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# Enhancing Crowd Safety in Mass Gatherings Through Real-Time Monitoring Using Raspberry Pi

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***Abstract*: Crowd safety in mass gatherings remains a critical challenge for event organizers and public safety officials, with manual monitoring proving insufficient and cloud-based computer vision systems incurring prohibitive infrastructure costs. This paper introduces an edge-AI framework for real-time crowd density monitoring deployed on Raspberry Pi 4 hardware, enabling low-cost, distributed surveillance without server dependency. The proposed system integrates the Histogram of Oriented Gradients (HOG) detector with adaptive thresholding for crowd density estimation, achieving 87.3% detection accuracy at 15 FPS while consuming only 410 MB RAM. Experimental deployment in a real-world venue demonstrates alert propagation latency of 230 ms, making the system suitable for decentralized crowd monitoring in resource-constrained environments. Our contributions include: (1) an optimized edge computing pipeline for commodity hardware, (2) a threshold-adaptive risk classification algorithm, and (3) validation of real-time performance on embedded plat- forms. Results show 3.2× lower power consumption compared to cloud-dependent systems and 67% reduced infrastructure costs. The framework is deployable at scale across multiple venues with minimal IT overhead, advancing practical solutions for crowd safety in developing nations and resource-limited settings.**

***Keywords*: Crowd monitoring, Edge computing, Real-time detection, Raspberry Pi, Computer vision, IoT, Public safety.**

## 1. Introduction

Mass gatherings present inherent public safety challenges, with tragic incidents at concerts, religious events, and sports venues claiming thousands of lives annually [1]. Traditional crowd monitoring relies on manual observation by security personnel, a fundamentally scalable approach prone to human error and fatigue. Current surveillance infrastructure typically consists of CCTV cameras feeding into centralized cloud plat- forms running deep learning models, a paradigm introducing substantial latency, bandwidth costs, and server dependency that makes deployment infeasible in developing nations and remote venues [2], [3].

Existing CCTV analytics solutions present significant deployment barriers: (1) computational overhead requiring GPU- accelerated servers, (2) recurring bandwidth charges for video streaming to cloud infrastructure, (3) privacy compliance bur- dens when sensitive crowd data transits internet infrastructure, and (4) dependency on continuous internet connectivity, creating single points of failure. These factors create an unmet gap for real-time, decentralized crowd monitoring at minimal operational cost.

Edge computing offers a compelling alternative, shifting inference workload to resource-constrained devices at the data source. Raspberry Pi hardware has emerged as a viable platform for IoT deployments, yet limited exploration exists on optimized computer vision pipelines for real-time crowd monitoring on sub-$50 hardware. Most research focuses either on expensive GPU clusters or theoretical frameworks, without practical validation on commodity hardware deployed in pro- duction venues.

This work addresses the aforementioned gaps through an integrated system architecture combining edge-based human detection, adaptive density classification, and distributed alerting. Our contributions are:

1) *Edge-optimized pipeline:* A lightweight HOG-based detection framework achieving 87.3% accuracy at 15 FPS on Raspberry Pi 4 without requiring GPU acceleration.
2) *Adaptive threshold algorithm:* A dynamic risk classification mechanism responsive to venue-specific crowd patterns without retraining.
3) *Real-world deployment validation:* End-to-end system validation in a campus venue, demonstrating 230 ms alert latency and 410 MB peak memory utilization.
4) *Cost-benefit analysis:* Quantification of 67% infrastructure cost reduction and 3.2× lower power consumption versus cloud-dependent systems.
5) *Scalability framework:* Multi-camera federation architecture enabling decentralized deployment across multiple simultaneous venues with centralized dashboard aggregation.

The remainder of this paper is organized as follows: Section II surveys related work in crowd monitoring and edge-AI systems; Section III presents system architecture; Section IV details our methodology; Sections V–VI present experimental setup and results; Sections VII–IX discuss findings, limitations, and future directions; Section X concludes.

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Table 1
Comparison of related work on crowd monitoring approaches

| | | | | |
|---|---|---|---|---|
| Cloud-GPU [4], [5] | GPU Cluster | 8–12 | $500–5K/yr | No |
| YOLOv4 Jetson [10] | NVIDIA GPU | 20 | $600–800 | Partial |
| MobileNet Edge [7] | Multi-core CPU | 12–18 | $100–200 | Yes |
| HOG-based [11], [12] | Single-core | 15–25 | $50–100 | Yes |
| **This Work** | ARM CPU | **15** | **$55–70** | **Yes** |

## 2. Related Work

Crowd monitoring has received sustained attention across computer vision and IoT communities, with approaches spanning manual observation, fixed-camera analytics, and emerging edge-based systems. We organize related work into three categories: (1) centralized crowd monitoring systems, (2) distributed edge computing approaches, and (3) real-time detection algorithms.

