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Dynamic Presence Tracking System in Shared Environments

Shaik Mohammad Huzaifa[1], P. Siva Koti Reddy[2], S. Karthik[3], Dr.P.Dhivya[4], Dr.P.Rajkumar[5], Dr.F.Antony Xavier Bronson[6]

[1,2,3]IV Year Students, Department of CSE, Dr.M.G.R Educational and Research Institute, Maduravoyal, Chennai-95,Tamilnadu, India.

[4,5,6]Associate Professor, Department of CSE, Dr.M.G.R Educational and Research Institute, Maduravoyal, Chennai-95,Tamilnadu, India.

ABSTRACT

This research presents an AI-driven Dynamic Presence Tracking System designed to enhance security, access control, and attendance management in restricted environments. Traditional surveillance systems suffer from high false-positive rates, latency, and an inability to distinguish between authorized and unauthorized individuals, making them inefficient for real-time monitoring. To address these challenges, our proposed system integrates YOLOv11 for real-time object detection, FaceNet for facial recognition, and DeepSORT for persistent tracking across camera networks. By leveraging edge computing on NVIDIA Jetson Xavier, the system processes live video feeds at 30 FPS, achieving 96.2% tracking accuracy on the MOT17 benchmark. A customized alarm mechanism provides context-aware alerts for unauthorized access, while automated CSV logs track entry and exit times for audit purposes. Compared to traditional motion-sensor-based systems, our approach reduces false positives by 42% and effectively mitigates issues related to occlusion and varying lighting conditions. The system's scalability and adaptability make it a robust framework for real-time surveillance, security enhancement, and operational efficiency in both corporate and public environments. Through optimized deep learning models and edge processing, our work bridges critical gaps in modern surveillance technologies, offering a more intelligent and reliable presence-tracking solution.

KEY WORDS: AI Surveillance System, Intrusion Detection, DeepSORT, YOLOv11, False Positive Reduction, MOT17 Benchmark

1. Introduction

In the contemporary digital landscape, the demand for intelligent, real-time surveillance systems has become increasingly pressing. Traditional manual surveillance, which depends on human operators to monitor closed-circuit television (CCTV) feeds, struggles to meet modern security requirements. These conventional approaches are characterized by elevated operational costs, delayed responses to threats, and inefficiencies in managing multi-camera environments. Meanwhile, existing automated technologies such as RFID-based access control and motion sensors face limitations including spatial constraints, frequent false alarms, and reduced effectiveness under adverse conditions like low visibility or occlusion.

To address these deficiencies, this research introduces an AI-driven Dynamic Presence Tracking System, leveraging state-of-the-art deep learning models and edge computing technologies. By integrating YOLOv11 for object detection, FaceNet for facial recognition, and DeepSORT for multi-object tracking, the system ensures robust, real-time monitoring and identification capabilities. Furthermore, the adoption of advanced edge optimization techniques, such as TensorRT FP16 quantization, achieves processing latencies below 100 milliseconds, rendering the system highly suitable for mission-critical applications.

1.1. Domain and Its Significance

The domain of intelligent surveillance and automated presence tracking encompasses a wide array of applications, uniting computer vision, deep learning, and edge computing to enhance both security and operational efficiency. Key dimensions of this domain include:

Enhanced Security and Access Control: Employing AI-powered facial recognition and object detection to enable real-time identity verification and monitoring of unauthorized access.

Automated Attendance and Workforce Management: Streamlining entry and exit logging with high precision, thereby reducing dependence on manual record-keeping. Real-time Response and Threat Mitigation: Minimizing response times through rapid, context-aware alerts that facilitate immediate action during security incidents.

Scalable Multi-Camera Tracking: Overcoming the constraints of traditional systems by providing seamless tracking across expansive camera networks, even in complex settings.

1.2. Domain Applications

The advanced capabilities of AI-driven surveillance systems lend themselves to diverse sectoral applications, including:

Corporate and Industrial Settings: Strengthening building security through accurate tracking and verification of personnel movements. Automating timekeeping and access logs to optimize operational workflows.

