# **Crowd Counting Using Machine Learning**

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#### Abstract

Effective crowd management is essential for ensuring public safety in large gatherings. Traditional deep learning approaches for crowd analysis, including people counting, detection, and movement tracking, often require high computational resources, making them unsuitable for real-time applications on edge devices. This paper presents a Convolutional Neural Network (CNN)-based model designed to efficiently process crowd data while optimizing computational and memory demands. The proposed system enables real-time people detection, tracking, and movement estimation, allowing authorities to monitor and manage crowds proactively. By leveraging lightweight deep learning techniques, the model ensures high accuracy while maintaining efficiency, making it suitable for smart surveillance and public safety applications.

Keywords: Crowd Management, Real-Time Crowd Analysis, People Detection, Tracking, Convolutional Neural Network (CNN), Edge Computing, Deep Learning, Movement Estimation, Smart Surveillance, Public Safety

#### **INTRODUCTION**

Managing large crowds efficiently is crucial for ensuring public safety, especially in high-density gatherings such as festivals, sporting events, and transportation hubs. Traditional methods rely on manual monitoring or high-resource deep learning models, which are often impractical for real-time applications on edge devices. These approaches struggle with computational inefficiencies, leading to delays in detecting potential risks and responding effectively.

To address these challenges, this paper presents a Convolutional Neural Network (CNN)-based crowd management system that enables real-time people detection, tracking, and movement estimation. The model is optimized for computational efficiency, making it suitable for deployment on edge devices. By leveraging deep learning techniques, the system enhances surveillance capabilities while minimizing resource consumption. This solution provides a scalable and cost-effective approach to crowd monitoring, improving response times and reducing the risk of accidents in large public gatherings.

## LITERATURE SURVEY

- [1] "Realtime Crowd Monitoring—Estimating Count, Speed, and Direction of People Using Hybridized YOLOv4", utilizes the YOLOv4 model to enhance real- time object detection and tracking. This research, published in IEEE Access Transactions (2022), demonstrates how YOLOv4 can effectively estimate the number of people in a crowd, analyze their movement speed, and predict their direction, providing a reliable solution for large-scale crowd management.
- [2] "The Limo Powered Crowd Monitoring System: Deep Life Modeling for Dynamic Crowd With Edge-Based Information Cognition", focuses on using multi-sensor devices and edge cloud computing to improve dynamic crowd analysis. Published in the IEEE Sensors Journal (Volume: 22, Issue: 18,

September 2022), this research highlights the advantages of edge-based information processing, reducing latency and enhancing real-time decision-making in dynamic crowd environments.

- [3] "Crowd Monitoring and Classification", published in IEEE Access Transactions (2022), explores advanced techniques in Intelligent Systems and Computing for crowd analysis. This study emphasizes how intelligent computing methods can be applied to classify different crowd behaviors, ensuring efficient monitoring and safety management in public spaces.
- [4] "A Unified Multi-Scale Deep Convolutional Neural Network for Fast Object Detection in Computer Vision— ECCV (Lecture Notes in Computer Science)", published in IEEE Access Transactions (September 2022), presents a multi-scale deep learning approach for improving object detection speed and accuracy. This method enhances real- time performance in crowd surveillance systems by leveraging deep convolutional neural networks to quickly and efficiently detect individuals in crowded scenes.

## METHODOLOGY

The proposed system follows a structured approach to enable real-time crowd detection, tracking, and movement estimation. It begins with data collection and preprocessing, where images and videos from public crowd datasets are gathered to train the model. To improve model accuracy and generalization, data augmentation techniques such as scaling, rotation, and noise addition are applied. The collected images are then resized, normalized, and formatted to ensure compatibility with deep learning models, enhancing the efficiency of feature extraction.

For model selection and implementation, the system employs YOLOv3 (You Only Look Once v3), a realtime object detection model known for its speed and accuracy. A lightweight Convolutional Neural Network (CNN) is used to extract spatial features, improving detection precision. To enhance real-time tracking, techniques such as Deep SORT and Kalman Filtering are implemented, allowing the system to track individual movements within a crowd. Additionally, optical flow analysis and Recurrent Neural Networks (RNNs) help predict movement direction and identify potential risks, such as overcrowding or sudden changes in crowd behavior.

After detection and tracking, the system performs post-processing for crowd counting, where it analyzes the detected individuals to estimate the total crowd size. The system also incorporates anomaly detection to flag irregular crowd behavior, such as unexpected gathering patterns or potential safety hazards. This ensures that security personnel receive timely alerts for any potential risks, enabling proactive intervention.

To assess system reliability, evaluation metrics such as precision, recall, and F1-score are used to measure the accuracy of crowd detection. Additionally, latency is tested to ensure the system operates in real time without significant delays. The model's performance is also compared with existing crowd monitoring solutions to validate its effectiveness and efficiency in diverse environments.

For real-world deployment, the trained model is integrated into IoT-enabled smart cameras, allowing on-site data processing. To enhance efficiency, optimization techniques like quantization and pruning are applied, reducing computational demands without compromising accuracy. Frameworks such as TensorRT and TensorFlow Lite (TFLite) further accelerate the model's performance, ensuring smooth operation on edge devices.