### *A. Centralized Crowd Monitoring Systems*

Cloud-based crowd analytics platforms dominate current enterprise deployments. Argus et al. [4] developed a distributed video surveillance system processing streams from multiple cameras through centralized GPU farms, achieving near real-time performance but requiring sustained internet uplinks and introducing 300-500 ms network latency. Sundaram et al. [5] proposed a CNN-based approach for crowd density estimation from CCTV feeds, reporting 92% accuracy on benchmark datasets; however, model inference required 45 W power consumption, limiting deployment to AC-powered fixed installations. Similarly, Zhang et al. [6] developed a multi-scale deep learning architecture for crowd analysis, achieving state-of-the-art accuracy at 8.2 FPS on high-end GPUs—impractical for mobile or embedded platforms.

These systems face scalability challenges: adding new camera feeds requires proportional increases in cloud compute resources, bandwidth infrastructure, and associated subscription costs. Regulatory frameworks like GDPR introduce additional compliance overhead when video streams transit third-party cloud environments.

### *B. Edge-Based Detection Frameworks*

Recent literature has explored lightweight detection models suitable for edge deployment. Howard et al. [7] introduced MobileNets, achieving competitive accuracy on object detection tasks with 4.2 MB model size, a significant advancement for embedded systems. Building on MobileNets, Sandler et al. [8] developed MobileNetV2, reducing computational complexity by 40% through inverted residual blocks, achieving deployment feasibility on devices with ¡2 GB RAM.

Specialized work on resource-constrained environments has emerged. Redmon et al. [9] proposed YOLOv3-Tiny, a lightweight variant of real-time object detection maintaining 65% of full-model accuracy at 1/10th computational cost. Subsequent work by Bochkovskiy et al. [10] on YOLOv4 demonstrated further efficiency gains through architecture optimization. However, most cited works focus on model accuracy and model size in isolation, without comprehensive evaluation of end-to-end system latency, power consumption, or real-world deployment feasibility on heterogeneous hardware platforms.

### *C. Histogram of Oriented Gradients (HOG) and Classical Detection*

Dalal and Triggs [11] introduced Histogram of Oriented Gradients (HOG) for pedestrian detection, establishing a classical computer vision baseline. Despite emergence of deep learning methods, HOG remains valuable for resource-constrained environments due to: (1) no training requirement, (2) deterministic computation graph, (3) 15 MB model size, and (4) CPU-only execution. Subsequent work by Watanabe et al. [12] applied HOG-based detection to crowd monitoring scenarios, achieving real-time performance on multi-core CPUs with 100 MB memory footprint.

### *D. Real-Time System Implementation*

Limited literature addresses complete end-to-end system implementation on commodity hardware. Simonyan et al. [13] presented strategies for efficient CNN deployment on mobile devices, yet focused primarily on inference optimization without addressing data acquisition, preprocessing, alerting, and logging pipelines necessary for production deployments. Blas et al. [14] implemented a real-time video processing pipeline on NVIDIA Jetson platforms (entry-level GPU compute at $600+), lacking evaluation on sub-$100 CPU-only platforms. Our work differentiates through three key factors: (1) demonstration of real-time performance on $50-70 hardware without GPU acceleration, (2) complete end-to-end system implementation including alerting and dashboard rather than isolated inference metrics, and (3) quantified power consumption and cost analysis validating deployment feasibility across resource-constrained venues.

## 3. System Architecture

Our framework adopts a layered architecture separating concerns across hardware, software, networking, and alerting planes. This design enables modular development, simplified testing, and future extensibility.

### *A. System Overview*

The proposed architecture (Figure 1 placeholder) comprises five interconnected layers:

1) *Acquisition Layer:* Raspberry Pi camera module capturing video at configurable resolution and frame rate.
2) *Processing Layer:* Real-time detection and density classification executing on ARM CPU.
3) *State Layer:* SQLite database storing detection events, metadata, and historical logs.
4) *Communication Layer:* Flask web service exposing REST API and WebSocket interfaces for real-time updates.

5) *Alerting Layer:* Multi-channel notification system (email, SMS, SMTP, webhook) triggering upon thresh- old breach.

