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Class Pulse AI: An AI-Powered Real-Time Classroom Monitoring, Automated Attendance, and Behavioral Telemetry Platform

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Abstract: Educational institutions require scalable, non-intrusive techniques to quantify classroom attention, verify attendance, and monitor pedagogical engagement in real time. Conventional roll-call procedures waste valuable instruction time, remain susceptible to proxy marking, and provide no contextual insights into learner comprehension. Furthermore, covert mobile device usage in large lecture environments continues to distract students and degrade pedagogical outcomes. This paper presents Class Pulse AI, an intelligent, multi-stage computer vision and behavioural telemetry system designed for smart classroom environments. ClassPulse AI unifies real-time face detection via Media Pipe and OpenCV, proxy-free biometric attendance tracking using 128-dimensional DeepFace and Face Net embeddings, class-room affective state estimation (attentive, distracted, sleepy, and confused) via deep convolutional neural networks, and handheld mobile device distraction identification utilizing YOLOv8. The architecture persists session data to a cloud-managed Postgre SQL Supabase database and renders real-time telemetry, historical roll-call logs, and attentiveness indices via aNext.js and Recharts web dashboard. Empirical testing conducted on a live edge-computing prototype demonstrates real-time inference exceeding 30 frames per second, reliable proxy-free attendance verification, sub-second distraction flagging, and dynamic engagement analytics.

Index Terms: Classroom Telemetry, Face Recognition Attendance, Affective Computing, YOLOv8, Emotion Classification, Edge Computing, Smart Classroom.

I. INTRODUCTION

Classroom education is limited by observational capacity. In traditional academic institutions, the student-to-teacher ratio is high, and a single instructor can observe only a small fraction of the classroom at any given moment [1]. Effective teaching therefore requires timely feedback on whether students are attentive, confused, or disengaged during the delivery of complex topics [2]. In India, higher education curricula under technical universities demand rigorous attendance tracking and student performance records [3]. At the classroom level the situation is largely unassisted. Instructors rely on manual roll-call sheets or sporadic visual scans, which consume 10–15% of lecture time and do not prevent proxy attendance [2]. Distracted students, particularly those using hidden mobile phones, often go unnoticed [4]. Where automated attendance systems are attempted, they are typically standalone tools that provide no feedback on student attention or comprehension [5]. ClassPulse AI addresses these gaps in one unified platform. A classroom camera captures the lecture in real time, an integrated AI core verifies attendance without manual intervention, and cognitive models track attention, drowsiness, and confusion throughout the session. Mobile phone usage is detected and logged automatically, and instructors receive real-time telemetry through an interactive dashboard.

A. Key Objectives

- Deliver automated, contactless biometric attendance using deep metric embeddings to eliminate proxy verification.
- Classify student affective states into four operational categories: attentive, distracted, sleepy, and confused.

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- Flag unauthorized in-class smart phone distractions using edge-accelerated single-stage object detection.
- Provide real-time data persistence to a cloud PostgreSQL database with live WebSocket telemetry synchronization.
- Present an intuitive web portal for educators to review attendance ledgers, attentiveness trends, and distraction histories.

II. LITERATURE REVIEW

Real-time classroom monitoring combines object detection, metric biometric verification, and facial expression analysis.

A. Object Detection for Distraction Tracking

The You Only Look Once (YOLO) family of single-stage convolutional detectors offers an optimal trade-off between inference throughput and bounding-box accuracy. Kasetty and R.K. evaluated YOLOv4, YOLOv5, YOLOv7, and YOLOX across multi-class aerial benchmarks, establishing that one-stage detectors achieve mean Average Precision (mAP) values between 88% and 92% with sub-second edge latency [1]. Qiu demonstrated that structural pruning and 8-bit quantization enable YOLO models to operate efficiently on embedded edge hardware without substantial precision degradation [6]. Chen constructed an 8,845-image classroom behavior corpus utilizing YOLOv8, reporting detection accuracies above 91% for behaviors including note-taking, sleeping, and mobile handset usage [4].

B. Contactless Biometric Attendance Verification

Deep metric learning models generate compact, distance-preserving embeddings for facial identity verification. Deli and Kurmash a presented an automated attendance architecture utilizing YuNet for spatial face detection and SFace for metric extraction, achieving 100% attendance logging accuracy and 98.14% facial recognition reliability [2]. Ramesh and Rajasree surveyed modern facial verification methodologies, demon- strating that 128-dimensional hyper spherical vector representations provide in variance to moderate variations in illumination and head yaw [9]. Yuan and Dai highlighted that frame-level bit stream analysis and distortion mitigation are essential to maintain detection stability over networked RTSP camera streams [3].

