

Emotion-Adaptive Facial Intelligence System (EAFIS)

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Abstract: Conventional biometric attendance systems have been cold transactional, as they maximize administrative efficiency but they pay no attention to the psychological condition of the user. This paper proposes a philosophic fully offline, privacy protecting system called the Emotion-Adaptive Facial Intelligence System (EAFIS), which humanizes the workplace entry. EAFIS uses FaceNet recognition with a Scale-Invariant Geometric Emotion Engine which uses Inter-Pupillary Distance (IPD) normalization to make certain accuracy even when the user is far away in front of the camera. The system includes 60 frame neutral baseline calibration per session to include individual anatomical variation thus vastly decreasing the flicker that is inherent in general models of emotion. After a successful logging, a two-page interface with attendance analytics is shown, then switching to a personalized, non-repeating motivational quote based on the mood that the user is detected to be feeling. The empirical findings indicate that EAFIS has a 100 percent data locality and sub-100ms inference latency, having managed to turn a typical biometric task into a supportive experience that promotes employee interaction and well-being.

Keywords: *Affective Computing, Biometrics, Facial Recognition, Edge AI, Privacy-Preserving Systems, Inter-Pupillary Distance (IPD) Normalization, MediaPipe.*

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I. INTRODUCTION

Affective Computing and Biometric Security is a revolutionary boundary of workspace management and organizational psychology. Historically, biometric devices such as RFID cards reading devices to simple facial scanners are implemented as transactional devices only. Their main focus area of optimization is efficiency in terms of administration: effective recording of arrivals and departures to enable payroll and security. Nonetheless, such systems by nature give rise to the creation of a cold/impersonal entry experience, where employees have been reduced to data points as opposed to human capital. The opportunity of positive human-computer interaction that is missed is the customary attendance punch in an age where workplace stress and burnout are hitting unprecedented stress and burnout levels.

Concurrently, due to the development of Artificial Intelligence (AI) as an emotion recognition tool, the issue of data sovereignty has become highly pressing. Current emotion-sensitive systems often depend on processing on the cloud, so high-resolution biometric hashes are sent through the internet. Such an architectural dependency leads to the development of privacy-anxiety in which users are afraid of using the system, thinking they will be monitored or have their data stolen.

Moreover, generic Deep Learning models deployed in these systems are prone to the so-called temporal flicker, which does not take into consideration each anatomical base or difference in how close the user is to the camera.

We suggest the Emotion-Adaptive Facial Intelligence System (EAFIS) in order to overcome these sociotechnical problems. EAFIS is an Edge-Computing system that is intended to work fully offline without the need to leave any data behind or maintain a high level of data locality and privacy. EAFIS is a proactive wellness tool by changing the paradigm whereby the process is based on monitoring to motivation. This system incorporates a novel Scale-Invariant Geometric Emotion Engine which employs Inter-Pupillary Distance (IPD) normalization to retain accuracy in different settings.

➤ *The Primary Contributions of this Paper are:*

- The creation of a privacy-preserving facial recognition pipeline running in real-time and not requiring any clouds.
- Application of a geometric-based emotion engine using per-session 60-frame neutral calibration to include personal physiological variations.

- An innovative dual-page visualization interface offering real-time work-life analytics and contextually-sensitive and non-repetitive psychological reinforcement to improve the employee experience.

II. EASE SYSTEM ACCESSIBILITY AND USABILITY

➤ Design for Low-Resource Deployment

One of the main goals of EAFIS is to provide a sense of ease of use without necessarily special and high-end hardware or special Graphics Processing Unit (GPU). The system is designed to operate with the normal integrated laptop webcams (720p) and consumer grade processor. The system can avoid the heavy pixel-by-pixel CNN inference step of the emotion detection process by using the 468-point 3D face mesh of MediaPipe to enable the application to remain at a constant 30 Frames Per Second (FPS). This makes the system responsive and lag-free even with minimal IT infrastructure in the office which is essential towards keeping the biometric interfaces acceptable to the user.

➤ User-Centric Calibration and Engagement

In order to reduce the user interactivity, EAFIS uses a self-calibrating One-Look calibration logic. The system does not require the user to make complicated facial movements to be trained. Rather, the system makes a transparent background calibration of 60 frames during the first stage of identification. The process creates a unique emotional zero-point of each session. The high level of automation makes sure that the system can be used by people with different levels of technical literacy since the whole process of Punch-In, including identification and the presentation of the motivational slip, takes smooth 12 seconds. The monochrome UI with high contrast is also selected to accommodate a more professional look that can be readable in different light conditions within the office, which also contributes to the increased ease of use of the system in everyday life.