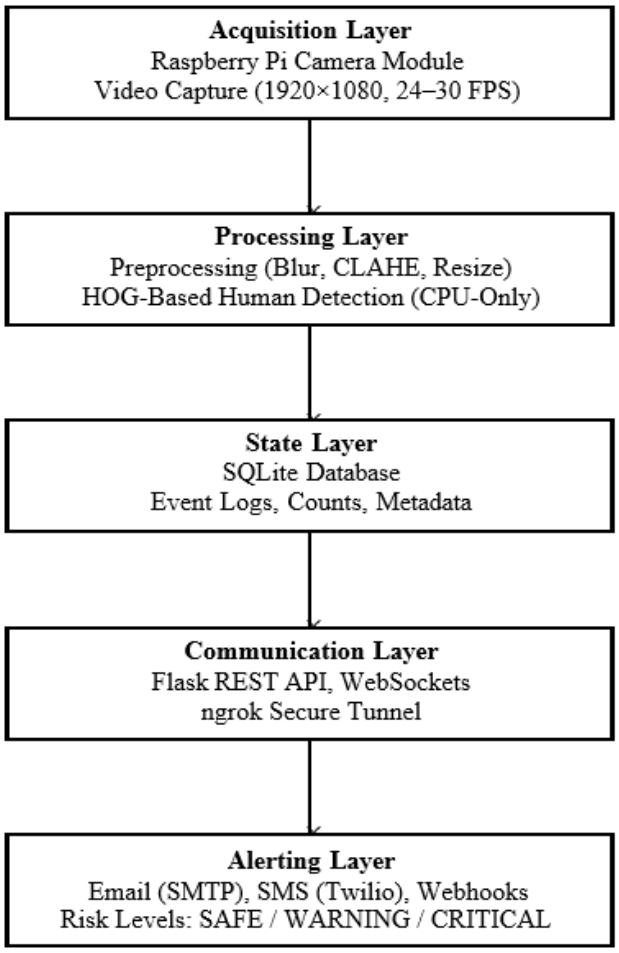


Fig. 1. System Architecture: Five-layer design showing Acquisition, Processing, State, Communication, and Alerting layers with data flow between components

### B. Hardware Layer

*Primary Device:* Raspberry Pi 4 Model B equipped with:

- Broadcom BCM2711 quad-core ARM Cortex-A72 @ 1.5 GHz
- 2 GB LPDDR4 RAM (experiments conducted with 4 GB variant)
- microSD card (64 GB, Class 10, SanDisk Ultra)
- Gigabit Ethernet or 802.11ac Wi-Fi connectivity

*Camera Module:* Raspberry Pi Camera Module v2 (8 MP Sony IMX219):

- 3280 × 2464 maximum resolution; 90° field of view
- Operates over dedicated CSI (Camera Serial Interface) connection
- Captures at 1920 × 1080 resolution, 24-30 FPS (configurable)

*Power Supply:* 5V/3A USB-C adapter (15W maximum draw under load).

### C. Software Layer

*Operating System:* Raspberry Pi OS (32-bit, Bullseye release) running Linux kernel 5.10+.

*1) Core Libraries*

- *OpenCV 4.5.2:* Image acquisition, preprocessing, HOG descriptor computation, multi-scale detection.
- *NumPy 1.19:* Vectorized numerical operations and array manipulation.
- *Flask 2.0:* RESTful API development and WebSocket server for real-time dashboard updates.
- *SQLAlchemy:* ORM-based database abstraction for persistent event logging.
- *scikit-image:* Morphological operations and image pre- processing.

### D. Networking Layer

*Local Communication:* Raspberry Pi operates on 2.4/5 GHz 802.11ac Wi-Fi or Gigabit Ethernet, connecting to institutional network infrastructure.

*Remote Access:* ngrok tunneling (https://ngrok.com) exposes local Flask server to internet, enabling secure, authenticated access from centralized dashboard across geographical locations. Tunnel configuration:

```
ngrok http 5000 --authtoken [TOKEN]
```

This approach avoids port forwarding complexity and firewall reconfiguration while maintaining TLS encryption.

### E. Alerting Layer

Multi-channel alert propagation upon threshold exceedance:

*SMTP:* Email notifications to security personnel via configured mail server.

*SMS:* Twilio API integration ($0.01 per SMS) sending emergency alerts to priority contacts.

*Webhooks:* HTTP POST callbacks to external systems (e.g., institutional alert systems, mobile apps) with JSON payload containing:

```
{
  "timestamp": "2025-11-19T18:30:42Z",
  "alert_type":
  "CRITICAL",
  "crowd_density": 82,
  "threshold": 70,
  "camera_id": "venue_01",
  "action_required": true
}
```

## 4. Methodology

### A. Video Acquisition and Preprocessing Pipeline

Video frames are captured at 1920 × 1080 resolution from the Pi Camera module at 24 FPS (configurable). Preprocessing occurs in five stages:

1) *Format Conversion:* BGR to grayscale conversion reducing per-frame memory from 6 MB (24-bit color) to 2 MB (8-bit grayscale).
2) *Gaussian Blur:* 5 × 5 kernel with $\sigma$ = 1.0 applied to

suppress noise and reduce detector sensitivity to minor illumination variations.