C. Affective Computing and In-Class Engagement

Assessing cognitive engagement via facial telemetry requires robust affect classification. Mollahosseini et al. developed the AffectNet benchmark of over 400,000 in-the-wild facial images, establishing that deep convolutional networks can generalize continuous valence and arousal parameters despite variations in subject pose and lighting [10]. Vishnumo-lakala et al. designed the iSEEDS frame work, integrating gaze tracking with convolutional networks to quantify attention and confusion states with recall rates of 84% [7]. Gowthambalagi et al established that centralized telemetry dashboards enhance teaching effectiveness by presenting instructors with synthesized engagement trends [5]. Acoustic emotion classification surveyed by Bhavani et al. offers complementary modalities, though classroom reverberation limits pure acoustic deployments [8].

Table I presents a structured comparative analysis of foundational approaches in the literature alongside Class Pulse AI.

III. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The ClassPulse AI platform is structured across four de-coupled layers: Video Ingestion, Edge AI Processing, Cloud Persistence, and Interactive Dashboard Presentation (Fig. 1).

A. Hardware and Sensor Specifications

InferenceexecuteslocallyonanAppleM2computingwork-station (8-core CPU, 10-core GPU, 16GB unified memory) accelerated via Metal Performance Shaders (MPS). Optical capture is supplied by a high-resolution 4K Ultra HD wide-angle camera supporting wide dynamic range (WDR) operating at 30–120 FPS. Network telemetry synchronization communicates over high-speed local channels (≥50Mbps, <15mslatency).

B. Edge Vision Engine

The pipeline is implemented in Python 3.10 utilizing PyTorch, OpenCV, and MediaPipe. Incoming video frames are normalized and evaluated through parallelized worker threads:

- **Face Localization:** Media Pipe processes frames to isolate student faces, assigning persistent spatial centroid tracking IDs.
- **Biometric Identification:** Bounded face regions are mapped to 128-dimensional unit hyper spherical vector $\vec{se} \in R^{128}$via FaceNet. Vectors are compared against reference embeddings using Euclidean distance: where $\tau=0.55$ defines the match tolerance. Confirmed identities update the attendance ledger to “Present”.
- **Cognitive State Modeling:** A deep CNN evaluates seven micro-expressions (neutral, happy, surprised, sad, angry, fearful, disgusted) and maps predictions to four high-level states: attentive, distracted, sleepy, and confused.
- **Distraction Flagging:** YOLOv8 evaluates frame crops for handheld smart devices. Detections exceeding a 0.50 confidence threshold trigger an immediate is traction flag tied to the student’s spatial zone.

C. Cloud Database and Web Dash board

Database operations utilize a managed Supa base PostgreSQL instance comprising relational tables: students, enrolled_roster, sessions, attendance_records,and phone_distraction_logs. Realtime WebSocket subscriptions push telemetry updates to a Next.js web application styled with TailwindCSS and animated using Framer Motion. Recharts generates visual telemetry showing session turnout, emotion distributions, and alert frequencies.

D. Data Processing Workflow

Fig.2 illustrates the end-to-end data flow. The continuous pipeline operates in five progressive steps:

1. Stream Acquisition: Video frames are captured at 30FPS and buffered in memory.
2. Detection & Registration: Faces are isolated and normalized to standard 160 ×160resolution.

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3. Vector Comparison: FaceNet representations are evaluated against database records to authenticate students.
4. Cognitive Analytics: Softmax outputs from convolutional models determine real-time attentiveness indices.
5. Event Emission: Instant alerts and calculated telemetry are streamed via WebSockets to update the dashboard.