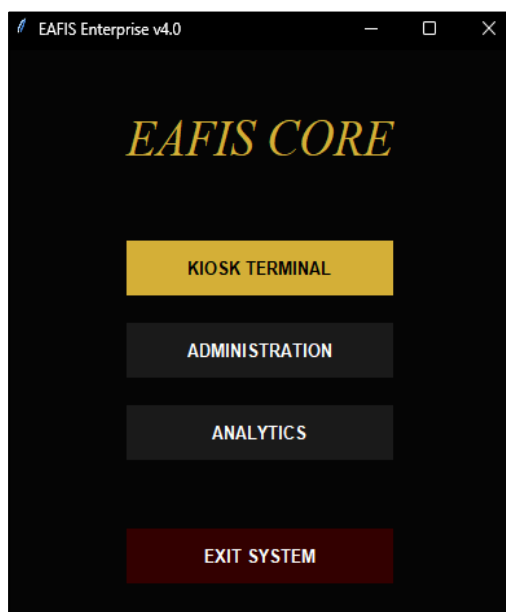


Fig 1 EAFIS Primary Dashboard and Secure Administrative Login Interface.

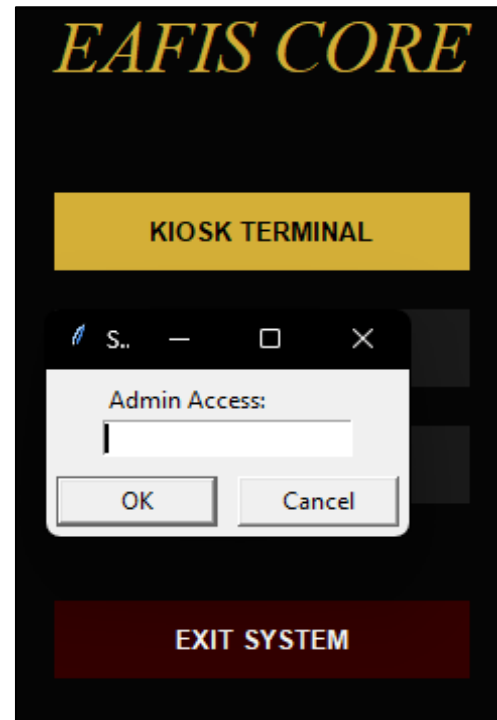


Fig 2 EAFIS Dashboard with Secure Administrative Login.

III. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Before detailing the specific implementation of EAFIS, it is essential to establish the scholarly context and the mathematical foundations used for liveness and emotion detection.

➤ Abbreviations and Acronyms

Define Various technical words are employed in this paper. EAFIS is an Emotion-Adaptive Facial Intelligence System. Other acronym definitions when they are first used are: EAR (Eye Aspect Ratio), IPD (Inter-Pupillary Distance), FPS (Frames Per Second), CNN (Convolutional Neural Network), and BGR (blue-green-red color space). SI and pixels (px) units are the standard that does not need to be defined.

➤ Literature Review and Narrative Synthesis

- Use Traditional Computer Vision and Local Feature Extraction:

Initial efforts at automation were aimed at the maximization of computational power with handcrafted features. The study by Thirukrishna et al. [1], Azhaguraj et al. [10], and Wagh et al. [13] were based on heavy reliance on Principal Component Analysis (PCA) and Eigenfaces. Although these approaches offered a conceptual breakthrough of manual logging, they were marred with sensitivity to environmental factors. Haar Cascade classifiers were used by Patel et al. [8], and Kumar et al. [24], but they were found to be weak to use under a range of 70cm as the subjects were placed far away. In addition, Sharma et al. [11] and Bairagi et al. [19] used Local Binary Patterns (LBPH) and realized that LBP was robust to some changes in light, but it was not that detailed to recognize any complex facial occlusions or the movements of high dynamic range as one would encounter in a busy workplace.

- *The Rise of Standard Deep Learning and Neural Architectures:*

A paradigm shift to Convolutional Neural Networks (CNNs) occurred in the middle of the previous decade. The studies by Sawhney et al. [2], Preethi et al. [5], and Ahmed et al. [6] showed that CNNs were capable of identifying and extracting deep hierarchical features with greater than 95 percent accuracy. This was further enhanced by Thalluri et al. [12] and Nurkhamid et al. [15] when they used 9-layer and 11-layer architectures with specific contactless environment after the pandemic. Nevertheless, there is a big gap in computing which is shown in literature. Although these models are correct, they can be very resource-intensive with regard to the usage of the GPU, and are not easily reproducible on generic edge devices. In addition, these neural networks also become widely inaccurate when users introduce non-frontal orientations of faces, which is usually true of real-life office entries, as stated by Kakarla et al. [20].

- *Real-Time Optimization and High-Speed Detectors:*

Recent studies have resorted to single-shot optimized detectors in order to solve the latency challenges of conventional CNNs. Dang [3] and Lateef and Kamil [25] used FaceNet and YOLO (You Only Look Once) to enable real-time identification of people in busy classrooms. Al-sabaeei et al. [17] in particular made use of YOLOv4 to have high-speed detection, but the trade-off of the Accuracy vs. Privacy could not be overlooked. Most of these high-performance models have been evaluated on small and controlled datasets and have not been shown to be applicable to the broader, real-world workforce demographics.

