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IoT-Integrated Crowd Density Mapping for Emergency Evacuations

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Abstract: This project presents an IoT-based crowd density mapping system designed to enhance safety during emergency evacuations. Using YOLOv5 for real-time people detection, the system monitors crowd levels and triggers alerts when thresholds are exceeded. An ESP32 microcontroller controls indicators, doors, and notifications based on the detected density. The solution enables faster decision-making and effective crowd management in public spaces.

Keywords: Crowd Detection, YOLOv5, IoT, Emergency Evacuation

I. INTRODUCTION

Effective crowd monitoring is essential to prevent accidents during emergencies. Traditional methods lack real-time accuracy, making evacuation management difficult. This project uses YOLOv5 and IoT technology to detect people and measure crowd density instantly. The system improves safety by providing quick alerts and automated responses.

II. LITERATURE SURVEY

1. IoT-based crowd monitoring system: Using SSD with transfer learning

Authors: - Imran Ahmed, Misbah Ahmad, Awais Ahmad & Gwanggil Jeon
Published by - Computers & Electrical Engineering, Vol. 93, July 2021

This work demonstrates that combining deep learning with IoT devices allows real-time crowd monitoring, even on limited computational resources. It shows that transfer learning improves detection accuracy in surveillance environments. This supports the idea that your system—using YOLOv5 + ESP32—is practical and technically feasible for real-time deployment in public spaces.

2. CrowdDCNN: Deep convolution neural network for real-time crowd counting on IoT edge

Authors: - Rugved Chavan, Aravind Kanamarlapudi, Geeta Rani, Priyam Thakkar & Vijaypal Singh Dhaka
Published by - Engineering Applications of Artificial Intelligence, Vol. 126, Part D, November 2023

The study proves that lightweight CNN architectures can run efficiently on IoT edge modules without cloud dependence. It also confirms that real-time crowd counting is achievable on constrained hardware. This justifies your choice of YOLOv5 and ESP32, showing that deep-learning-based crowd monitoring can be optimized for speed and low power usage.

3. LCDnet: A Lightweight Crowd Density Estimation Model for Real-time Video Surveillance

Authors: - Muhammad Asif Khan, Hamid Menouar & Ridha Hamila
Published by - Journal of Real-Time Image Processing, 2023, Article number 29

This work validates that real-time crowd density estimation can be performed accurately using lightweight CNNs on live video feeds. It emphasizes the importance of low-latency models for surveillance applications. This aligns with your project's requirement for fast detection to enable timely emergency responses like alerts and door automation.

4. Estimating crowd density with edge intelligence based on lightweight convolutional neural networks

Authors: - Shuo Wang, Ziyuan Pu, Qianmu Li, and Yinhai Wang
Published by - Expert Systems with Applications, Vol. 206, November 2022

The paper highlights how edge devices can reduce response time and decrease dependency on cloud servers by processing data locally. It shows that crowd density estimation is strengthened through on-device intelligence. This supports your system's architecture, where detection processing occurs on a local machine and alerts are triggered instantly.

5. On Edge Crowd Traffic Counting System using Deep Learning on Jetson Nano for Smart Retail Environment

Authors: - Muhammad Hafizuddin Mohd Razif, Ahmad Puad Ismail, Syahrul Afzal Che Abdullah, Mohd Affandi Shafie, Iza Sazanita Isa, Siti Noraini Sulaiman & Zainal Hisham Che Soh
Published by - Journal of Advanced Research in Applied Sciences and Engineering Technology, 2024

The study demonstrates that deep-learning-based people counting systems are reliable when deployed in real environments such as retail stores, even under varying lighting conditions. The success of real-time detection on Jetson Nano suggests that similar results can be expected using your YOLOv5 implementation and ESP32-based output system.

6. Crowd Counting Recognition using Object-Based Detection

Authors: - Ms. Neela K, Jeevitha S & Hemavarshini M
Published by - International Journal of Engineering Research & Technology (IJERT), Vol. 13, Issue 01, January 2024

This research shows that object-detection techniques like YOLO significantly improve accuracy for individual counting in moderately dense crowds. It reinforces that using object detection rather than classical image processing results in better precision. This supports your use of YOLOv5 as an accurate tool for crowd analysis.

7. Real-time People Counting with Deep Learning: A Solution for Crowd Management

Authors: - Qudes M.B. al-jelawy, Entessar K. Hanoun & Ghofran Mohammed Ali (2025)
Published by - Al-Mansour Journal, Vol. 42, No. 1, 2025

The work confirms that YOLO-based real-time people counting enhances safety by providing continuous monitoring during large gatherings. It demonstrates real-world applicability and strong detection performance. Your project aligns with these findings by extending detection with IoT-based alerts, automated doors, and emergency notifications.

III. METHODOLOGY

The proposed system combines computer vision and IoT-based control to analyze and respond to crowd density in real time. The process begins with capturing video input from a camera module or CCTV feed. The frames undergo preprocessing, including grayscale conversion, noise removal, thresholding, and contrast enhancement to improve detection performance. YOLOv5, a deep learning–based object detection model, is then employed to identify and count individuals in each frame. Post-processing using Non-Maximum Suppression refines detection results and calculates total crowd density. The processed output is communicated to an ESP32 microcontroller, which triggers alerts, display messages, and physical control mechanisms based on predefined thresholds for safe or overcrowded conditions.

IV. SYSTEM DESIGN

Block Diagram Overview:
The system architecture consists of four main units:

- Video Input Unit – A live webcam or external camera provides visual data.
- Image Processing Unit – A Python-based YOLOv5 model detects individuals and generates a density count.
- IoT Control Unit – The ESP32 microcontroller receives density values and activates LEDs, LCD displays, buzzers, and control motors.