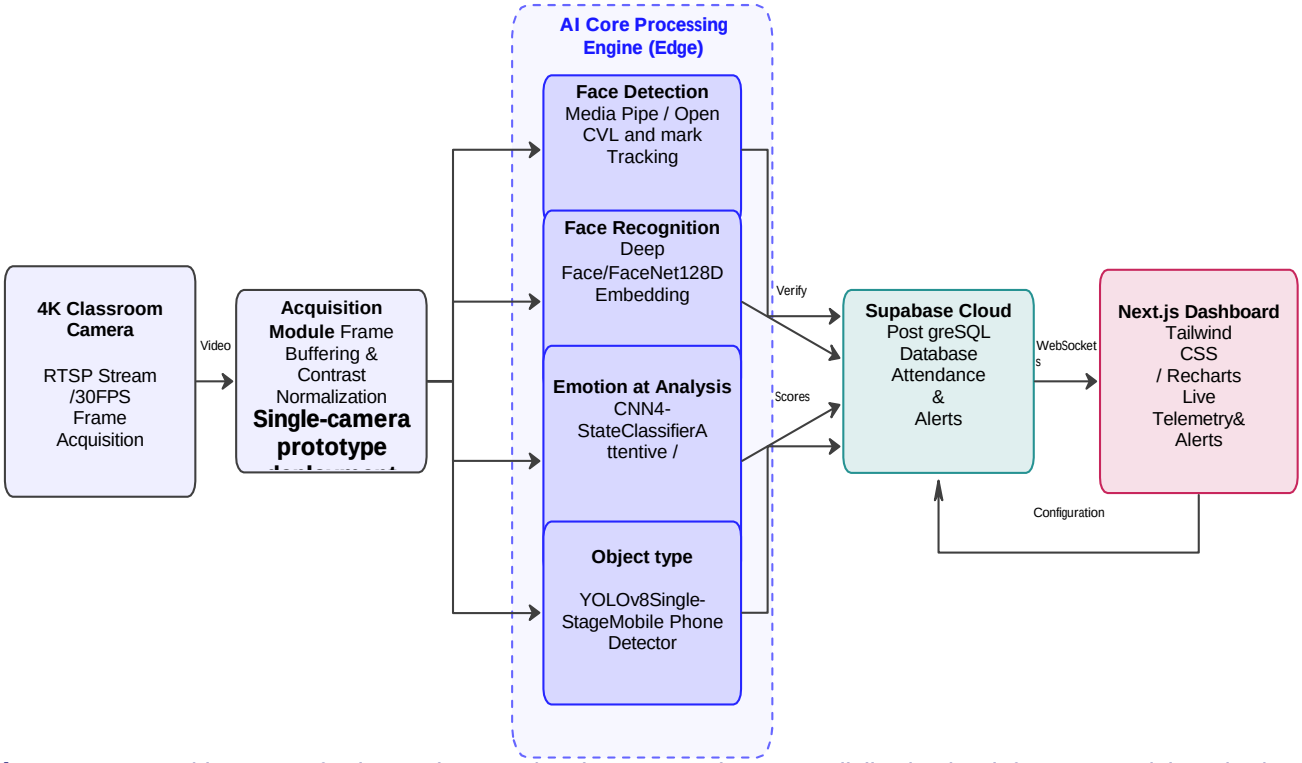


Fig.1. System architecture of Class Pulse AI, showing camera input, parallelized edge inference modules, database persistence, and the telemetry dashboard.

Table I – Comparative Analysis of Methodologies in Literature and Proposed Work

Reference/Work	Algorithm/Model	Target Task	Reported Metric	Key Strength	Operational Limitation
Kasetty&R.K.[1]	YOLOv4, v5, v7, YOLOX	Object Detection	mAP:88–92%	Real-time inference speed	Small rotated targets
Deli & Kurmasha [2]	YuNet + SFace	Attendance Logging	Acc: 100%, Rec:98%	Proxy-free verification	Sensitivity to lighting
Yuan & Dai[3]	Bit stream & Frame Analysis	Video Stream Audit	Acc: 90–94%	Real-time distortion check	Video quality only
Chen [4]	Fine-tuned YOLOv8	Behavior Tracking	Acc:91–94%	Action classification	Dense crowding Occlusions
Gowtham Balagi et al.[5]	Cloud AI Architecture	Classroom Telemetry	Acc:88–92%	Longitudinal Analytics	High architectural Complexity
Qiu[6]	Quantized Edge YOLO	Embedded Vision	Acc:87–90%	Low-power execution	Slight accuracy Penalty
Vishnumolakala et al. [7]	CNN+Gaze Tracking	Engagement Tracking	Acc/Rec: ~84%	Continuous focus indices	Vulnerable to gaze drift
Bhavani et al.[8]	Deep Acoustic Neural Net	Speech Emotion	Acc:80–86%	Visual-free estimation	Acoustic background noise
Ramesh & Rajasree [9]	Metric Learning Survey	Biometric Verification	Acc:90–97%	Feature space separation	Extreme head Pose variations
Mollahosseini Et al. [10]	Affect Net CNN Engine	Facial Affect Analysis	Acc:60–65%	Large in-the-wild dataset	High subjective Label variance
Class Pulse AI (Ours)	Media Pipe+ Face Net+ YOLOv8 + CNN	Biometric Attendance & Behavioral Telemetry	30 + FPS, 100% Turnout Sync	Unified attendance, emotion,and distraction alerts	Single-camera prototype deployment

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The ClassPulse AI prototype was evaluated across physical classroom trials conducted at the Department of Computer Science and Engineering (AIML), Vemana Institute of Technology.

