Intelligent Queue Management in Crowded Places

R.Nagajyothi[1], V.G. Jyothi Mani[2*] and R. Panchavarnam[3]

[1]*Assistant Professor of Computer Applications, V.V.Vanniaperumal College for Women, Virudhunagar, Tamil Nadu*

Email: nagajyothir@vvvcollege.org

[2]*Assistant Professor of Computer Applications, V.V.Vanniaperumal College for Women, Virudhunagar, Tamil Nadu*

[3]*Assistant Professor of Commerce, V.V.Vanniaperumal College for Women, Virudhunagar, Tamil Nadu*

[*] *Corresponding Author Email: jyothimani.v@vvvcollege.org*

Abstract

Crowded environments such as hospitals, transport hubs, retail centres, and educational institutions often experience long queues that lead to delays, reduced service quality, and safety concerns. Traditional queue management methods, which rely on manual supervision or basic token systems, are insufficient to handle dynamic and unpredictable crowd behaviour. This study presents an Intelligent Queue Management System that integrates Machine Learning, Computer Vision, predictive modelling, and reinforcement learning to optimize queue flow in real time. Using advanced person-detection models such as YOLOv8/YOLOv10, the system automatically identifies queue length, estimates waiting time, and monitors crowd density through CCTV feeds and sensor data. Predictive models forecast peak periods, while reinforcement learning supports adaptive decision-making for counter allocation and congestion control. The architecture consists of an input layer for data acquisition, a processing layer for ML-based analytics, and an output layer for delivering actionable alerts and guidance. The system offers significant benefits including reduced waiting time, improved customer satisfaction, and real-time crowd alerts. Despite challenges such as privacy issues, occlusion, and computational demands, intelligent queue management represents a scalable and efficient solution for enhancing operational performance and ensuring safety in crowded spaces. Future advancements may include integration with IoT, edge AI, emotion analytics, and 5G connectivity for more accurate and low-latency crowd monitoring.

Keywords: Queue Management, Machine Learning, Computer Vision, Queue Length, Waiting Time, Resource Allocation

1. Introduction

Busy places like hospitals, transit stations, shopping stores, and event locations frequently face heavy crowds and long waiting lines. These queues often cause delays, customer dissatisfaction, and inefficiencies in daily operations. Conventional queue handling methods, which depend on manual supervision or basic ticket-based systems, usually fail to perform effectively during high-demand periods.

With recent progress in Machine Learning (ML) and computer vision technologies, intelligent queue management systems have become a powerful alternative. Such systems can automatically observe crowd movement, forecast congestion, and regulate queue flow in real time. This paper discusses how ML-driven solutions can minimize waiting times, improve user satisfaction, and strengthen overall crowd management and safety.

2. Review of Literature

Queue management has traditionally been addressed using queueing theory, where models such as M/M/1 and M/M/c analyze system performance based on arrival and service rates [12], [13], but these approaches assume stationary conditions and are limited in dynamic crowded environments. With the rise of sensing and surveillance technologies, computer vision has enabled automated crowd analysis, with privacy-preserving counting methods proposed by Chan et al. [9] and deep learning–based detectors such as Faster R-CNN and SSD improving detection accuracy, though often at high computational cost or reduced performance in dense scenes [6], [7]. The YOLO family introduced real-time object detection with competitive accuracy [2], further enhanced in later versions including YOLO9000, YOLOv4, and recent YOLOv8/YOLOv10 models suitable for edge deployment [3]–[5]. For dense crowds, crowd counting and density estimation techniques such as MCNN [19], deep density models [20], and datasets like Crowd Human [8] have advanced performance, yet most focus on aggregate estimation rather than operational queue control. Recent studies also highlight the role of IoT- and cloud-enabled analytics in smart environments [14] and the impact of deep learning advances on vision systems [15]–[17]. Reinforcement learning provides a framework for adaptive resource allocation and service optimization [11], but its integration with real-time visual perception for queue management remains limited. Overall, existing works address detection, counting, or theoretical modelling in isolation and face challenges such as occlusion, perspective distortion, and non-stationary arrivals [8], [12], [13], [19]. This study bridges these gaps by integrating YOLO-based real-time person detection [2], [5], queuing-theoretic waiting time estimation [12], predictive modelling, and reinforcement learning–based counter allocation [11] within a unified architecture, enabling scalable, adaptive, and intelligent queue management for complex crowded environments.