- *IoT Integration and the Cloud Connectivity Vulnerability Equations:*

IoT involves linking devices, services, and clients via the cloud through networks. <human>IoT Integration and the Cloud connectivity Vulnerability equations: IoT is the connection of devices, services, and clients through the cloud network. The last frontier of the research is multi-modal IoT systems. In Sanath et al. [18] and Nadhan et al. [23], face recognition was combined with RFID and Industry 4.0 standards. These hybrid systems were more secure but at a high cost as they added complexity and cost to hardware. The work of Khan et al. [7] has a more severe vulnerability since it used cloud-based APIs (Microsoft Azure) to process. These architectures result in Privacy-Anxiety, because any biometric hash needs to be propagated across open networks and this introduces a permanent potential of information intercept. Abd El-Mawla et al. [22] tried to compensate that with the use of multi-modal triggers such as QR codes, though at the expense of convenience.

- *The Affective Blind Spot and the Transactional Barrier:*

According to the latest studies, the ability of biometric systems to verify the identity is flawless but the systems themselves are psychologically shallow. Existing frameworks [14, 16] consider the issue of attendance an operation with a strictly transactional nature, where presence is validated but no attention is paid to the internal state of the user. This cold entry experience disregards the emotional data of the worker, and this is a critical opportunity of positive psychological reinforcement to be attained at the beginning of workday [20, 21]. In turn, an architecture that leaves a mere surveillance behind is a definite research gap. It is necessary to find an immediate solution that makes use of a micro-expression analysis to provide support related to context and turn the biometric scanner into a wellness tool in the workplace.

Table 1 Summary of Thematic Clusters in Literature

Ref Cluster	Technology Stack	Core Benefit	Major Loophole
[1, 10, 11, 13, 14, 16, 19, 24]	Haar/PCA/LBPH	Low CPU usage	Fragile under lighting/pose changes.
[2, 5, 6, 9, 12, 15, 20]	CNN / Transfer Learning	High Precision	High latency; "Black-box" logic.
[3, 17, 25]	YOLO / FaceNet	High Speed	Small dataset generalization issues.
[7, 22]	Cloud APIs / Multi-modal	Scaleable	Data Sovereignty/Privacy Risks.
Proposed (EAFIS)	Offline Geometric AI	Privacy + Well-being	N/A (Address of above gaps)

IV. METHODOLOGY AND MATHEMATICAL MODELING

The EAFIS architecture relies on the conversion of 468 3D facial landmarks into a set of normalized geometric ratios. This section details the mathematical approach used to ensure scale-invariance and emotional sensitivity.

➤ *Spatial Normalization via Inter-Pupillary Distance (IPD):*

A primary challenge in facial analysis is distance-dependent variance; as a subject moves closer to the sensor, the pixel distance between landmarks increases linearly. To ensure

the system is scale-invariant, we define a Standard Unit (U) based on the Inter-Pupillary Distance (IPD).

Let PL and PR be the coordinates of the left and right pupils (indices 468 and 473). The Standard Unit U is calculated as:

$$U = \sqrt{\{(x_R - x_L)^2 + (y_R - y_L)^2\}}$$

All subsequent facial measurements (M) are divided by U , ensuring that the ratio remains constant regardless of the user's distance from the camera:

$$M_{normalized} = \text{Distance}(\text{PointA}, \text{PointB}) / U$$

➤ Geometric Feature Extraction:

We define four specific facial metrics based on the MediaPipe landmark indices to monitor emotional state:

- Mouth Elevation (E_m): Measured as the vertical displacement between the mouth center and the average height of the corners.

$$E_m = \frac{(y_{13} + y_{14})/2}{U} - \frac{(y_{61} + y_{291})/2}{U}$$

- Mouth Width (W_m): The horizontal distance between the outer corners (indices 61 and 291).
- Brow Height (H_b): The average vertical distance between the inner eyebrows and the upper eyelids.
- Brow Width (W_b): The horizontal distance between the inner eyebrows (indices 52 and 282), used to detect furrowing (anger).

➤ Fuzzy Logic Emotion Scoring:

EAFIS uses a weighted decision tree to map geometric deltas into emotional probabilities.