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A. Biometric Verification and Attendance Turnout

Students registered biometric profiles via webcam captures thatgenerated128-dimensionalembeddingvectorsstoredin the cloud roster. During live lecture tracking, incoming crops were matched against enrolled embeddings. Across five recorded test sessions (Fig. 3), Session 4 recorded three active attendees, reaching a100% verified turnout rate. Biometric match confidence spanned from 28.0% to 91.2% depending on subject distance and ambient illumination.

B. Attentiveness and Distraction Event Correlation

Under baseline lecture conditions with students actively listening, the dominant emotional expression registered as Neutral (100% channel distribution). During distraction stress testing, simulated smart phone usage was introduced. At t= 4.02min into the trial, YOLOv8 registered a phone in hand, and the calculated Attentiveness Score registered an immediate decline from 100% down to 85% (Fig. 4). In total, 15 individual distraction alert events were logged with precise timestamps and student identifiers during the trial.

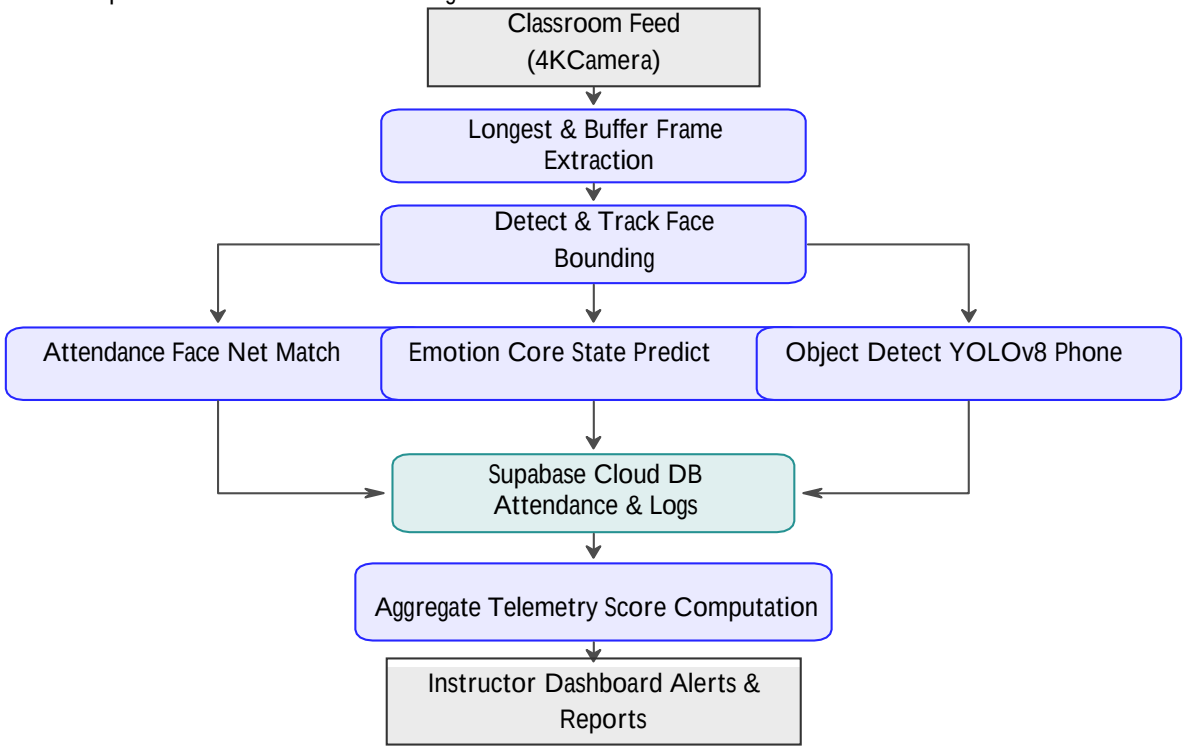


Fig.2. Level-1 Data Flow Diagram tracing frame ingestion, multi-task edge inference branches, cloud persistence, and telemetry presentation.