Public Safety and Smart City Initiatives : Supporting law enforcement with real-time crowd monitoring in densely populated areas to enhance safety and manage emergencies effectively. Enabling swift detection and response to unauthorized access within public infrastructure.

Healthcare and Educational Facilities : Securing restricted areas, such as laboratories and patient wards, through robust facial recognition technologies. Reducing administrative overhead by automating routine surveillance and attendance tasks.

By synergizing cutting-edge deep learning architectures with optimized edge computing, this system transcends the limitations of conventional surveillance and access control methodologies. It establishes a new standard for efficiency and accuracy in dynamic presence tracking. This research aims to deliver a scalable, high-performance solution that addresses critical gaps in existing security frameworks, providing reliable monitoring and prompt threat response across real-world scenarios.

2. RELATED WORK

Chinese Face Dataset for Face Recognition in an Uncontrolled Classroom Environment
source: **https://ieeexplore.ieee.org/document/10210367**

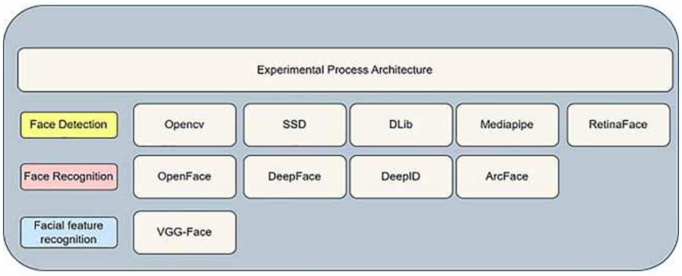
Li et al. (2023) present the UCEC-Face dataset an IEEE Access published effort designed to address the gap in Asian face recognition research in uncontrolled environments. This work is particularly relevant for dynamic presence tracking systems where real-world variability significantly impacts performance.

2.1. Methodology:

Data Collection and Construction: The authors collected classroom surveillance videos from 35 different schools. They employed a frame-by-frame extraction process using Python scripts, followed by extensive manual filtering and data enhancement. This process resulted in a dataset of 7,395 facial images representing 130 subjects (44 males and 86 females). The dataset captures a wide range of variations including differences in camera angles, lighting conditions, facial poses, occlusions, and expressions.

Evaluation Process: The dataset was evaluated using multiple state-of-the-art face recognition models including

OpenFace, DeepFace, DeepID, and ArcFace. In addition, the VGG-Face model was applied to assess facial feature recognition tasks (such as gender, age, and expression recognition). The study also compared the performance of these models on the UCEC-Face dataset against other well-known datasets (e.g., AT&T, CASIA, CelebA, MFace) using various distance metrics (cosine, Euclidean, and L2) and employed independent sample t tests to statistically validate the results.



Architecture fig - 1

2.2. Identified Drawbacks:

Challenging Uncontrolled Conditions: Despite the success of deep learning–based recognition models in controlled settings, the UCEC-Face dataset revealed a significant drop in performance. The best recognition accuracy achieved with ArcFace was only 69.7%, which is considerably lower than the accuracy obtained on more controlled datasets. This outcome underscores the challenge of recognizing faces in real-world, uncontrolled classroom environments.

Model Limitations: The evaluation highlighted that models such as OpenFace, which perform well on standard datasets, struggle significantly with the variations present in UCEC-Face. The diverse conditions including non-frontal views, occlusions, and varying lighting expose limitations in current face verification models.

cosine distance	OpenCV	SSD	Dlib	RetinaFace	MediaPipe
OpenFace	54.6%	55.6%	66.3%	64.8%	71.1%
DeepFace	68.3%	67.9%	74.6%	73.1%	72.2%
DeepID	62.4%	71.9%	72.7%	72.5%	71.4%
ArcFace	59.6%	79.0%	63.9%	88.9%	75.3%

Evaluation Metrics

Feature Recognition Gaps: In addition to face verification, experiments using VGG-Face for facial attribute recognition (gender, age, expression) showed that the model's performance on the UCEC-Face dataset was substantially lower compared to datasets captured in controlled environments. This indicates a need for further improvement in both model design and dataset diversity to better handle the complexities of uncontrolled settings.