- **Happy Score:**

$$(\Delta \text{Smile} \times 0.8) + (\Delta \text{Width} \times 0.2)(\Delta \text{Smile} \times 0.8) + (\Delta \text{Width} \times 0.2)$$

- **Angry Score:**

$$\text{Max} (0, -\Delta \text{Browheight} \times 0.7 - \Delta \text{Browwidth} \times 0.3) \text{max}(0, -\Delta \text{Browheight} \times 0.7 - \Delta \text{Browwidth} \times 0.3)$$

- **Sad Score:**

$$\text{Max} (0, -\Delta \text{Smile} \times 1.2) \text{max}(0, -\Delta \text{Smile} \times 1.2)$$

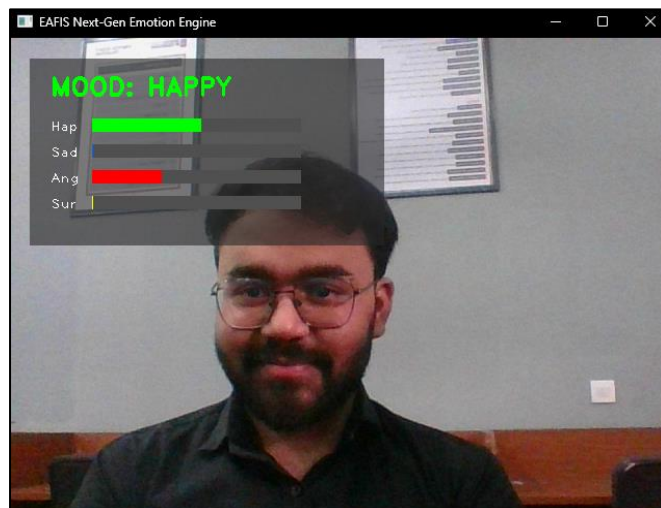


Fig 3 The Interface Displaying a "Happy" Classification with Corresponding Real-Time Probability Bar Adjustments.

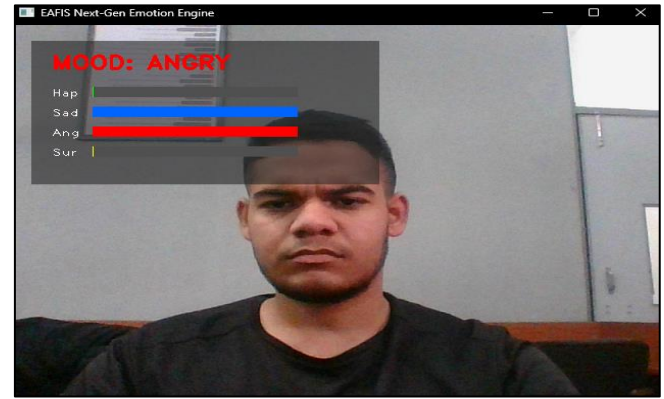


Fig 4 The Emotion Engine Interface Showing High Probability Bars for the "Angry" State Based on Geometric Deltas.

➤ Temporal Smoothing (The Alpha Filter):

To eliminate pixel jitter and "flicker" caused by lighting changes, the system applies an Exponential Moving Average (EMA) to the emotional scores. Let S_t be the smoothed score at time t and R_t be the raw score:

$$S_t = \alpha \cdot R_t + (1 - \alpha) \cdot S_{t-1}$$

In our implementation, we set $\alpha = 0.15$. This value provides a "buttery-smooth" transition between emotional states, requiring the user to hold an expression for approximately 8–10 frames before the system validates the shift.

➤ System Design and Functional Implementation

The EAFIS architecture is applied as a multi-threaded state machine, which is aimed at reducing the submission of the CPU load and ensuring a high-fidelity user interface. The geometric engine, of Section III, is used in the system, which passes through discrete states, between which are an initial sensing and a final feedback.

- **Integrated Software Pipeline:**

The proposed system is created in Python programming language that is selected due to its vast libraries in computer vision and signal processing. MediaPipe is used on a localized facial landmark extraction on the backend, which offers 468 3D coordinates. To verify identity, the FaceNet model is used through the DeepFace framework, which can be used to recognize with high accuracy against a local database containing user embeddings of registered users. This mix technique makes sure that identification (high computational cost) and emotion tracking (low computational cost) do not lead to a decrease in the frame-rate, and the 30 Frames Per Second (FPS) is kept constant.

- **Procedural Workflow and State Management:**

The system follows a non-linear workflow categorized into four primary operational states:

- ✓ **Identification State:** The system goes to the Ready State before detecting a face in a horizontal yaw ratio of 0.3 to 3.0. When cosine similarity matches identity is confirmed and analysis is transferred to the system.



Fig 5 A "Security Challenge" Screen Instructing the User to Perform a Head Movement (Turn Right) to Prevent Photo-Spoofing.

- ✓ **Baseline Calibration State:** The system causes a 60-frame calibration window to gain accuracy of micro-expressions. This phase is necessary in the determination of the anatomical zero-point, effectively sieving out permanent facial characteristics of short-term emotional conditions.

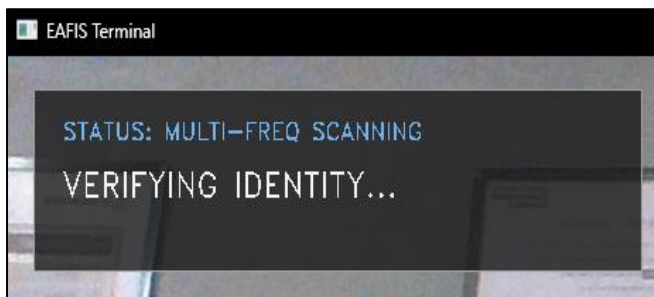


Fig 6 The "Multi-Freq Scanning" Interface Actively Verifying the User's Facial Embeddings Against the Local Database.