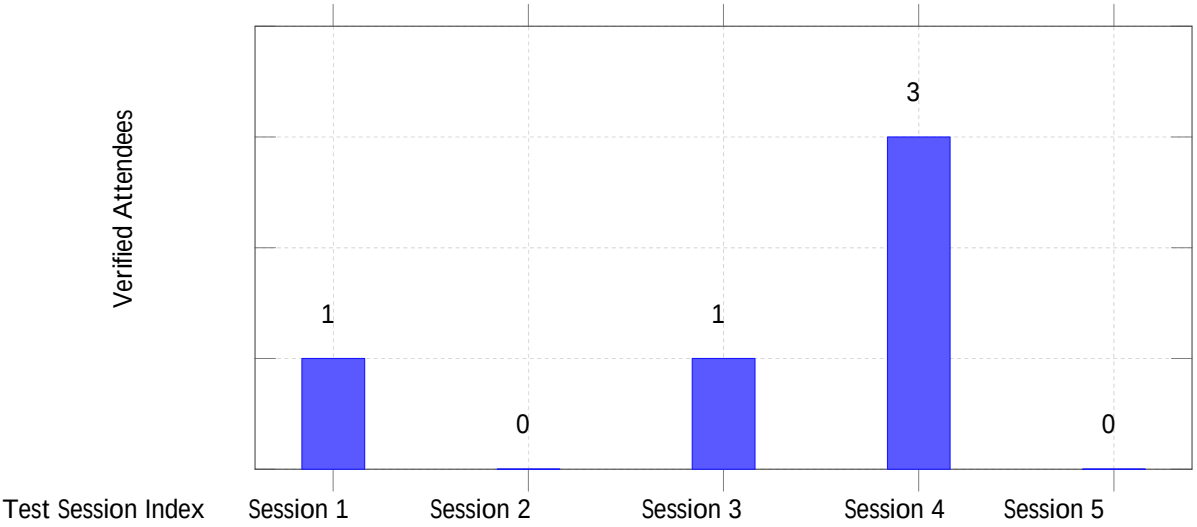


Fig. 3. Attendance volume recorded across five test sessions on the prototype deployment.

C. Throughput and Latency Performance

Executing on local Apple M2 unified memory, facial land-marking and object detection maintained real-time through-put above 30 FPS. Web Socket event writes and database transactions to Supabase maintained an average round-trip latency below 120ms, validating the system's capacity for live telemetry.

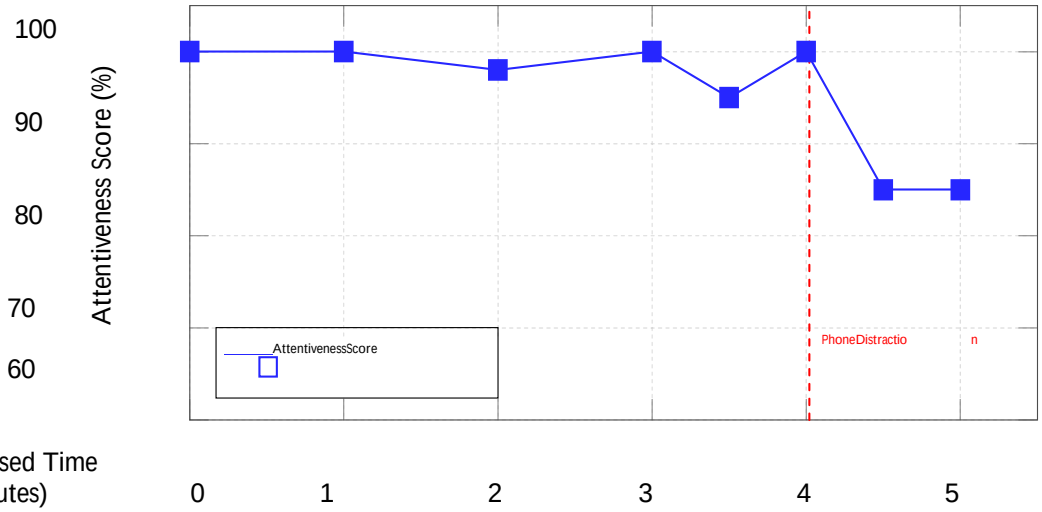


Fig.4. Real-time attentiveness score trajectory. The detected phone distraction at $t = 4.02$min corresponds to an immediate drop from 100% to 85%.