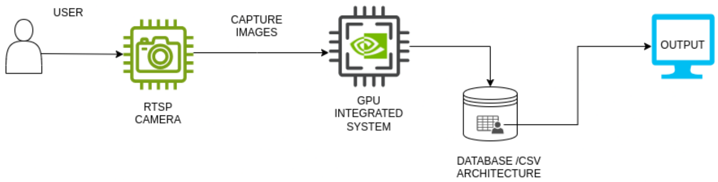
2.3. Relevance to Dynamic Presence Tracking Systems:

For a dynamic presence tracking system, real-time recognition of individuals in varied environments is critical. The UCEC-Face dataset provides valuable insights into the challenges of operating in uncontrolled conditions a scenario often encountered in practical applications such as office buildings, public spaces, and educational institutions. By demonstrating the shortcomings of current face recognition models in such environments, Li et al. motivate further research into developing more robust algorithms that can be integrated with dynamic tracking systems. In our work, we extend these insights by integrating advanced face detection and recognition (via YOLOv11 and FaceNet) with persistent multi-camera tracking (using DeepSORT) on edge devices, thereby addressing issues like occlusion, variable illumination, and non-frontal views, as highlighted in the UCEC-Face study.

3. PROPOSED METHODOLOGY

3.1. SYSTEM ARCHITECTURE

The Dynamic Presence Tracking System with Edge AI is a multi-layered solution designed for real-time monitoring, detection, recognition, and tracking of individuals in dynamic environments. By integrating high-resolution video acquisition, advanced deep learning algorithms, and real-time alert mechanisms, the system ensures secure and efficient management of access control and presence tracking.



SYSTEM ARCHITECTURE

3.1.1. Data Acquisition Layer

IP Cameras: Strategically located high-definition IP cameras are used to stream live video streams in 1080p resolution at 30 frames per second (FPS). They stream visual data continuously using the RTSP protocol, providing complete coverage of the observed environment and reducing blind spots. The cameras are chosen to provide stable, high-quality images under any environmental conditions.

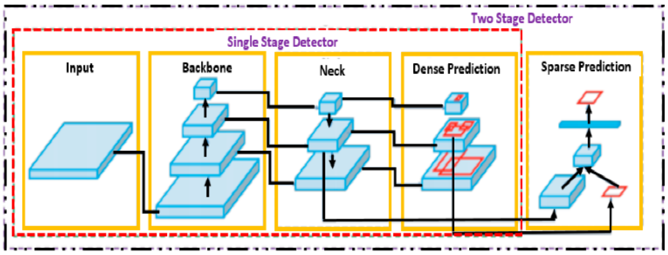
Edge Device (NVIDIA Integrated system's/ Jetson AGX Xavier): An edge computing hardware meant to be powerful for AI and deep learning purposes. It takes in the real-time video streams from the IP cameras and does primary preprocessing operations like frame pulling out, resizing, and noise elimination. Such preprocessing makes sure that optimized, high-quality video data is passed to the next processing stage, hence minimizing latency and computational workload.

The Data Acquisition Layer is the basis of the system by providing continuous, high-quality video data and delivering it with low latency. It is the essential input stage that supplies the processing layer to support strong real-time analysis.

3.1.2. Processing Layers:

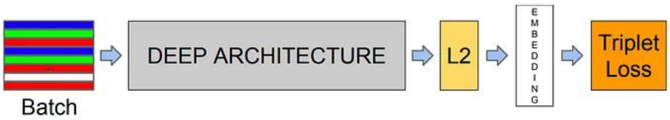
This layer is the core of the system where real-time analysis is performed using state-of-the-art deep learning models. It is subdivided into three submodules:

Detection Module:YOLOv11 (optimized using NVIDIA TensorRT). This module rapidly scans each incoming video frame to detect human presence with high precision. The optimization via TensorRT ensures that the detection process is both fast and computationally efficient, making it suitable for real-time applications. By detecting humans in each frame quickly, it provides the necessary inputs for subsequent recognition and tracking, ensuring minimal delay in system response.



