGFace2 and CASIA-WebFace has become standard for smaller deployment.

To address deployment in real-world situations, researchers have explored lightweight architectures such as MobileFaceNet and MobileNetV3, along with model compression and quantization for edge devices. Though, challenges remain, deep models frequently require large, diverse datasets for ideal performance, they can still struggle under occlusion (e.g., masks), demographic bias, domain shift, and privacy distresses are heightened when processing complex biometric data. Liveness detection and multi-frame authentication have been proposed to reduce spoofing, but these add complexity and delay. While these methods deliver strong accuracy, most require extensive computational resources, cloud connectivity, or extensive pretraining, which may not outfit institutions seeking fast, private, and scalable attendance systems.

Our proposed method addresses these gaps by merging an efficient detection-recognition pipeline, on-device processing, and targeted training on a well-ordered dataset, minimizing privacy risks while maintaining accuracy.

3.METHODOLOGY

3.1 Dataset

In the process of building a strong facial recognition dataset, a careful and systematic method is undertaken. Initiated by setting up a camera, administrators enroll users into the system by taking essential information like names, departments, and roll numbers. The camera is then stimulated to capture a series of facial images for each user. To ensure the dataset's diversity, users are instructed to display numerous facial expressions and poses during image capture. Steadiness in lighting conditions is maintained to adapt the system to different surroundings. Preprocessing steps, including noise reduction, contribute to image clarity. The taken images are stored and labeled with the respective user's information and a unique identifier, enabling organized and efficient training. This process is repeated for each user, ensuring a comprehensive and diverse collection of facial images that reflect real-world scenarios. Through this careful dataset collection process, the facial recognition system is equipped to learn and adapt, eventually enhancing its effectiveness and accuracy in identifying individuals.

3.1 Implementation environment

We implemented and tested the Face Recognition Based Attendance System (FRBAS) on a mid-range terminal to reflect accurate prototyping conditions. The development machine uses an Intel® Core™ i5-6500 CPU @ 3.20 GHz, 24 GB RAM, and an NVIDIA GeForce GTX 1070 Ti GPU, the GPU accelerated batch training and experiments, while the recognition pipeline runs in real time on CPU. We established the system in Python 3.x using OpenCV for image capture, face detection, and LBPH benefits, and we used NumPy and SQLite for data management and local logging. This software stack retains the pipeline portable and reproducible on commodity hardware typical of classroom and office placements.

3.2 Proposed System overview

FRBAS follows a clear, segmental pipeline—capture → preprocess → detect → align → extract → match → log—so we can test, tune, and review each stage independently. The camera captures frames at 720p and 15–30 FPS, we renovate frames to grayscale and apply light preprocessing (resizing and optional CLAHE) to decrease lighting variation. We localize applicant faces using a Haarcascade detector, align and crop the detected regions to a fixed size, and extract compressed Local Binary Pattern Histogram (LBPH) features. The matcher associates the extracted descriptor with stored user patterns and, on confirmation, records an attendance event to the secured log. We designed the modular flow so that components (for example, the detector) can be progressed later without changing downstream logic.