V. LIMITATIONS AND FUTURE SCOPE

- **Low-Light Scenarios:** Verification confidence declines under darkened lecture hall lighting during slide projections; future work will incorporate adaptive contrast enhancement.
- **Off-Axis Poses:** Extreme head orientations beyond 45° reduce facial verification precision.
- **Multi-Camera Calibration:** Expanding coverage across large tiered auditoriums requires multi-sensor spatial calibration to avoid duplicate attendance entries.
- **Data Privacy Compliance:** Production deployments will enforce local, on-device vector generation without retaining raw visual footage, adhering to institutional privacy guidelines.

VI. CONCLUSION

ClassPulse AI demonstrates that contactless biometric attendance, cognitive engagement analysis, and smart device distraction monitoring can be unified into a single edge-accelerated telemetry platform. By integrating Media Pipe face tracking, FaceNet embeddings, convolutional emotion classifiers, and a YOLOv8 detector with an interactive Next.js dashboard, the system provides educators with real-time feed-back on student attentiveness and participation. Experimental validation confirms that the prototype maintains throughput above 30 FPS, ensures proxy-free roll calls, and identifies distraction events accurately.

AUTHOR CONTRIBUTION STATEMENT

Conceptualization: Sowjanya S
Literature Review and Methodology design: Aashuraj S,Guruprasad S
Validation: Tharun Kumar S,Vikas S
Investigation: Aashuraj S,Guruprasad S
Resources: Sowjanya S
Writing original draft preparation: Aashuraj S,Guruprasad S
Writing review and Editing: Tharun Kumar S,Vikas S
Supervision: Sowjanya S
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REFERENCES

1. S.B.Kasetty and R.K., "Advancing object detection in remote sensing: A rigorous evaluation of YOLO models," in Proc. IEEE Int. Conf. on Communication, Signal Processing (ICCSP), 2025. https://doi.org/10.1109/ICCSP64183.2025.11088554
2. Z.Yuan and R. Dai, "A real-time video quality monitoring system for networked cameras," in Proc.IEEE Int.Conf. on Multimedia InformationP rocessing and Retrieval (MIPR), 2025. https://doi.org/10.1109/MIPR67560.2025.00094

3. Y.Chen,"Recognition model construction and analysis of college students' classroom behavior," in Proc. IEEE Conf. on Vision, Imageand Deep Learning (CVIDL), 2025. https://doi.org/10.1109/CVIDL65390.2025.11085660
4. S.K.Vishnumolakala,V.S.Vallamkonda,S.C.C.,N.P.Subheesh,J.Ali,"In-class student emotion and engagement detection system (iSEEDS)," in IEEE Conference Publication, 2024. https://doi.org/10.1109/EDUCON54358.2023.10125254
5. A.Mollahosseini,B.Hasani,M.H.Mahoor, "AffectNet : A database for facial expression, valence, and arousal computing in the wild, "IEEE Transactions on Affective Computing, vol. 10, no. 1, pp. 18–31, 2019. https://doi.org/10.1109/TAFFC.2017.2740923
6. Jenifer,Sanjana,Meghana,Monika(2025),FALSIFYX: Guarding Truth in the Age of Synthetic Media, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 08 of 2025 pages 317-322 https://doi.org/10.26562/ijiris.2025.v1108.02
7. Jenifer,Prashantha,Manjunath,Maaz,Faizaan(2025),I-Quiz, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 08 of 2025 pages 323-327 https://doi.org/10.26562/ijiris.2025.v1108.03
8. Selvarani,Nikhil,Kethan,Prajwal,Sogi(2025),AI Based Crime Pattern Prediction, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 08 of 2025 pages 328-332 https://doi.org/10.26562/ijiris.2025.v1108.04
9. Prof.Selvarani,Sanjana,Madhumitha,Sandhya,Shravani(2025),Plant Disease Detection & Autonomous Spraying Robot, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 08 of 2025 pages 333-337 https://doi.org/10.26562/ijiris.2025.v1108.05
10. Prof.Malar,Sakthisobith,Varsha,Kavinath(2025),Automated Cell Counting in Deep Learning, IJIRIS: International Journal of Innovative Research in Information Security, Volume 11, Issue 08 of 2025 pages 338-342 https://doi.org/10.26562/ijiris.2025.v1108.06