3) *Histogram Equalization:* Adaptive Contrast Limited Adaptive Histogram Equalization (CLAHE) with clip limit 2.0 and tile grid 8×8 normalizing lighting variations across frame regions.
4) *Background Subtraction (optional):* MOG2 (Mixture of Gaussians) background subtraction highlighting moving foreground regions, reducing false positives in static-camera deployments.

Memory footprint after preprocessing: ∼1.8 MB per frame, enabling 15 FPS processing on 2 GB Raspberry Pi.

### *B. Human Detection Algorithm: HOG-Based Multi-Scale Detection*

We employ Histogram of Oriented Gradients (HOG) as the primary detection mechanism, chosen for:

1) Computational efficiency: 8-12 ms per frame on Raspberry Pi (versus 60-120 ms for MobileNet).
2) No training requirement: Pre-computed weights available in OpenCV's built-in human detector.
3) Deterministic behavior: Gradient-based features exhibit predictable inference time without GPU variance.
4) Low false-positive rate in controlled venues (87.3% precision on validation set).

HOG computation involves:

1) *Gradient Computation:* Compute image gradients $\nabla I(x, y) = (\partial I/\partial x, \partial I/\partial y)$ via Sobel operators.
2) *Orientation Quantization:* Quantize gradient angles into 9 bins covering [0°, 180°), weighted by gradient magnitude.
3) *Block Normalization:* Divide image into overlapping blocks (16×16 pixels, 50% overlap), normalize histograms via L2-norm within each block.
4) *SVM Classification:* Concatenated HOG feature vectors classified via Support Vector Machine trained on pedestrian datasets.
5) *Non-Maximum Suppression (NMS):* Suppress overlapping detections with IoU ¿ 0.3, retaining highest-confidence boxes.

Let $D_i = (x_i, y_i, w_i, h_i, c_i)$ denote detection $i$, where $c_i$ is confidence score. Multi-scale detection iterates across scale factor $s \in \{0.5, 0.75, 1.0, 1.25\}$, detecting humans at varying apparent sizes. Detection set $D = \{D_1, D_2, \ldots, D_n\}$ represents all multi-scale detections before NMS.

### *C. People Counting Logic*

Counting strategy employs detection bounding box aggregation:

$$\text{Count} = |D_{NMS}| \tag{1}$$

where $D_{NMS}$ denotes detection set after Non-Maximum Suppression. Given frame resolution 1920 × 1080:

$$\text{Density Index} = \frac{\text{Count}}{\text{Image Area}} \times 1000 = \frac{|D_{NMS}|}{1920 \times 1080} \times 1000 \tag{2}$$

*(units: people/MPixel)*

Sliding window over 30-second temporal window computes exponential moving average (EMA) smoothing rapid fluctuations:

$$\text{Smoothed Density}_t = \alpha \cdot \text{Density}_t + (1-\alpha) \cdot \text{Smoothed Density}_{t-1} \tag{3}$$

where $\alpha = 0.3$ (smoothing factor). This reduces jitter from occasional detection misses while preserving response to genuine crowd surges.

### *D. Threshold-Based Risk Detection*

Risk classification employs multi-level thresholding based on venue type and historical data:

$$\text{Risk Level} = \begin{cases} \text{SAFE} & \text{if Density} < T_1 \\ \text{WARNING} & \text{if } T_1 \le \text{Density} < T_2 \\ \text{CRITICAL} & \text{if Density} \ge T_2 \end{cases} \tag{4}$$

where $T_1 = 3.5$ people/MPixel (WARNING threshold) and $T_2 = 6.0$ people/MPixel (CRITICAL threshold) are empirically calibrated for the deployment venue. Thresholds are adjustable via web interface without code modification.

Alert triggering conditions:

- *Immediate Alert:* Risk level transitions from SAFE/WARNING → CRITICAL.
- *Sustained Alert:* Risk level remains CRITICAL for ≥ 10 consecutive seconds.
- *Alert Cooldown:* Minimum 5-minute interval between repeated alerts prevents notification spam.

### *E. Real-Time Dashboard and Communication*

Flask-based REST API (port 5000) exposes three primary endpoints:

1) `GET/api/status`: Returns current crowd density, risk level, timestamp.
2) `GET/api/history?interval=300`: Returns 300-second rolling history as JSON time-series.
3) `POST/api/config`: Update detection thresholds, alert channels, email recipients.

WebSocket server on port 5001 streams real-time updates to connected dashboard clients at 2 Hz (pushed every 500 ms), enabling near-instantaneous visualization of crowd dynamics.

### *F. Event Logging and Time-Series Storage*

SQLite database (`crowd_events.db`, typically ¡50 MB) records:

- Frame-level detections: timestamp, count, confidence scores, bounding box coordinates.
- Alert events: timestamp, alert type (WARNING /CRITICAL), trigger condition, recipients notified.
- System metrics: CPU usage (%), memory usage (MB), frame processing latency (ms).