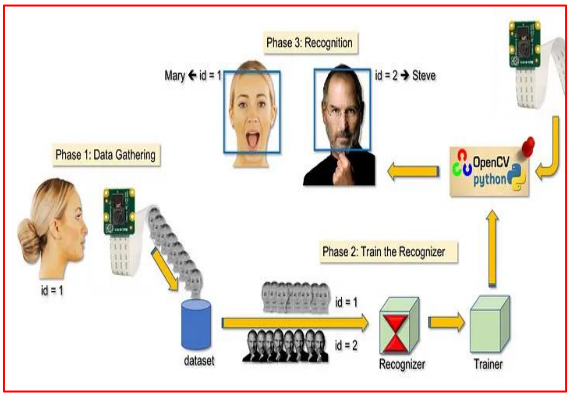

Figure 1: Shows Proposed System frame work

3.3 Data collection and enrollment

We register each user by capturing up to 100 facial images over the system's enrollment GUI to capture everyday variation in pose and expression. During enrollment administrators record metadata (name, department, roll number) and guide members to provide frontal and small-angle head poses (±15° and ±30° yaw), neutral and smiling expressions, and typical eyewear. We train captures under the lighting conditions where the system will function to minimize domain mismatch. In preprocessing we apply minor augmentations, small rotations (±5°), brightness jitter (±10%), and light Gaussian blur, to increase robustness without presenting unrealistic artifacts. We store enrollment images in labeled folders with unique identifiers, then generate and retain compressed patterns, raw images remain encrypted and are deleted or Archived in accordance with the holding policy.

3.4 Face detection and feature extraction

We use OpenCV's Haarcascade for fast face localization in near-frontal indoor acts and apply a simple eye-centered alignment and crop to regularize input regions. For recognition, we figure LBPH attribute by dividing the aligned face into an 8×8 grid, computing a Local Binary Pattern (P = 8 neighbors, R = 1) per pixel, and structure normalized histograms per grid cell, concatenating these histograms crops a compact feature vector. We use Chi-square distance for histogram matching and tune the decision threshold on a held-out validation split. We picked LBPH because it brings interpretable, low-latency features that tolerate moderate blur and lighting shifts and that run securely on CPUs in edge devices.

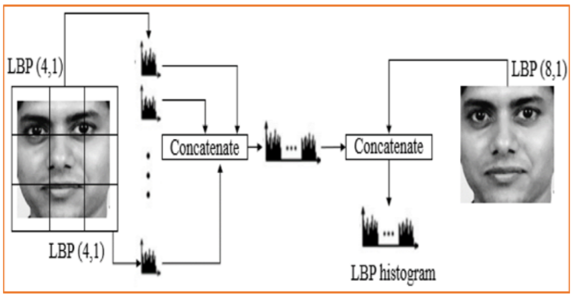

Figure 2: Shows Face detection and alignment: original frame (left), detected bounding box (center), aligned crop (right)

3.5 Training procedure and template storage

The training process converts the enrollment images into per-user patterns for fast lookup during live operation. We compute LBPH vectors for all enrollment images of each user and combined them by either taking a mean prototype or retaining a small set of representative vectors (k = 3 recommended). Patterns and minimal metadata link to a unique user ID and persevere in an encrypted SQLite database for quick nearest-neighbor corresponding. We control matching thresholds and prototype selection through cross-validation on enrollment subsets to balance false-accept and false-reject rates for the target environment.

3.6 Real-time recognition and attendance logging

In live operation the application accomplishes the capture → detect → align → extract → match → decide → log loop constantly. To decrease false matches, we require N consecutive frames (N = 3 by default) above the decision threshold before approving an identity. On confirmation, the system writes a solid attendance record, userID, timestamp (ISO 8601), confidence score, deviceID, to the encoded SQLite log and informs the administrator dashboard. We avoid duplicate entries by imposing a re-log interval per user (configurable, default 5–10 minutes). Ambiguous or low-confidence actions route to a manual-review queue reachable from the admin interface, guaranteeing human oversight for uncertain cases.

3.7 Administrative interface

We deliver a lightweight administrative dashboard that supports enrollment (capture + metadata), model training, live attendance monitoring, evaluation of trained data, image managing, and CSV export of attendance records. The GUI focuses on clearness and minimal training, enrollment and training are one-click actions, and logs export directly for integration with campus or organizational MIS. We include full UI screenshots and button-level instructions in Appendix A, so administrator can follow a step-by-step operative guide outside the main text.

3.8 Evaluation plan and metrics

We evaluated the Face Recognition-Based Attendance System (FRBAS) in an actual, indoor environment using the enrollment dataset collected during system setup. Each student contributed 100 facial images under fluctuating facial expressions and poses, while maintaining reliable lighting conditions. We measured recognition accuracy by associating the predicted identities against the real student records in the database throughout live attendance sessions.