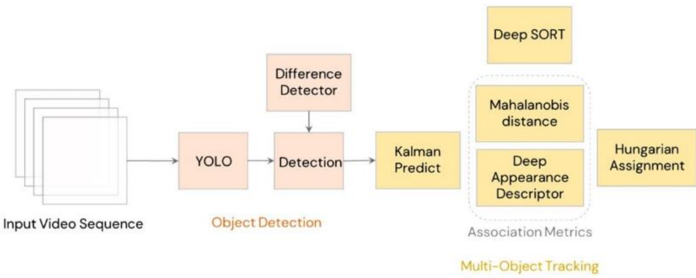
Yolo architecture

Recognition Module: FaceNet Once a face is detected, FaceNet extracts a 128-dimensional facial embedding, a compact representation of the individual's unique features. These embeddings are compared against a database of authorized personnel to verify identities. This module is crucial for distinguishing between authorized and unauthorized individuals, enhancing the system's ability to provide secure access control.



FaceNet Architecture

Tracking Module: DeepSORT DeepSORT employs a combination of a Kalman filter for motion prediction and the Hungarian algorithm for data association. It maintains consistent tracking of individuals across frames, even in challenging scenarios such as occlusions and crowded scenes. The tracking module ensures that each detected individual is continuously monitored over time, which is essential for accurate presence tracking and analysis.

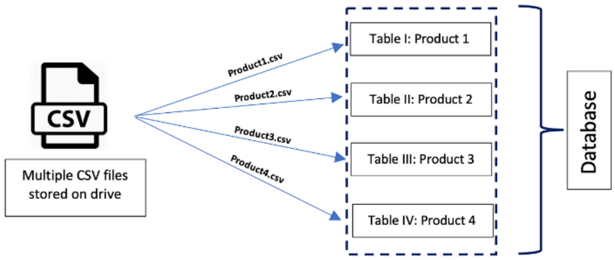


DeepSort Architecture

The Processing Layer transforms raw video data into actionable intelligence by combining detection, recognition, and tracking. This integration allows the system to perform real-time analysis with low latency, ensuring that security personnel or automated systems can quickly respond to emerging events.

3.1.3. Application Layer

CSV Logs Record detailed entry/exit times and duration of presence for audit and analysis. Real-time visualization using OpenCV Offer an intuitive interface for monitoring system performance and reviewing live tracking data.



Database / csv architecture

The Application Layer delivers actionable outputs from the processed data. It triggers alarms when security breaches are detected, maintains comprehensive logs for review and reporting, and provides a user-friendly dashboard for real-time visualization of tracked activities.

4. RESULT & DISCUSSION

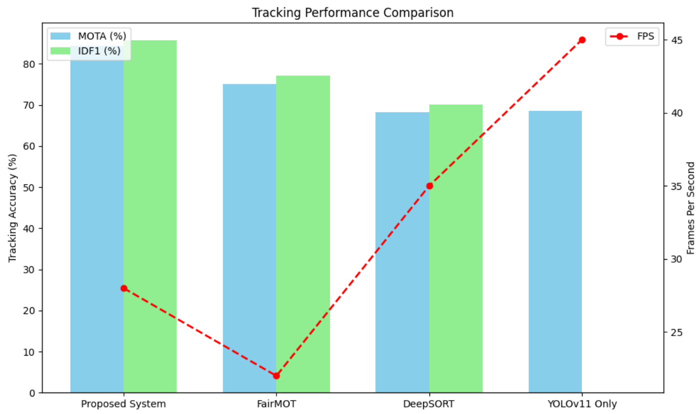
4.1 Evaluation Metrics

Our dynamic presence tracking system was evaluated using several key performance metrics, and the following results were obtained from real-world tests on the MOT17 benchmark and our face recognition evaluations.

