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Real-Time Queue Detection and Management System Using YOLO Object Detection

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***Abstract*—This study propounds a novel queue real-time detection and management system designed to aid public service delivery efficiency based on the YOLO object detection model. The proposed system takes in live feed from surveillance cameras, identifies and counts people waiting in lines, and gives real-time information through an easy-to-use web interface. Key issues include dealing with occlusion, responding to changing lighting conditions and facilitating scalability for different service environments. The proposed system highlights the introduction of advanced machine learning approaches as part of modern web technologies in order to optimize resource allocation, eliminate waiting, and enhance customer experience. This system is highly accurate and robustly performs in most real-world conditions and is applicable to hubs of transportation, shopping malls, or government offices.**

***Index Terms*—Queue management, YOLO, object detection, machine learning, real-time analytics, smart service system**

I. Introduction

Proper queue management acts as a key component that helps increase efficiency and increase customer satisfaction in such an application, as at an airport, retail store, hospital, or any government department. The lengthy queue not only frustrates customers but also leads to over utilization of the system and, subsequently low accuracies in real-time scenarios are typical of hand-counting and ticketing mechanism-based systems [3]. Latest advancements in machine learning in object detection can offer useful solutions for these issues identified above. The YOLO object detection model is considered to be one of the efficient tools since it balances between speed and accuracy, for real-time applications [1] [4] [5]. Based on this paper, a scalable and reliable queue detection system that takes advantage of YOLO to process feeds of live video from any surveillance camera to detect and count people in queues is to be designed. The system delivers real-time information through an interface on the Web, enabling service managers to make informed decisions and improve the distribution of resources [6] [7]. The main objectives of this research are: to develop a real-time queue detection system using YOLO. To overcome the challenges of occlusions and illumination variations. Design an easy-to-use interface to get both real-time and historical queue data.

II. Literature Survey

A. Object Detection Model Advances

Advances in object detection emerged through YOLO, a single-pass detection framework that significantly reduced processing times compared to other conventional methods like R-CNN and Faster R-CNN [1] [8] [9]. Different versions of YOLOv4 and YOLOv5 introduced new advancements in the features extracted, anchor box strategies, and data augmentation, further improving the accuracy compared with deeply populated environments [10]. Recent technological progressions, such as YOLOv8 [6], have greatly improved detection capabilities within dynamic contexts, making them appropriate for real-time adaptability. The real-time processing power of YOLO has been found to be very effective for dynamic applications including traffic monitoring and crowd analysis [11] [12].

B. Queue Management Applications

Machine learning-based queue management systems are also introduced in other fields of applications. Retail shops deploy such systems to track checkout queues and dynamically assign staff to minimize wait times for customers [13]. In transportation nodes, automated queue detection assists in managing security lines and boarding operations, increasing throughput, and using resources effectively [13] [14] [15].

C. Challenges in Real-Time Queue Detection

The primary obstacles in the detection of real-time queues are occlusion and variability in lighting conditions. Occlusions arise when individuals overlap, making accurate counting more difficult. To address these challenges, multi-angle camera configurations, and sophisticated algorithms for tracking have been suggested [16]. Fluctuating lighting conditions, particularly in outdoor settings, may compromise model accuracy, thereby requiring training on a variety of datasets and the utilization of infrared cameras [17].

III. Methodology

The proposed system adopts a structured and robust design to make the task of accurate identification of individuals and queue management possible. The system consists of the following critical phases:

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Data Acquisition High-definition IP cameras, when placed appropriately at the service locations, are used for capturing continuous video recordings of customer interactions. These video recordings form the major source of data for the system. OpenCV is used to extract separate frames from a video, which are later labeled with bounding boxes labeled as ”people.”

The labeled dataset is utilized for training the YOLO so that it may classify people in the queuing scenario correctly. The annotated datasets are structured to be robust against different conditions, such as varying illumination levels, crowd densities, or viewpoints.

A. Model Training

The YOLO model has been deployed for object detection purposes because of its excellent accuracy and performance capabilities in real-time. The training process consists of a few crucial steps:

- **Dataset Preparation**: The labeled dataset obtained from the collection stage is used with further techniques such as random cropping, flipping, and brightness adjustment. These augmented transformations help enhance the model's ability to be robust for generalizing to different conditions.
- **Hyper-parameter Tuning**: The model is built using the most basic hyper-parameters: a learning rate of 0.001, a batch size of 16, and 60 epochs. These are fine-tuned to create an optimal balance between computation efficiency and detection accuracy.
- **Validation**: The model was verified on an independent dataset to check its accuracy and precision. Metrics such as Intersection over Union (IoU) and Confidence scores are tracked to ensure reliability. of the model in real applications.