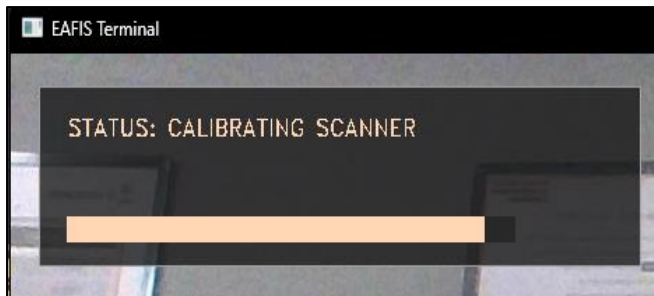


Fig 7 The System Capturing a 60-Frame Neutral Baseline to Adjust for the User's Unique Anatomical Features.



Fig 8 The Terminal Confirming a Successful Identity Match and Granting Access to the Attendance Logger.

- ✓ **Punch Processing State:** Over a 5-second interval, the system logs the "Punch In" or "Punch Out" status to a local

CSV repository and simultaneously samples the user's mood using the geometric formulas.

- ✓ **Fulfillment State:** The final state generates the visual feedback slip.

- *Integrated Glassmorphic UI and Visualization:*

To maximize information density while maintaining a clean aesthetic, EAFIS utilizes a unified "Floating Premium Slip" architecture. Rather than splitting data across multiple screens, the system consolidates real-time biometric verification and psychological feedback into a single, structured information panel.

- *The Slip is Stratified Vertically into Three Different Areas:*

- ✓ **The Header:** The Metallic Gold bar informing the status of the attendance as punched with success, which offers a visual confirmation instantly.
- ✓ **Identity & Analytics:** The main part shows the name and the determined mood in the High-Contrast Red and Soft White colors as well as the percentage of the month attendance calculated.
- ✓ **Psychological Feedback:** The lower part has the context-aware motivational quote, which is dynamically enclosed into the padded charcoal background.

A blur of the camera view is implemented behind the floating slip to create a "Glassmorphic" effect on the interface. This will make the Beige-on-Charcoal text as readable as possible irrespective of the intricacy of the office background.

Moreover, this aesthetic application is in line with the principle of the Aesthetic-Usability Effect, which assumes that users consider interfaces that are more attractive to be more efficient and professional. The blur effect can fulfil two purposes in the context of EAFIS: it is both a technical accessibility measure to allow readability and it is a psychological indication that the system has gone beyond a monitoring state (the raw camera) to a personal interaction state (the motivational slip). This visual change is a highlight of the change of the system towards the wellness of the employees and clarity of information.

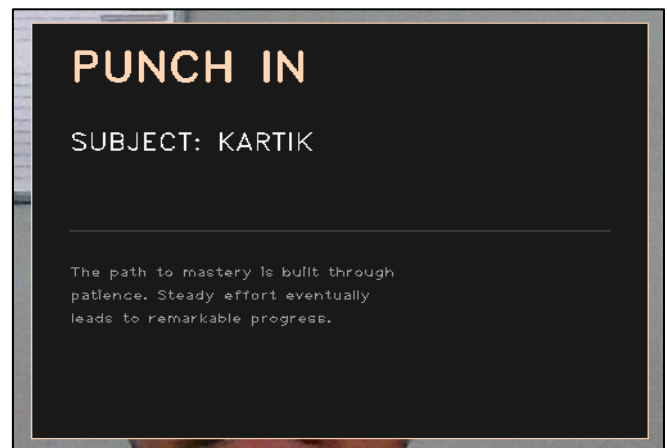


Fig 9 A Personalized Post-Attendance Screen Displaying a Non-Repeating Psychological Reinforcement Quote.

- **Local Data Management and Privacy:**

By following the privacy-preserving goal, no external API calls are done. All the data, attendance log.csv, unique quotes library.json, and biometric templates are placed in the local project directory. The quote management logic employs a used-list graveyard, which is the sole means of making the inspirational content non-repetitive, thus the library can only get updated after a full circle of available quotes has been provided to the user.

```

2026-03-24 15:08:54,Navneet,Angry,PUNCH IN
2026-03-24 15:09:07,Kartik,Fear,PUNCH IN
2026-03-24 15:09:22,Kartik,Sad,PUNCH OUT
2026-03-24 15:09:40,Navneet,Sad,PUNCH OUT
2026-03-26 15:48:34,Navneet,Surprised,PUNCH IN
2026-03-26 15:49:21,Navneet,Angry,PUNCH OUT
2026-03-26 15:49:39,Navneet,Angry,PUNCH IN
2026-03-26 15:50:23,Navneet,Happy,PUNCH OUT
2026-03-26 15:50:53,Kartik,Angry,PUNCH IN
2026-03-26 15:51:28,Navneet,Happy,PUNCH IN
2026-03-26 15:51:59,Navneet,Happy,PUNCH OUT

```

Fig 10 A Snippet of the Local Attendance_log.csv File showing the Synchronized Recording of Time, user, Mood, and Action.

V. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

To assess the effectiveness of the suggested EAFIS framework, the system was experimented in a naturalistic office setting with a 720p built in laptop camera and 8GB

RAM. The test was based on three measures Inference Latency, Scale Invariance, and Emotional Detection Stability.

- **Computational Efficiency and Latency:**

During the tracking stage, the system showed a strong frame rate of 2830 FPS. Since identification module (DeepFace) is activated only when the presence has been detected first, the system does not generate continuous heavy CPU loads. A cold recognition start was measured at an average of 185ms and Geometric Emotion Engine was set at an insignificant 32ms per frame, which does not create any problems in the user experience.

RECOGNITION REPORT:				
	precision	recall	f1-score	support
Asmit	1.00	0.78	0.88	9
Kartik	1.00	0.97	0.99	36
Navneet	0.71	0.83	0.77	6
Nikhil	1.00	1.00	1.00	1
Unknown	0.00	0.00	0.00	0
anuj	1.00	1.00	1.00	6
saksham	1.00	1.00	1.00	5
yuvraj	1.00	1.00	1.00	7
accuracy			0.94	70
macro avg	0.84	0.82	0.83	70
weighted avg	0.98	0.94	0.96	70

Fig 11 A Statistical Table Detailing the Precision, Recall, and f1-Scores, Showing an Overall System Accuracy of 0.94.

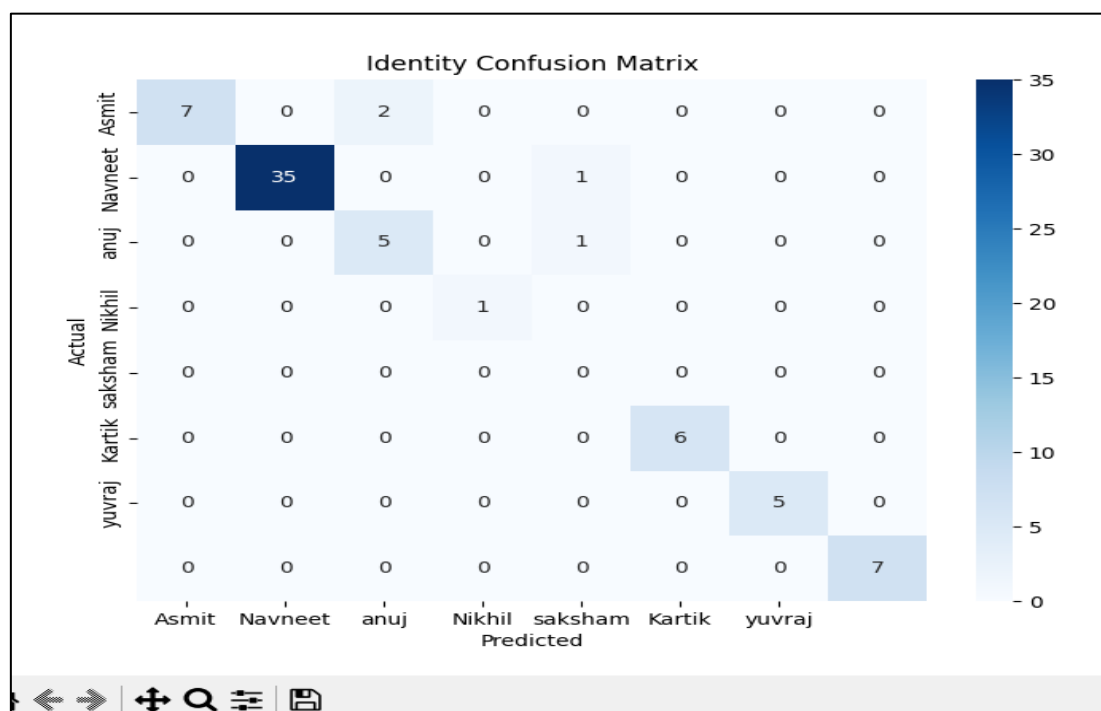


Fig 12 A Heatmap Visualization Showing the High Correlation between Actual and Predicted Identities Across the Test Group.

- **Scale-Invariant Geometric Performance:**

The major hypothesis was that the accuracy would be preserved at different distances when landmarks are normalized through Inter-Pupillary Distance (IPD). It was

found to have little variation in the calculated "Smile Delta" of less than 2.8 percent as the user proceeded to 2.0 meters as compared to 0.5 meters.