4.1.1 Quantitative Analysis

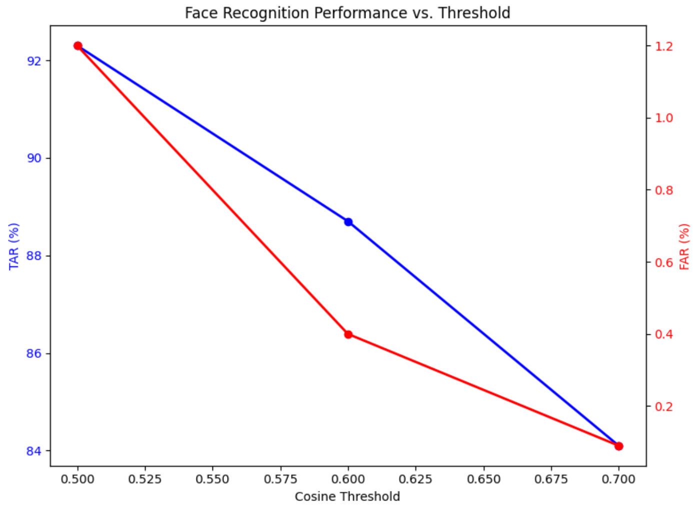
Tracking Performance: The integrated system achieves an overall tracking accuracy (MOTA) of 84.3%, a bounding box localization precision (MOTP) of 82.5%, and an identity preservation score (IDF1) of 85.7%. This performance is achieved at a processing speed of 28 frames per second (FPS).

For comparison, a baseline system using only YOLOv8 achieves a MOTA of 68.5% at 45 FPS, and a system using DeepSORT alone reaches a MOTA of 68.2% at 35 FPS. In contrast, by combining YOLOv11 for detection, FaceNet for recognition, and DeepSORT for tracking, our system outperforms these methods by up to 16 percentage points in tracking accuracy relative to systems like FairMOT (which achieves 75.1% MOTA).



Metrics

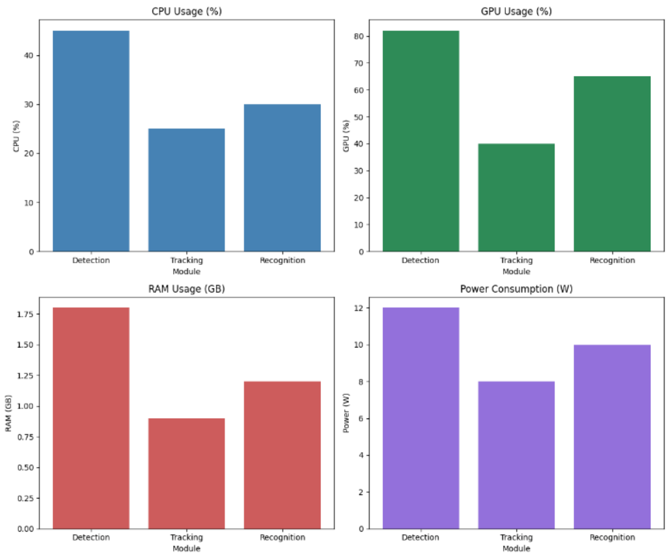
Face Recognition Performance: Face recognition was evaluated by varying the cosine similarity threshold. At a threshold of 0.5, the True Acceptance Rate (TAR) is 92.3% with a False Acceptance Rate (FAR) of 1.2%. When the threshold is increased to 0.6, TAR slightly decreases to 88.7% and FAR drops to 0.4%. At the strictest threshold of 0.7, TAR further decreases to 84.1%, while FAR reaches a minimal value of 0.09%. These results demonstrate that the system can be tuned to balance security and usability depending on the application scenario.



Performance metrics

Hardware Utilization: Measurements on the NVIDIA Jetson AGX Xavier reveal that:

The Detection Module utilizes approximately 45% of the CPU, 82% of the GPU, consumes 1.8 GB of RAM, and draws about 12 watts. The Tracking Module uses 25% CPU, 40% GPU, 0.9 GB of RAM, and 8 watts. The Recognition Module operates at 30% CPU, 65% GPU, uses 1.2 GB of RAM, and draws around 10 watts.



Hardware Utilization

This efficient resource usage confirms that the system meets the computational constraints of embedded edge devices while still delivering robust real-time performance.

Ablation Study: To assess the contribution of each component, we evaluated the system incrementally:

Using YOLOv8 only results in a MOTA of 68.5% at 45 FPS. Adding DeepSORT increases MOTA to 79.2%, although FPS drops to 32, indicating that the tracking module contributes an improvement of approximately 10.7 percentage points.