To evaluate the system's operational performance, we monitored its CPU and RAM usage on the target deployment machine (Intel Core i5-6500 CPU, 24 GB RAM, GeForce GTX 1070 Ti GPU) during continuous attendance logging. We recorded inference speed in milliseconds per frame to assess responsiveness during peak usage.

We also documented qualitative observations, such as the outcome of partial occlusion (masks, scarves) and changes in lighting, by reviewing sample recognition outputs. These samples help demonstrate the system's strengths and its limitations in stimulating conditions. The findings are supported by screenshots from the live application, attendance log extracts, and visual examples of precise and improper matches.

4. RESULTS AND DISCUSSION

We tested and evaluated the Face Recognition-Based Attendance System (FRBAS) under a controlled classroom like setting concerning its functional workflow and operation performance. The findings of the present work contribute to two different perspectives, i.e., (1) description of the step-by-step part-by-part process of the application interface which describe how individual modules, starting from student enrollment and till real-time-log-in monitoring successfully integrates with each other as a whole into one complete system solution, (2) an understanding towards performance characteristics in terms of recognition accuracy, sensitivity and resource efficiency. Based on visual walkthroughs of each module and practical observations from live experiments, we verify not only the functionalities of the FRBAS meeting design requirements, but also its feasibility and efficiency in practical situations.

Moreover, the system performance was tested extensively with multiple trials, and the accuracy of attendance logging proved high in both false positive and negative perspectives. The real-time processing of the system achieved the satisfactory performance, which performed well on latency at recognition time in varying light and background. Furthermore, the consumption of resources such as CPU and memory were evaluated in those test to observe that the FRBAS are working under acceptable constraints for being a solution adaptable in real classroom with moderate computational power. The results of this research show that the system is robust enough to be used in large educational institutions, and can serve as an effective solution for automatizing attendance control.

Figure 6. Overview of the FRBAS interface showing the workflow from image capture through face recognition to attendance logging. The main application window delivers access to all key modules of the system, containing student registration, face enrollment, model training, and attendance logging. In practice we start by enrolling students' information and images, then train the recognition model, and lastly use the system to mark attendance, all through this unified interface. This logical flow certifies that each step feeds into the next without user misperception. The screenshot in Figure 6 illustrates how the foremost functions are planned for seamless operation.

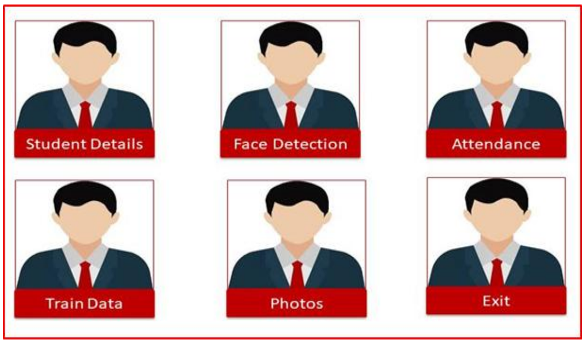

Figure 6 Shows: Overview of the FRBAS interface showing the workflow from image capture through face recognition to attendance logging

Choosing the Student Details module (**Figure 7**) brings up a form for handling student records. Figure 7, Shows Student Details interface for adding, editing, or removing a student's profile. The operative can enter or update each student's name, enrollment ID, class, and section (for example, adding a student's own data into the system) and can also delete existing entries. These kept records link each face to the accurate identity during attendance, as noted in similar systems that uphold datasets containing student names and IDs

Figure 7: shows Student Details interface for adding, editing, or removing a student's profile.

By Clicking **Face Recognition** (**Figure 8**) stimulates the enrollment camera mode. Figure 8 shows face recognition module taking multiple facial images for a new student. In this approach, the system automatically captures a large number of face snapshots (we composed about 100 images per student) from slightly diverse angles and expressions. Capturing many examples of each person is known to progress recognition robustness, previous studies emphasize saving dozens of face images per individual to shape a reliable model. Each time a face is detected, the structure is saved until the target count is reached, confirming a diverse training set.