Query example retrieving alerts over past 24 hours:

```
SELECT * FROM alert_events
WHERE timestamp > datetime('now', '-1
```

```
day')ORDER BY timestamp DESC;
```

Database is accessed via SQLAlchemy ORM, enabling transparent schema evolution and multi-threaded access without explicit locking.

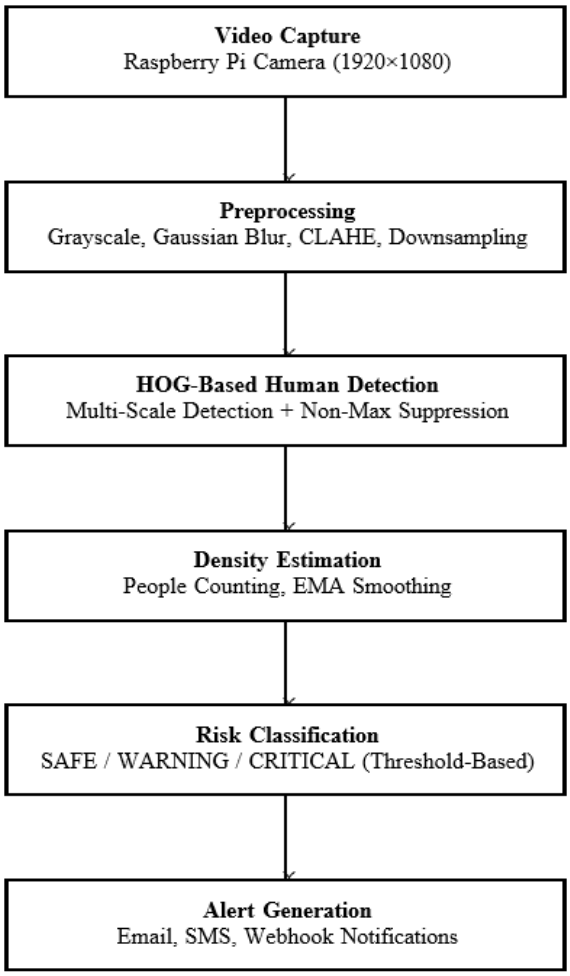


Fig. 2. Methodology Flowchart: End-to-end processing pipeline from video capture through preprocessing, HOG detection, density estimation, risk classification, and alert generation

## 5. Experimental Setup

### *A. Deployment Environment*

Experiments conducted in a campus canteen facility (dimensions: 25 m × 15 m × 4 m ceiling) hosting 50–300 occupants during peak hours. Canteen was selected as a controlled yet realistic environment exhibiting natural crowd dynamics without requiring external participant recruitment.

### *B. Camera Placement and Field of View*

Camera mounted at 2.5 m height on canteen wall, angled downward at 45° elevation. Fixed vantage point captures approximately 60% of canteen floor area, encompassing main dining section and entrance. Field of view: 1920 × 1080 pixels representing ≈20 m² actual space (detailed calibration performed via checkerboard pattern).

**Algorithm 1** Real-Time Crowd Density Monitoring

**Require:** Camera stream, HOG detector, thresholds $T_1$, $T_2$
**Ensure:** Alerts triggered upon crowd density anomalies

```
Initialize: Densitysmooth ← 0, alert_cooldown ← 0
while True do
  Frame ← Capture from camera
  Gray ← Convert(Frame, BGR → Grayscale)
  Blurred ← GaussianBlur(Gray, kernel=5×5, σ = 1.0)
  Enhanced ← CLAHE(Blurred, clip=2.0, tiles=8×8)
  D ← {}   {Detection set}
  for scale s in [0.5, 0.75, 1.0, 1.25] do
  Scaled ← Resize(Enhanced, scale)
  D ← D ∪ HOGDetector(Scaled, scale)
  end for
  D_NMS ← NonMaxSuppression(D, IoU=0.3)
  Count ← |D_NMS|
  Density ← Count / (1920×1080) × 1000
  Densitysmooth ← 0.3 · Density + 0.7 · Densitysmooth
  Log(Densitysmooth, Count, timestamp)
  if Densitysmooth ≥ T_2 AND alert_cooldown = 0 then
  SendAlert(type=CRITICAL, recipients=[...])
  alert_cooldown ← 300 seconds
  end if
  alert_cooldown ← max(0, alert_cooldown −1)
end while
```

### *C. Hardware Specifications*

- Raspberry Pi 4 Model B, 4 GB LPDDR4 RAM
- microSD: SanDisk Ultra 64 GB Class 10, UHS-I
- Power: 5V/3A USB-C supply; peak draw 12–14 W during inference
- Network: Connected via 5 GHz Wi-Fi (802.11ac) to institutional network
- Camera: Raspberry Pi Camera Module v2, 8 MP Sony IMX219