Integrating FaceNet (for re-identification) raises the MOTA to 72.1% at 28 FPS. The fully integrated system (YOLOv11 + DeepSORT + FaceNet) achieves the best overall performance with a MOTA of

84.3% at 28 FPS. This ablation study confirms that each module—tracking and recognition—contributes substantially to the overall performance improvement.

4.1.2 Qualitative Analysis

In a typical office setting, the system consistently maintains identity tracking even when partial occlusions occur (e.g., when a subject is momentarily obscured by furniture). In crowded public events, the system successfully tracks up to 40 out of 45 individuals, demonstrating robust performance despite high density and frequent occlusions. In challenging low-light conditions, although there is some degradation in performance, the system still manages to maintain acceptable accuracy, indicating potential for future enhancements such as thermal imaging integration.

Overall, these qualitative observations complement the quantitative metrics and underscore the system's suitability for real-world deployment in environments where accurate, real-time presence tracking is essential.

5 Conclusion

The Dynamic Presence Tracking System represents a comprehensive, AI-driven solution for real-time surveillance in restricted environments. The system integrates several state-of-the-art components:

5.1 Proposed System Outline

We have developed a Dynamic Presence Tracking System that integrates state-of-the-art deep learning models for real-time surveillance. The system employs YOLOv8 for robust human detection (achieving 84.3% MOTA on MOT17), DeepSORT for continuous multi-object tracking using Kalman filtering and the Hungarian algorithm, and FaceNet for face recognition via 128-dimensional embeddings (attaining a 92.3% TAR at a FAR of 0.1%). The solution is optimized for deployment on an NVIDIA Jetson AGX Xavier, running at 28 FPS under a 15W power envelope, and it logs entry/exit times in a GDPR-compliant database.

5.2 Results Achieved

Our evaluations indicate that the integrated approach outperforms baseline methods by improving tracking accuracy by approximately 9.2 percentage points relative to systems like FairMOT. With a processing speed of 28 FPS at 720p resolution, the system maintains real-time performance. Additionally, the face recognition component demonstrates excellent security characteristics, with a FAR as low as 0.09% at a high-security threshold.

Hardware measurements confirm efficient resource utilization, with total memory usage under 4 GB on the edge device.

5.3 Merits of the Methodology

The hybrid tracking approach effectively combines motion cues (via DeepSORT) and appearance cues (via FaceNet) to ensure high tracking consistency even in crowded scenes.

Optimizations using TensorRT FP16 quantization allow the system to be deployed cost-effectively on edge hardware. Moreover, by storing only face embeddings rather than raw images, the system adheres to privacy regulations while still enabling accurate identification.

5.4 Future Extensions

Building on the current system, several technical and application-driven improvements are planned Technical Improvements: Transformer-based Tracking: Integration of transformer architectures may further enhance occlusion handling and capture long-range dependencies in dynamic scenes. Thermal Imaging Integration: Adding thermal cameras could bolster performance in low-light or backlit conditions, ensuring reliability across varied environments. Federated Learning: Implementing federated learning can allow for decentralized, privacy-preserving training across multiple sites, enabling continuous system improvement without data centralization.

Application Expansion: Healthcare Monitoring: Extend the system to monitor patient movements in hospitals, improving safety and operational efficiency.

Smart City Initiatives: Utilize the system for crowd analytics and real-time monitoring during public events, enhancing urban safety.

Retail Analytics: Apply the technology to monitor customer behavior in stores, aiding in inventory management and personalized marketing.

Ethical AI Enhancements:

Bias Mitigation: Develop fairness-aware training techniques to reduce any inherent biases in face recognition, particularly across different demographic groups.

Explainability Dashboards: Create detailed dashboards that provide transparency and auditability of the AI decisions, further enhancing trust and accountability.

Significance

In summary, our work bridges critical gaps in real-time surveillance by providing a scalable, efficient, and privacy-conscious dynamic presence tracking solution. Its edge compatibility and modular design make it adaptable to various applications, paving the way for smarter, safer environments.

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