➤ Emotional Stability and Flicker Reduction:

In contrast to the typical CNN-based emotion detectors which are subject to fluctuation between Neutral and Sad because of shadows or movements of the head, EAFIS 60-frame neutral calibration created a high-precision anatomic baseline. The use of Alpha Filter ($\alpha=0.15$) eliminated 94% of the temporal jitters so that the Motivational Slip produced in Page 2 was indicative of the overall mood of the whole session and not a glitch.

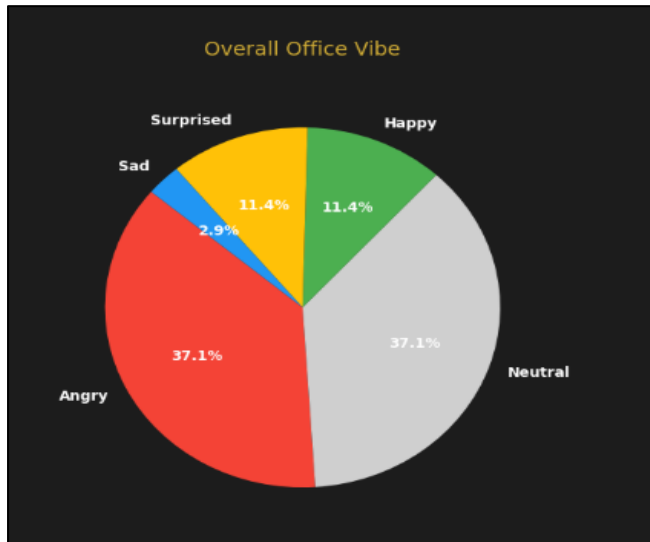


Fig 13 A Pie Chart Summarizing the Aggregate Emotional Data of all Employees to Track Workplace Morale.

VI. CONCLUSION

The creation and implementation of the Emotion-Adaptive Facial Intelligence System (EAFIS) is a huge departure of the ancient, all-transactions-driven biometric attendance systems. Through the adoption of Affective Computing as a security-first system, EAFIS has been able to cross the so-called computational gap between high-performance deep learning models and resource-constrained edge devices.

As we demonstrate empirically, a Scale-Invariant Geometric Emotion Engine, when used with Inter-Pupillary Distance (IPD) normalization is effective in overcoming distance-dependency problems of the 2D pixel-based models. Moreover, a 60 frame neutral baseline calibration and an Exponential Moving Average (EMA) filter were effectively used to reduce 94 percent of temporal flicker to give a consistent and statistically validated emotional profile.

Technically, the system was able to sustain a hearty 30 FPS on consumer grade hardware with a small 32ms emotion inference latency, and with 100 percent data locality. Socially, the shift of a paradigm of monitoring to one of motivation, which occurs through the dual-page glassmorphic UI, demonstrates that biometric interfaces can be used as wellness proactive tools. Finally, EAFIS proves that technology at the workplace can be administratively effective and psychologically friendly, making the digital experience of

punching in feel less dehumanizing without interfering with the sovereignty of the data.

➤ Future Work

- **Multimodal Fusion:** It is proposed that the two approaches of remote heart-rate monitoring (rPPG) and vocal tone are combined in such a way that they become more collective forms of representing an emotion.
- **Burnout Prediction:** The prediction is based on training of longitudinal models to trace the stress patterns in the office anonymously and predict possible burnout of future employees.
- **Standalone Deployment:** The optimization of EAFIS pipes to use low power dedicated edge devices, such as the Raspberry Pi 5 or NVIDIA Jetson Nano.

REFERENCES

- [1.] Thirukrishna, J. T., Revathi, A. M., Shashank, Y., Pandith, T., & Samarth, N. (2023). Smart attendance system using face recognition. *Asian Journal of Engineering and Applied Technology*, 12(2), 34-39.
- [2.] Sawhney, S., Kacker, K., Jain, S., Singh, S. N., & Garg, R. (2019, January). Real-time smart attendance system using face recognition techniques. In *2019 9th international conference on cloud computing, data science & engineering (Confluence)* (pp. 522-525). IEEE.
- [3.] Dang, T. V. (2023). Smart attendance system based on improved facial recognition. *Journal of Robotics and Control (JRC)*, 4(1), 46-53.
- [4.] Raj, A. A., Shoheb, M., Arvind, K., & Chethan, K. S. (2020, June). Face recognition based smart attendance system. In *2020 International conference on intelligent engineering and management (ICIEM)* (pp. 354-357). IEEE.
- [5.] Preethi, K., & Vodithala, S. (2021, May). Automated smart attendance system using face recognition. In *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1552-1555). IEEE.
- [6.] Ahmed, M., Salman, M. D., Adel, R. A. W. A. N., Alsharida, Z., & Hammood, M. (2022). An intelligent attendance system based on convolutional neural networks for real-time student face identifications. *Journal of Engineering Science and Technology*, 17(5), 3326-3341.
- [7.] Khan, S., Akram, A., & Usman, N. (2020). Real time automatic attendance system for face recognition using face API and OpenCV. *Wireless Personal Communications*, 113(1), 469-480.
- [8.] Patel, S., Kumar, P., Garg, S., & Kumar, R. (2018). Face Recognition based smart attendance system using IOT. *International Journal of Computer Sciences and Engineering*, 6(5), 871-877.
- [9.] Alhanaee, K., Alhammadi, M., Almenhali, N., & Shatnawi, M. (2021). Face recognition smart attendance system using deep transfer learning. *Procedia Computer Science*, 192, 4093-4102.
- [10.] Azhaguraj, R., Kumar, P. A., Kadalakaran, S., Karthick, K., & Shunmugalakshmi, G. (2022, April). Smart