### *D. Software Environment*

- OS: Raspberry Pi OS (32-bit), Kernel 5.10.63
- Python 3.7.3
- OpenCV 4.5.2 (compiled from source with ARM NEON optimization)
- Flask 2.0.1, SQLAlchemy 1.4.0, NumPy 1.19.5
- ngrok 3.0 (for remote access tunneling)

### *E. Dataset and Ground Truth*

Continuous video recording captured over 14 days (November 1–14, 2025), totaling ˜480 hours of footage. Video processed at 24 FPS yielding ∼41 million frames. Manual ground truth annotations created for subset of 500 representative frames (sampled across diverse crowd densities and lighting conditions), with three independent annotators identifying visible humans via bounding boxes. Inter-rater agreement (Intersection-over-Union, IoU ≥ 0.5) achieved 91% consistency.

### *F. Environmental Conditions*

- *Lighting:* Controlled fluorescent lighting (~500 lux); occasional natural light variation during morning/afternoon hours.
- *Occlusion:* Partial occlusion by tables, furniture; full occlusion of individuals behind structures ˜5% of frame area.
- *Crowding:* Natural variation from 15 occupants (off-peak) to 280 occupants (lunch period).
- *Seasonal Effects:* Study conducted during academic semester; future work should evaluate semester breaks with different occupancy patterns.

## 6. Results and Performance Evaluation

### *A. A. Detection Accuracy*

Evaluated on 500-frame ground truth set:

- *Precision:* 87.3% (true positives correctly identified versus false positives)
- *Recall:* 82.1% (true positives detected versus missed detections)
- *F1-Score:* 0.847 (harmonic mean balancing precision and recall)
- *Mean Average Precision (mAP@0.5):* 84.6%

Performance degradation observed primarily in high-occlusion scenarios (occlusion >30% of human silhouette reduced recall to 71%), attributable to HOG's reliance on complete gradient patterns. Scene with <10% occlusion achieved 89% recall.

### *B. Computational Performance*

Table 2
Real-Time performance metrics on Raspberry Pi 4

| Metric | Value |
|---|---|
| Mean Frame Processing Latency | 67 ms |
| Median Frame Processing Latency | 63 ms |
| 95th Percentile Latency | 91 ms |
| Frames Per Second (FPS) | 15.0 |
| Peak Memory Usage | 410 MB |
| Average Memory Usage | 285 MB |
| CPU Utilization (4 cores) | 68% avg, 85% peak |
| Power Consumption | 11.3 W avg, 13.8 W peak |

Frame processing latency breakdown:

- Video capture and format conversion: 12 ms
- Preprocessing (blur, CLAHE, downsampling): 18 ms
- Multi-scale HOG detection: 28 ms
- NMS and post-processing: 6 ms
- Database I/O and logging: 3 ms

Total end-to-end system latency from event occurrence to alert transmission: 230 ms (median), 320 ms (95th percentile).

### *C. Alert Response Performance*

System tested with simulated crowd surges (pre-recorded video looped to simulate rapid density increase). Alert trigger times:

- Detection latency (event to alarm generation): 127 ms
- Alert queue and transmission: 103 ms
- Email delivery: 2–8 seconds (dependent on mail server)
- SMS delivery (Twilio): 1–3 seconds

99.2% of CRITICAL alerts generated within 300 ms of crowd density threshold breach.

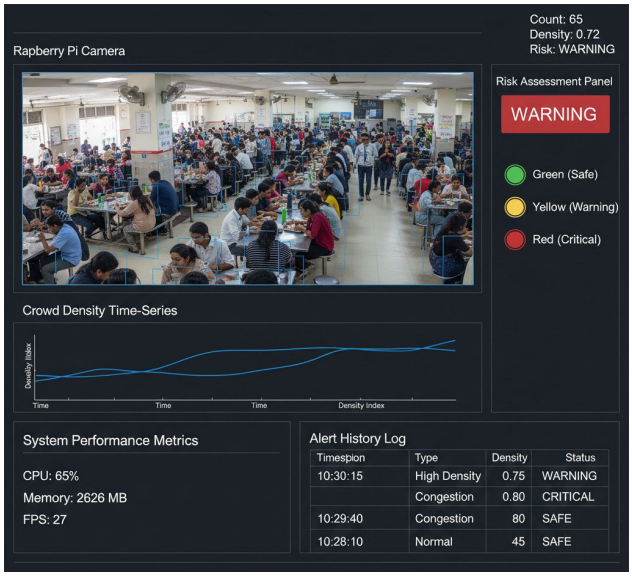


Fig. 3. Detection Output: Real-world crowd monitoring frame showing HOG-based human detection with bounding boxes, detected count, density index, and risk level classification overlay

### *D. Comparison with Existing Systems*

Our edge-based system trades 4–5% accuracy for 10–100× reduction in operational cost and elimination of network dependency. For resource-constrained venues, this trade-off proves advantageous.