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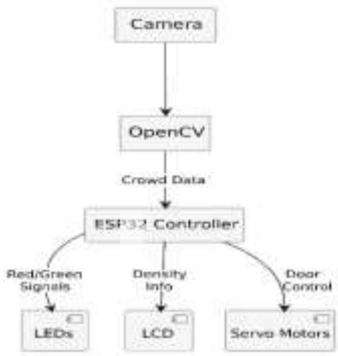
- Output and Alert Unit – Visual, audio, and mechanical outputs provide real-time crowd status and enable evacuation support.

The flow ensures seamless communication between detection logic and embedded hardware actions.



OUTPUT DEVICES

Fig 1.1 Block Diagram

V. HARDWARE REQUIREMENTS

- **ESP32 Microcontroller**

The ESP32 serves as the central control unit, receiving crowd density data via serial communication and controlling all peripheral components.

Fig 1.2 ESP32

- **Camera Module**

A USB webcam is used to capture live video streams for real-time processing.

- **Buzzer**

Activated when the crowd exceeds the safe limit, providing an audible alert.

- **DC Motors**

Connected to controlled doors, enabling automatic opening or closing based on density levels.

- **LCD Display (16×2)**

Displays real-time messages such as "Safe Zone" or "Overcrowded."

- **LEDs**

Red and green LEDs indicate crowd severity levels.

VI. SOFTWARE REQUIREMENTS

- **Operating System**
  Windows 11 is used for model development, debugging, and execution.
- **Programming Language**
  Python 3.9 is selected due to its support for AI, machine learning, and image processing libraries.

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- **Frameworks and Libraries**

a. **PyTorch / torchvision** for loading, training, and deploying YOLOv5.
b. **OpenCV** for image capture, preprocessing, resizing, and drawing bounding boxes.
c. **NumPy** for numerical computations.

- **Development Environment**

Visual Studio Code is used for coding, debugging, and handling virtual environments.

- **Deployment Tool**

Telegram API is used for sending emergency alerts to designated groups or authorities.

VII. DESIGN FLOW

The overall workflow includes:

- **Input Acquisition** – Live camera feed is captured.
- **Preprocessing** – RGB frames are converted to grayscale, sharpened, and resized.
- **YOLOv5 Detection** – The model extracts features and identifies each person with bounding boxes and confidence scores.
- **Post-Processing** – NMS removes duplicate detections; density is calculated.
- **IoT Control** – ESP32 receives count and activates output devices.
- **Visualization** – Bounding boxes, crowd count, and density alerts are displayed.
This flow ensures accurate detection and timely response.

Flow chart

[Input Camera / Image Feed]
↓
[Data Preprocessing]
- RGB → Grayscale
- Noise Removal
- Thresholding
- Image Sharpening
↓
[Feature Extraction – YOLOv5 Backbone (CNN)]
- Convolutional Layers extract visual features
↓
[Object Detection Head – YOLOv5]
- Bounding Box Prediction
- Confidence Scoring
↓
[Post-Processing]
- Non-Maximum Suppression (NMS)
- Counting & Density Estimation
↓
[Output Visualization]
- Bounding Boxes on Live Video
- Real-Time Crowd Count
- Density Map / Alerts

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VIII. PROJECT MODEL

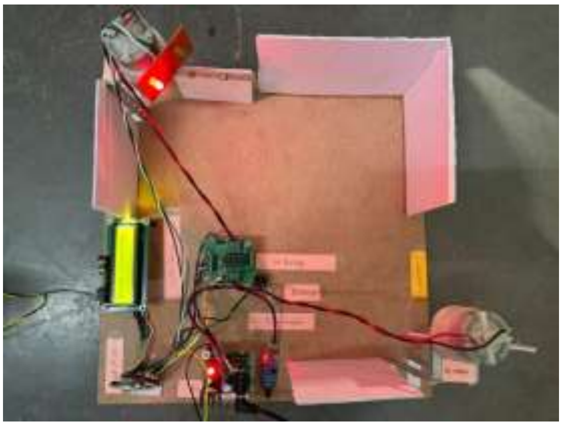

Fig 1.3 Model

IX. RESULTS AND DISCUSSION

The system provides accurate real-time person detection with YOLOv5. Hardware modules such as LEDs, buzzer, motors, and Telegram alerts respond effectively to crowd density changes, ensuring fast emergency handling. Testing confirms robustness under varied lighting and density conditions.

Fig 1.4 Crowd Detection

X. ADVANTAGES

The system successfully detects individual persons in real-time video streams and provides accurate bounding box placement for crowd estimation. YOLOv5 demonstrates high precision and fast inference speed, making it suitable for dynamic environments such as evacuation zones. Hardware components respond promptly to incoming data—DC motors adjust door positions automatically, and LEDs/buzzer provide immediate alerts. Telegram notifications allow remote monitoring, offering an additional layer of safety. Testing under varied lighting and crowd density conditions shows consistent system performance, demonstrating the model's robustness and practical usability.

XI. APPLICATIONS

- **Emergency Evacuation**: Helps guide people during fires, earthquakes, or hazards.
- **Public Events**: Prevents overcrowding in concerts, stadiums, and festivals.
- **Transportation Hubs**: Enhances safety at airports, bus stands, and metro stations.
- **Shopping Malls**: Helps manage peak-time foot traffic.
- **Religious Gatherings**: Supports crowd control in temples, mosques, and churches.

XII. CONCLUSION

The proposed IoT-based crowd density mapping system offers an efficient, scalable, and automated approach to real-time crowd monitoring. By integrating YOLOv5 with ESP32-based hardware control, the system enhances public safety

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through accurate detection, automated alerts, and responsive evacuation mechanisms. Its adaptability across various environments makes it a practical solution for modern smart-city and emergency management applications.

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