Finally, the system is integrated with surveillance networks for continuous monitoring. A real-time alert mechanism notifies security personnel of any unusual crowd activity, ensuring a swift response to potential

emergencies. Additionally, a dashboard visualizes key crowd metrics, such as density, movement patterns, and risk levels, providing authorities with a clear overview for better decision-making. The system undergoes real-world testing in large public gatherings to evaluate its scalability, usability, and reliability, ensuring a robust and effective crowd management solution.

#### **OBJECTIVE**

- 1. Accurate Estimation of Crowd Size The system aims to count the number of people in a specific area as accurately as possible. By using cameras and smart technology, it can analyze the crowd and estimate how many people are present at any given time. This helps in understanding how crowded a place is, whether it's an event, a public gathering, or a busy street.
- 2. Better Planning and Management of Resources Knowing the crowd size helps in distributing resources like security personnel, medical teams, and food supplies effectively. For example, if a concert or festival has more attendees than expected, organizers can quickly arrange for additional security and facilities to maintain order and ensure a smooth experience for everyone.
- 3. **Fire Detection for Safety** The system includes fire detection technology to identify potential fire hazards. If a fire is detected in a crowded area, the system can send an alert immediately. This allows authorities to act fast, evacuate people, and prevent injuries or damage.
- 4. Ensuring Safety in Large Gatherings Large crowds can sometimes become dangerous, especially in enclosed spaces like stadiums or auditoriums. The system continuously monitors crowd density and movement to detect signs of overcrowding, stampedes, or other safety risks. This ensures that people remain safe and emergencies can be prevented before they happen.
- 5. Quick and Effective Emergency Response In case of an emergency, such as a fire, medical issue, or security threat, the system helps authorities respond faster. By tracking the crowd and identifying high-risk areas, emergency teams can be directed to the right locations without delay. This improves the chances of saving lives and reducing harm.

Overall, the system is designed to improve public safety, manage crowds efficiently, and provide a reliable way to handle emergencies in busy places.

#### SYATEM ARCHITECTURE



Fig(a) : System Architecture

# FUCTIONAL REQUIREMENTS

- 1. Real-Time Crowd Detection: The system must detect and count individuals in a crowd using a CNN model.
- 2. People Tracking: It should track the movement of each detected person across multiple frames.
- 3. Movement Estimation: The system should predict the direction and speed of crowd movement using algorithms like optical flow or RNNs.
- 4. Anomaly Detection: Identify sudden density changes or irregular movement patterns and flag them as potential risks.
- 5. Alerts and Notifications: Automatically send real-time alerts to security personnel when crowd density exceeds a safe threshold or anomalies are detected.
- 6. Data Visualization: Display live crowd metrics, movement trends, and risk zones through a user- friendly dashboard.
- 7. Edge Device Deployment: The system must run efficiently on edge devices like smart cameras or Raspberry Pi.
- 8. Data Logging: Store historical data for future analysis and performance evaluation.

# NON FUCTIONAL REQUIREMENTS

- 1. Real-Time Processing: Ensure low latency for quick detection, tracking, and alert generation.
- 2. Scalability: Support multiple cameras and large crowds without compromising performance.
- 3. Accuracy: Maintain high detection accuracy for crowd counting and movement estimation.
- 4. Efficiency: Optimize computational and memory demands to run smoothly on edge devices.
- 5. Security: Implement data encryption for secure transmission and prevent unauthorized access.
- 6. Reliability: Ensure continuous system operation with minimal downtime, especially during public events.
- 7. User-Friendly Interface: Provide a simple, intuitive dashboard for real-time monitoring.
- 8. Maintainability: Ensure the system is modular, allowing for easy updates and enhancements.
- 9. Energy Efficiency: Optimize power consumption to extend edge device battery life.



#### RESULT



#### CONCLUSION

The proposed CNN-based crowd management system provides an efficient, real-time solution for monitoring and analyzing large public gatherings. By integrating deep learning techniques with real-time tracking and movement estimation, the system enhances safety, prevents overcrowding, and minimizes security risks. Optimized for edge devices, it ensures computational efficiency without compromising performance. The automated alert mechanism enables timely interventions, improving crowd control and event management. With high accuracy, scalability, and real-time responsiveness, this solution addresses the limitations of traditional surveillance systems, making it a valuable tool for smart city applications, public events, and emergency response planning. Future enhancements may include improved anomaly detection and integration with advanced AI-driven decision-making systems.

#### REFERENCES

- [1]Lamba and N. Nain, "Crowd monitoring and classification: A survey," in Advances in Computer and Computational Sciences (Advances in Intelligent Systems and Computing),2022
- [2]C. Santhini and V. Gomathi, "Crowd scene analysis using deep learning network," in Proc. Int. Conf. Current Trends Towards Converging Technol. (ICCTCT), Mar. 2023
- [3]Z. Cai, Q. Fan, R. S. Feris, and N. Vasconcelos, "A unified multi-scale deep convolutional neural network for fast object detection," in Computer Vision—ECCV (Lecture Notes in Computer Science), sept. 2022
- [4]T. Van Oosterhout, S. Bakkes, and B. Kröse, "Head detection in stereo data for people counting and segmentation," in Proc. VISAPP, 2022