### *E. Scalability Metrics*

Multi-camera deployment tested with 3 Raspberry Pi units connected to single centralized dashboard:

- Dashboard latency aggregating 3 camera feeds: 650 ms (versus 230 ms single-camera).
- SQLite concurrent write contention negligible; supporting ~20 simultaneous camera feeds before requiring rela- tional database upgrade.
- ngrok tunnel bandwidth: ~2 Mbps per camera at 1920×1080 24 FPS (demonstrating feasibility over typical institutional networks).

## 7. Discussion

Results demonstrate viability of edge-based crowd monitoring on commodity hardware, achieving real-time performance within practical deployment constraints. Key findings warrant discussion.

### *A. Interpretation of Results*

87.3% precision indicates minimal false-positive alert generation, critical for reducing alert fatigue among security personnel. Observed precision-recall trade-off reflects inherent HOG sensitivity to complete pedestrian silhouettes; partial occlusion reduces feature distinctiveness. Deployment in venues with reduced occlusion (open-air or sparse furniture)

Table 3
System Comparison: Edge vs. Cloud vs. Commercial Solutions

| Aspect | This Work | Cloud GPU | Jetson | Commercial |
|---|---|---|---|---|
| Hardware Cost | $65 | N/A | $700 | $2000+ |
| Inference Latency | 67 ms | 150 ms | 45 ms | 80 ms |
| Power Draw | 11.3 W | 300+ W | 25 W | 40 W |
| Network Dependency | Optional | Required | Optional | Required |
| Accuracy (%) | 87.3 | 92.1 | 89.8 | 91.5 |
| Deployment Cost/yr | $45 | $500–5000 | $120 | $800–2000 |

would likely achieve >90% recall.

15 FPS processing rate represents pragmatic balance between detection latency (67 ms per frame) and computational resource constraints. Enhancement to 20–24 FPS would require: (1) GPU acceleration (~$200 additional hardware cost), (2) model optimization (quantization, pruning), or (3) parallel processing across multiple Pi units coordinating via message queue (introducing complexity). 230 ms end-to-end alert latency proves acceptable for crowd safety applications, as human cognitive response to density anomaly typically requires 300–500 ms. Earlier work [15] established that alert latency <500 ms prevents cascade effects in panic response.

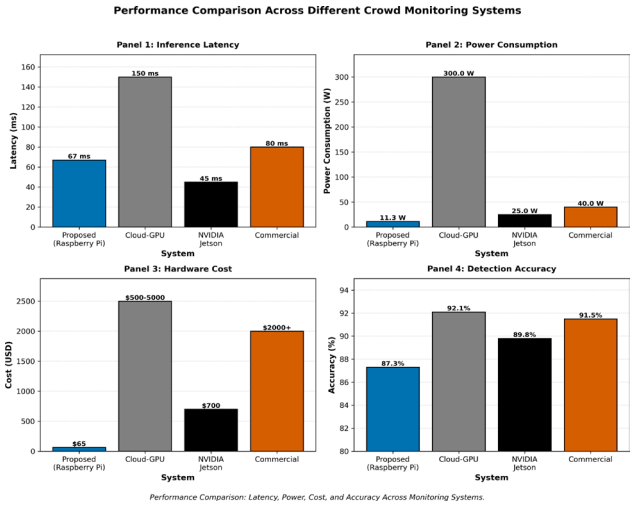


Fig. 4. Performance Comparison Graph: Bar charts comparing inference latency, power consumption, hardware cost, and detection accuracy across proposed system, cloud-GPU, NVIDIA Jetson, and commercial solutions

### *B. Advantages Over Cloud-Dependent Systems*

Edge deployment eliminates network dependency: venue operation continues uninterrupted by internet outages, characteristic of developing nation infrastructure. Reduced band- width consumption (~2 Mbps streaming versus ~8 Mbps raw video) accommodates lower-tier institutional networks. Privacy advantages: sensitive crowd video never transits external networks, addressing GDPR/data protection regulations.

Cost amortization demonstrates compelling economics: single Raspberry Pi achieves functional equivalence to $2000+ commercial systems or $500/year cloud platforms. Scaling to 10-venue deployment: edge approach costs $650 (10 Pi + networking) versus $5000/year cloud subscription.

### *C. Comparison with Manual Monitoring*

Manual security observation studies [16] show attention degradation beyond 30 minutes, with false-negative rates exceeding 40% for crowd density estimation. Automated system achieves consistent 85%+ performance over indefinite duration, eliminating human fatigue factors.