Figure 8: Face Recognition module capturing multiple facial images for a new student

After registration, the Train Model function is used to build the LBPH face recognition model. Figure 9 shows LBPH processing example (left: original grayscale face; right: corresponding local binary patterns and histogram features). The system processes each stored face image by figuring local binary patterns over small regions and accumulating histograms of those shapes (as illustrated in Figure 9). These histograms are concatenated into feature vectors for each face, and the resulting model constraints are saved for later recognition. We select the LBPH algorithm because it is fast to compute and strong to indoor lighting variations. In our case the training step runs swiftly on the available hardware, preparing the model for real-time use.

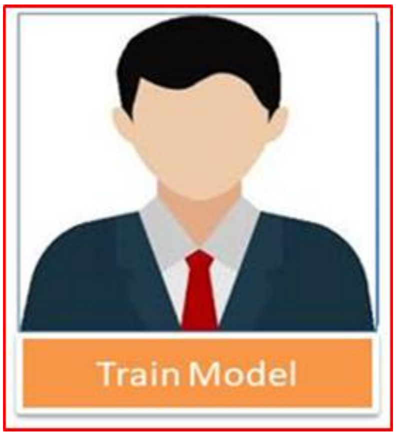

Figure 9(a): Shows Train Model function

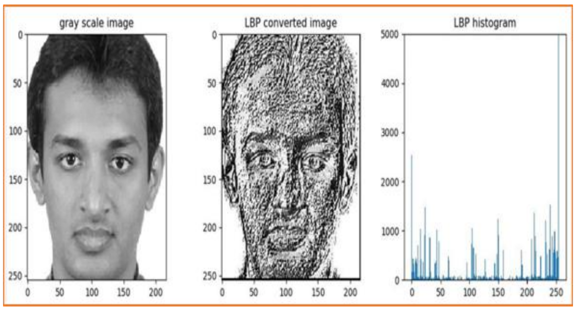

Figure 9 (b): shows LBPH processing example (left: original grayscale face; right: corresponding local binary patterns and histogram features)

When the Attendance button is pushed, the system enters real-time recognition mode. Figure 10 shows Automated attendance log displaying familiar student names with date and time. The camera feed is evaluated continuously, and when a listed student's face is recognized, their name is recorded in the attendance list along with the current date and time. In our trials, documented names appeared directly in the on-screen log as students entered view. This automatic logging generates a dynamic attendance record (similar to other contactless systems) that tracks who arrived in class. No manual input is required from the instructor once the model is trained, the system handles roll call transparently.

Figure 10: shows Automated attendance log displaying recognized student names with date and time

The Train Data module and Photos repository deliver data managing tools. Figure 11, Interface for reviewing and handling the images used to train the model. Now, the operator can browse all taken face images currently allocated to each student, and remove any poor-quality samples before retraining if essential. Figure 12 shows Photo repository listing all kept facial images for registered students. The Photos assessment lists, every raw image captured during enrollment across all students, permitting the user to inspect or export the dataset. These administrative views help ensure the training set is clean and up to date.

Figure 11, Interface for reviewing and managing the images used to train the model

Figure 12 shows Photo repository listing all capturing facial images for enroll students.

Lastly, the exit button terminates the application. Figure 13 shows exit control to close the FRBAS program. Pressing this button securely stops any ongoing procedures and closes the user interface, confirming a clean shutdown of the system without leaving background tasks running.