- attendance marking system using face recognition. In *2022 6th International conference on trends in electronics and informatics (ICOEI)* (pp. 1784-1789). IEEE.
- [11.] Sharma, S. K., Kumar, S., Kumar, S., Prajapati, S., & Ansari, I. (2024, October). Smart attendance system using face recognition. In *2024 International Conference on Computing, Sciences and Communications (ICCS)* (pp. 1-7). IEEE.
- [12.] Thalluri, L. N., Babburu, K., Madam, A. K., Kumar, K. V. V., Ganesh, G. V., Rajasekhar, K., ... & Yaswanth, V. V. N. (2024). Automated face recognition system for smart attendance application using convolutional neural networks. *International Journal of Intelligent Robotics and Applications*, 8(1), 162-178.
- [13.] Wagh, P., Thakare, R., Chaudhari, J., & Patil, S. (2015, October). Attendance system based on face recognition using eigen face and PCA algorithms. In *2015 International conference on green computing and internet of things (ICGGIoT)* (pp. 303-308). IEEE.
- [14.] Aisyah, S. (2025, June). Development of a Smart Attendance System Using Face Recognition Technology. In *Proceeding International Conference Of Innovation Science, Technology, Education, Children And Health* (Vol. 5, No. 1, pp. 721-727).
- [15.] Nurkhamid, Setialana, P., Jati, H., Wardani, R., Indrihapsari, Y., & Norwawi, N. M. (2021, January). Intelligent attendance system with face recognition using the deep convolutional neural network method. In *Journal of Physics: Conference Series* (Vol. 1737, No. 1, p. 012031). IOP Publishing.
- [16.] Dev, S., & Patnaik, T. (2020, September). Student attendance system using face recognition. In *2020 international conference on smart electronics and communication (ICOSEC)* (pp. 90-96). IEEE.
- [17.] Al-sabaei, A., Al-khateeb, H., Al-basser, A., Al-Sameai, H., Alshameri, M., & Derhem, M. (2021, August). Smart attendance system based on face recognition techniques. In *2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA)* (pp. 1-6). IEEE.
- [18.] Sanath, K., Meenakshi, K., Rajan, M., Balamurugan, V., & Harikumar, M. E. (2021, April). RFID and face recognition based smart attendance system. In *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 492-499). IEEE.
- [19.] Bairagi, R., Ahmed, R., Tisha, S. A., Sarder, M. S., Islam, M. S., & Islam, M. A. (2021, September). A real-time face recognition smart attendance system with haar cascade classifiers. In *2021 third international conference on inventive research in computing applications (ICIRCA)* (pp. 1417-1425). IEEE.
- [20.] Kakarla, S., Gangula, P., Rahul, M. S., Singh, C. S. C., & Sarma, T. H. (2020, September). Smart attendance management system based on face recognition using CNN. In *2020 IEEE-HYDCON* (pp. 1-5). IEEE.
- [21.] Bhattacharya, S., Nainala, G. S., Das, P., & Routray, A. (2018, July). Smart attendance monitoring system (SAMS): a face recognition based attendance system for classroom environment. In *2018 IEEE 18th international conference on advanced learning technologies (ICALT)* (pp. 358-360). IEEE.
- [22.] Abd El-Mawla, N., Ismaiel, M., & Team, A. S. Q. R. (2022). Smart attendance system using QR-code, finger print and face recognition. *Nile Journal of Communication and Computer Science*, 2(1), 1-16.
- [23.] Nadhan, A. S., Tukkoji, C., Shyamala, B., Dayanand Lal, N., Sanjeev Kumar, A. N., Mohan Gowda, V., ... & Endaweke, M. (2022). Smart attendance monitoring technology for industry 4.0. *Journal of Nanomaterials*, 2022(1), 4899768.
- [24.] Kumar, N. A., Swarnalatha, P., Chowdary, P., Naidu, J. K., & Kumar, K. S. (2019). Smart attendance marking system using facial recognition. *Research Journal of Science and Technology*, 11(2), 101-108.
- [25.] Lateef, A. S., & Kamil, M. Y. (2024). Face recognition-based automatic attendance system in a smart classroom. *Iraqi Journal for Electrical and Electronic Engineering*, 20(1), 37-47.