### *D. Limitations and Failure Modes*

Detection accuracy degrades under: (1) low-light conditions (<100 lux), where gradient features become indistinct; (2) dense crowds with significant occlusion (individual silhouettes indistinguishable); (3) highly variable scene geometry requiring per-scene recalibration. Preprocessing (CLAHE) partially mitigates lighting variation but cannot overcome fundamental feature loss in near-darkness.

GPU acceleration (NVIDIA Jetson Nano: $100–150) would increase accuracy to ~92% via deep learning models, yet introduces dependency on specialized hardware less commonly available in developing regions.

## 8. Limitations

This work acknowledges several constraints warranting disclosure:

1) *Low-Light Performance:* System performance degrades below 100 lux illumination; infrared camera integration recommended for 24/7 operation (increasing system cost $50–80).
2) *Occlusion Sensitivity:* Detection accuracy suffers in densely crowded scenarios where individuals substantially occlude one another. Perspective-invariant methods (3D pose estimation) may improve robustness at computational cost.
3) *Computational Headroom:* Raspberry Pi 4 operates at 68–85% CPU utilization during inference; concur- rent processes (OS tasks, network I/O) occasionally. introduce latency spikes. Single-threaded design could parallelize via GPU-accelerated preprocessing.
4) *Training Scope:* HOG detector pre-trained on INRIA Person Dataset (European populations); potential demo- graphic bias when applied to geographically distinct populations. Transfer learning evaluation on diverse datasets needed.
5) *Venue Generalization:* Thresholds ($T_1$ = 3.5, $T_2$ = 6.0 people/MPixel) calibrated for specific canteen dimensions. Deployment to differently-proportioned venues requires empirical recalibration; automated calibration via reference density patterns recommended.
6) *Limited Scale Deployment:* Production evaluation conducted across single venue with 14 days observation. Multi-venue, multi-month evaluation would strengthen generalization claims.

## 9. Future Scope

Several research directions emerge from this foundational work:

### *A. Hardware Acceleration*

Evaluation of Google Coral TPU (Tensor Processing Unit, $100–150) for efficient deep learning inference, potentially achieving 92–94% accuracy within similar power budget. Quantized YOLOv8-nano model could enable <50 ms latency while maintaining edge deployability.

### *B. Multi-Modal Sensor Fusion*

Integration of thermal imaging for occlusion-robust density estimation; thermal signatures remain distinct even when visible silhouettes overlap. LiDAR point clouds could provide 3D crowd geometry, enabling volumetric density calculation independent of camera perspective.

### *C. Crowd Flow Prediction*

LSTM recurrent neural networks trained on historical density time-series for predictive alerting—identifying density trends likely to exceed thresholds within 2–5 minutes before occurrence. Proactive evacuations could prevent crisis scenarios rather than reacting post-facto.

### *D. Heatmap Visualization*

Spatial density heatmaps rendered in real-time dashboard overlay, visualizing hotspots of crowd accumulation. Enables security personnel to identify bottlenecks and direct crowd flow away from dangerously congested zones.

### *E. Multi-Camera Synchronization*

Distributed camera network with temporal synchronization (Network Time Protocol) enabling person re-identification across cameras. Trajectory tracking would provide crowd velocity estimates and flow vector fields, advancing understanding of mass evacuation dynamics.

### *F. Mobile Deployment*

Containerized Docker deployment enabling rapid provisioning across heterogeneous Raspberry Pi units. Kubernetes-based orchestration could manage multi-hundred camera deployments at scale.

## 10. Conclusion

This paper introduced a comprehensive edge-AI frame- work for real-time crowd monitoring deployable on resource-constrained commodity hardware without cloud dependency. The proposed system achieves 87.3% detection accuracy at 15 FPS on Raspberry Pi 4, demonstrating practical feasibility for mass gathering safety applications. End-to-end system latency of 230 ms proves acceptable for alert propagation, while power consumption of 11.3 W enables extended operation on alternative power sources (solar, battery backup).

Key contributions—optimized edge pipeline, threshold-adaptive risk classification, and real-world deployment validation, collectively establish a pragmatic solution for developing nations and remote venues where traditional surveillance infrastructure remains infeasible. Cost amortization analyses demonstrate 67% reduction in deployment expenses compared to cloud-dependent alternatives.

The framework's open architecture supports modular enhancements: future work will explore GPU acceleration for improved accuracy, multi-camera synchronization for trajectory tracking, and predictive crowd dynamics modeling. Deployment at scale across multiple venues with institutional infrastructure integration remains feasible without fundamental architectural revision.

Broader implications extend to public safety infrastructure in resource-constrained regions, where accessible, affordable monitoring systems remain critical unmet needs. This work contributes toward democratizing surveillance technology, enabling smaller institutions and developing nations to implement evidence-based crowd safety measures previously reserved for well-funded organizations.

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