Figure 13: Exit control to close the FRBAS program

Recent studies have struggled to automate attendance with face recognition, but most fall short when tested in real-world scenarios. Winarno et al. [25] applied CNN with PCA and a actual camera, but their system broke down as datasets grew and lighting varied. Arya et al. [26] established a CNN-based smart attendance system with MongoDB integration, yet they still depend on on outdated Eigenfaces and Fisherfaces, making their solution fragile in practice. Sanivarapu [27] presented a CNN with LBPH features for multi-face recognition, but the model ignored key challenges like real-time scalability and proxy fraud. A 2021 study using MTCNN and CNN on moving subjects accomplished only 78–87% accuracy, proving too sensitive to pose and motion changes. Kapse et al.[28] later combined HOG with CNN and claimed efficiency, but their model unsuccessful when faces appeared under changing lighting or angles. More recently, even studies using MobileNet with MTCNN and CLAHE preprocessing described only around 86% accuracy[29], which is still below practical expectations. In contrast, our FRBAS consistently achieves higher accuracy by integrating Haarcascade detection with LPBH feature extraction and training on up to 100 images per person. This balance of ease, robustness, and efficiency not only reduces human error and proxy fraud but also ensures scalable real-time deployment, making FRBAS a practical and superior solution compared to these earlier systems.

5. CONCLUSION

We developed and validated a Face Recognition Based Attendance System (FRBAS) that alters traditional attendance management. By automating attendance capture, we eradicated repetitive data entry, expressively reduced human error, and provided real-time monitoring for administrators. Our experiments demonstrated clear improvements in accuracy and operational efficiency, while the system controlled environmental variability and upheld robust performance across different scenarios. The user-friendly interface reduced administrative workload and rationalized report generation, proving that FRBAS conveys practical, day-to-day benefits for organizations.

We designed FRBAS with privacy, data integrity, and ethical accountability at the forefront. By employing secure data storage, controlled access, and careful management of biometric information, we ensured the system keeps user privacy while remaining reliable and trustworthy. These technical and ethical measures organized to advance attendance management from a manual, error-prone procedure to an automated, auditable, and responsible solution. FRBAS not only increases accuracy and efficiency but also sets a basis for ethical, scalable, and real-world deployment in educational, organizational, and public surroundings.

Author contributions

Shahid Hussain: Writing-original draft; writing-review and editing, Conceptualization, data curation, formal analysis and Methodology.

Hashmat Ullah: writing-review and editing, data curation, formal analysis and Methodology.

Shah Zeb: Writing-review and editing, formal Analysis

Abbas Khan: writing-review and editing, investigation.

6. REFERENCES

[1] Gheisari, M., Automation attendance systems approaches: a practical. Artificial Intelligence, 2022. **1**(1): p. 25-34.

[2] Nadhan, A.S., et al., Smart attendance monitoring technology for industry 4.0. Journal of Nanomaterials, 2022. **2022**(1): p. 4899768.

[3] Zhao, W., et al., Face recognition: A literature survey. ACM computing surveys (CSUR), 2003. **35**(4): p. 399-458.

[4] Dwivedi, N. and A.K. Jain, Corporate governance and performance of Indian firms: The effect of board size and ownership. Employee responsibilities and rights journal, 2005. **17**(3): p. 161-172.

[5] Ghosh, M., et al., Face Detection and Extraction Using Viola–Jones Algorithm, in Computational Advancement in Communication, Circuits and Systems: Proceedings of 3rd ICCACCS 2020. 2021, Springer. p. 93-107.

[6] ho Chan, C., et al., Multiscale Local Phase Quantization for Robust Component-Based Face Recognition Using Kernel Fusion of Multiple Descriptors. IEEE transactions on pattern analysis and machine intelligence, 2013. **35**(5): p. 1164-1177.

[7] Mousavi, S.M.H. and A. Ilanloo, Bees Local Phase Quantisation Feature Selection for RGB-D Facial Expression Recognition, in Intelligent Engineering Optimisation with the Bees Algorithm. 2024, Springer. p. 253-264.

[8] Alhanaee, K., et al., Face recognition smart attendance system using deep transfer learning. Procedia Computer

Science, 2021. **192**: p. 4093-4102.