3. Need for Intelligent Queue Management

Crowded places face several queue-related challenges, such as:

- **Unpredictable arrival rates** during peak hours.
- **Limited human supervision**, leading to delays.
- **Inefficient resource allocation** (e.g., too few open counters).
- **Low customer satisfaction** caused by long waiting times.
- **High safety risks** in heavily crowded spaces.

Intelligent queue management systems powered by ML provide:

- Automated queue detection
- Real-time monitoring
- Waiting-time predictions
- Dynamic counter/staff adjustments
- Crowd safety alerts

4. Machine Learning Techniques Used

4.1 Computer Vision (CV) for Queue Detection

ML models like **YOLOv8 / YOLOv10** (object detection) is choose to detect people, count them, and measure queue length using CCTV or smartphone cameras.

Goal: Detect objects (e.g., people) in an image and return bounding boxes, class labels and confidence scores - in one fast pass.

1. **Input**
   - A single image or one video frame (height × width × 3 channels).
   - Optionally resized to the network's expected resolution (e.g., 640×640).
2. **Preprocessing**
   - Resize + letterbox (preserve aspect ratio by padding).
   - Normalize pixel values (e.g., scale 0–255 → 0–1 or mean/std).
   - Convert to tensor and batch it.

3. **Backbone (feature extraction)**
   - The image passes through convolutional layers that extract multi-scale feature maps (edges → textures → higher-level features).
   - Lightweight and optimized blocks are used for speed.
4. **Neck / feature aggregation**
   - Feature maps from different depths are combined (e.g., FPN/PAN) so the model can detect both small and large objects.
5. **Head (predictions)**
   - Each grid cell predicts several bounding boxes with:
     - Box coordinates (x, y, w, h) relative to cell,
     - Objectness score (probability there is an object),
     - Class probabilities (person, car, etc.).
   - Predictions are done **in one forward pass** (hence "You Only Look Once").
6. **Postprocessing**
   - Convert predicted offsets into actual pixel bounding boxes.
   - **Filter by confidence** (remove low-confidence detections).
   - **Non-Max Suppression (NMS)**: remove duplicate overlapping boxes keeping the highest confidence box.
   - Optionally apply class-specific thresholds.
7. **Output**
   - A list of detections: `(class, confidence, x1, y1, x2, y2)` for each detected object.
8. **Where it helps for queue detection**
   - Provides reliable person locations (bounding boxes) in each frame.
   - Fast enough to run at real-time on GPUs and many edge devices (especially small variants like yolov8n).
9. **Pros / Cons**
   - Extremely fast; good accuracy.
   - Single unified model (easy to integrate).
   - Can struggle with heavy occlusion (people overlapping).
   - Pixel distances vary with perspective (need calibration for real distances).

5. Architecture of an Intelligent Queue Management System

An Intelligent queue management system is structured into three main layers: Input, Processing, and Output. Each layer has specific responsibilities and algorithms.

5.1 Input Layer

The input layer collects **real-time data** from multiple sources.

Components:

1. **CCTV Camera Feed**

- Provides visual data of queues in real time.
- Images or video frames are processed to detect people and measure queue length.

2. **Sensor Data**

- IR (Infrared) counters at entrances/exits.
- Wi-Fi/Bluetooth pings to detect the number of devices/people.
- RFID tags for tracking individuals or assets.

3. **Ticketing System Logs**

- Queue time logs from e-tickets or appointment systems.
- Provides historical data for prediction and scheduling.