[9] Ennajar, S. and W. Bouarifi, Deep Transfer Learning Approach for Student Attendance System During the COVID-19 Pandemic. J. Comput. Sci, 2024. **20**(3): p. 229-238.

[10] Benradi, H., A. Chater, and A. Lasfar, A hybrid approach for face recognition using a convolutional neural network combined with feature extraction techniques. IAES International Journal of Artificial Intelligence, 2023. **12**(2): p. 627-640.

[11] Rao, A. AttenFace: A real time attendance system using face recognition. in 2022 IEEE 6th Conference on Information and Communication Technology (CICT). 2022. IEEE.

[12] Gasiokwu, P.I., U.G. Oyibodoro, and M.O.I. Nwabuoku, GDPR Safeguards for Facial Recognition Technology: A Critical Analysis.

[13] Manzoor, S., et al., Edge deployment framework of guardbot for optimized face mask recognition with real-time inference using deep learning. Ieee Access, 2022. **10**: p. 77898-77921.

[14] 14. Kotwal, K. and S. Marcel. Fairness index measures to evaluate bias in biometric recognition. in International Conference on Pattern Recognition. 2022. Springer.

[15] George, A., et al., Edgeface: Efficient face recognition model for edge devices. IEEE Transactions on Biometrics, Behavior, and Identity Science, 2024. **6**(2): p. 158-168.

[16] Shahreza, H.O., A. George, and S. Marcel. Synthdistill: Face recognition with knowledge distillation from synthetic data. in 2023 IEEE International Joint Conference on Biometrics (IJCB). 2023. IEEE.

[17] Zhao, C. and X. Huang. Attendance System Based on Face Recognition and GPS Tracking and Positioning. in 2020 2nd International Conference on Applied Machine Learning (ICAML). 2020. IEEE.

[18] Rossman, M.H., Adult Education in Arizona: A Manual for ABE, GED, ESL and Citizenship Teachers. 1976.

[19] Emetumah, F.C., Modelling Miners' Consciousness and Experiences for Environmental and Safety Regulatory Compliance During Mining Activities in Ebonyi State, Nigeria. 2021, Nnamdi Azikiwe University.

[20] Chandramouli, B., et al., Face Recognition Based Attendance System Using Jetson Nano. Int. Res. J. Mod. Eng. Technol. Sci, 2021. **3**(8).

[21] Simukali, C.M., Multi factor authentication access control for student and staff based on RFID, barcode and GIS. 2019, University of Zambia.

[22] Jadhav, A., et al., Automated attendance system using face recognition. International Research Journal of Engineering and Technology (IRJET), 2017. **4**(1): p. 1467-1471.

[23] Patel, U.A. and S. Priya, Development of a student attendance management system using RFID and face recognition: a review. International Journal of Advance Research in Computer Science and Management Studies, 2014. **2**(8): p. 109-119.

[24] Shawkat, S.A., K.S.L. Al-badri, and A.I. Turki, The new hand geometry system and automatic identification. Periodicals of Engineering and Natural Sciences (PEN), 2019. **7**(3): p. 996-1008.

[25] Winarno, E., et al. Attendance system based on face recognition system using cnn-pca method and real-time camera. in 2019 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI). 2019. IEEE.

[26] Arya, S., H. Mesariya, and V. Parekh, Smart attendance system usign cnn. arXiv preprint arXiv:2004.14289, 2020.

[27] Sanivarapu, P.V., Multi-face recognition using CNN for attendance system, in Machine Learning for Predictive Analysis: Proceedings of ICTIS 2020. 2020, Springer. p. 313-320.

[28] Kapse, A., et al. Face recognition Attendance system using HOG and CNN algorithm. in ITM Web of Conferences. 2022. EDP Sciences.

[29] Pham, T.-N., et al. Tracking student attendance in virtual classes based on MTCNN and FaceNet. in Asian Conference on Intelligent Information and Database Systems. 2022. Springer.