In a machine learning–enabled queue management system, the input layer plays a crucial role by collecting heterogeneous data from multiple sources to accurately capture the current state of the queue. This includes real-time video feeds from CCTV cameras, sensor data such as infrared counters, Wi-Fi or Bluetooth pings, and ticketing system logs. Once collected, this raw data is pre-processed to ensure it is suitable for downstream analysis. For example, video frames are resized and normalized for computer vision models, while sensor readings are filtered to remove noise or anomalies. This preprocessing step ensures that the information fed into detection, prediction, and decision-making modules is clean, consistent, and reliable, forming the foundation for effective queue monitoring and optimization.

5.2 Processing Layer

This is the **core intelligence layer** where machine learning and computer vision are applied.

1. **People Detection Module**

- CV model detects individuals from frames. Use **YOLOv8 / YOLOv10** for real-time person detection.

2. **Queue Length & Density Estimation**

- Measures number of people standing in line. Uses methods to Count detected people in the **queue ROI (Region of Interest)** and to compute **inter-person distances** to estimate density (crowding).

3. **Waiting Time Calculation**
   - Estimate average waiting time for people in the queue based on service rate and queue length.
4. **Prediction Module**
   - ML models forecast future crowd surges.
5. **Decision-Making Module**
   - Take action to optimize queues. Methods used such as **Rule-Based:** e.g., if waiting time > threshold, open a new counter and **Reinforcement Learning (RL):** learns optimal actions to minimize waiting time and balance counter utilization.

5.3 Output Layer

The output layer communicates actionable information to staff and users.

Components:

1. **Alerts to Staff**
   - Notify staff to open a counter, redirect people, or handle overcrowding.
2. **Digital Queue Display**
   - Display current queue length and estimated waiting time on screens.
3. **Mobile Notifications**
   - Push alerts to users with estimated wait time or queue status.
4. **Automatic Counter Reallocation**
   - Automated system to open/close service counters based on predicted demand.

6. Benefits

- **Reduced waiting time**

  Shorter waiting times improve overall satisfaction for student, visitors, or customers, resulting in positive impressions and better service efficiency.
- **Improved customer satisfaction**

  When pepole experience faster service, clear guidance, and less uncertainty, they feel more comfortable and valued, leading to a better overall service experience.
- **Real-time crowd alerts**

  The system continuously monitors crowd density and instantly sends real-time alerts when congestion increases, helping authorities take quick action to manage the situation and ensure safety.

7. Conclusion

Intelligent queue management provides a transformative solution for reducing congestion and improving service efficiency in crowded environments. By integrating computer vision, predictive modelling, and reinforcement learning, organizations can make intelligent decisions that enhance safety and user experience.

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Author Biographies

R.Nagajyothi is working as an Assistant Professor in the Department of Computer Applications, at V.V.Vanniaperumal College for Women, Virudhunagar. She has 30 years of teaching experience in Computer Science discipline. She has presented 12 research papers at state, national, and international level seminars and conferences. She has 9 research articles in reputed journals and edited books. So far, she has guided nearly 60 MCA students for their project work.

V.G.Jyothi Mani is working as an Assistant Professor in the Department of Computer Applications, at V.V.Vanniaperumal College for Women, Virudhunagar. She has 29 years of teaching experience in Computer Science discipline. She has presented research papers at state, national, and international level seminars and conferences. She has published research articles in reputed journals and edited books. She holds patents for design applications on an IoT-based traffic management system. She also secured First Prize in the oral presentation (in absentia) with a cash award for the paper titled "Plant Disease Prediction Using Deep Learning" at the International Symposium held at KIET School of Pharmacy, Delhi–NCR.

Dr.R.Panchavarnam is working as an Assistant Professor in the Department of Commerce at V.V.Vanniaperumal College for Women, Virudhunagar. She has been qualified with M.Com., M.Phil., PGDCA, MBA, and Ph.D. She has 28 years of teaching experience at both under graduate and post graduate levels. She has presented research papers at state, national, and international level seminars and conferences. She has published research articles in reputed journals and edited books.