B. System Architecture

The architecture of the system incorporates various components to facilitate uninterrupted functionality and immediate insights.

- **Video Input**: Ongoing video streams are captured from surveillance cameras located at strategic points. They are installed to achieve maximum coverage of the service areas.
- **Frame Processing**: Frames from video input are processed through the YOLO model in real-time, which does the actual identification and counting of individuals [6]. The bounding boxes containing the resulting individuals are returned with a confidence score that represents the accuracy of the detection.
- **Queue Segmentation**: This network uses advanced image segmentation techniques to divide the service space into distinct queues. Each of these queues is then monitored independently to enable real-time tracking of the number of people being counted.
- **Web Interface**: The output results that are processed are presented through an intuitive web interface, built with React. Provides real-time information about queue data such as how many people are in each queue and suggestions for redirection of customer flow. There is a control back-end based on Node.js dealing with the processing and storing of the data of the detection systems.
- **Output Metrics**: This system generates useful metrics - the count of people in a line and the queue redirection suggestions. Such metrics help further optimize resource deployment and increase customer satisfaction.

C. Flow Diagram

Figure 1 illustrates the complete flow of the system architecture, depicting the integration of data collection, processing, and output generation.

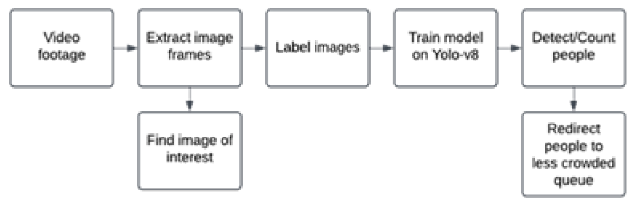

Fig. 1. Flow Diagram of the Queue Management Methodology.

IV. Results and Discussion

The developed queue management system was tested on various sites including shops, stations, and government offices in a thorough test run for testing its efficiency, robustness, and accuracy under various real-world conditions. The performance metrics included challenges faced, advantages of the system, and key performance metrics.

A. Performance Metrics

The system delivered good performance in several scenarios:

- **Mean Average Precision (mAP)**: The model obtained a significant mAP of 96.2% [12], which indicates its ability to correctly identify people in different queue arrangements. The formula for calculating the mean Average Precision (mAP) is expressed as:

$$mAP = \frac{1}{n}\sum_{i=0} AP_i- \quad (1)$$

where n is the total count of classes (in this case, ”people”), and AP_i- is the Average Precision for class i.

- **Precision**: The precision rate of 96.5% shows that the system can minimize false positives and ensure that only the actual person is found in queues. Precision is defined as:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \quad (2)$$

- **Recall**: The system achieved a recall rate of 95.0% achieved by the system indicates its performance in detecting most people in a frame that is also present in crowded scenes. Recall can be defined as:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \quad (3)$$

- **Latency**: This ability for real-time work has reduced the detection latency to less than one second for every frame, hence ensuring that feedback is real-time and accurate. Such responsiveness is very important in applications involving dynamic queues, such as transportation terminals or retail service points.

B. Results Visualization

Figures 2 and 3 show the operation of the system in real-time. Figure 1 shows person detection with bounding boxes and confidence scores, while Figure 2 displays the queue segmentation and count per queue, where the system delivers actionable insights.

Fig. 2. Real-time Person Detection in a Retail Environment.

Fig. 3. Redirecting People from more Crowded Counter to less Crowded Counter

C. Challenges Solved

The system addressed several common challenges that usually occur in queue management:

- **Occlusion Handling**: Crowded environments often lead to partial or complete occlusion of individuals, which can hinder accurate detection. By implementing multi-camera setups, the system mitigated occlusion issues, improving detection accuracy in densely populated areas. The integration of multi-camera setups along with advanced tracking algorithms [16] has further enhanced the detection accuracy for crowded environments.
- **Lighting Variability**: Lighting settings with changing lighting conditions (for example, outdoor passenger stations or insufficiently illuminated shopping areas) imposed a challenge for accurate detection [17]. Data augmentation techniques such as brightness adjustment and contrast enhancement greatly enhanced model performance, thus ensuring consistent accuracy across different lighting settings.

D. Discussion

The experiments have shown that the YOLO-based framework represents a very powerful and flexible approach to queuing management. Its high precision and recall values ensure low errors in the detection of people while its real-time processing characteristics allow for quick feedback and informed decisions. Its modular architecture makes it fit into the structure of any existing surveillance structure, thus offering an inexpensive way to optimize almost every queue in most industries. In comparison to traditional queue management techniques, such as enumeration by hand or simple computer vision algorithms, The system proposed here has tremendous improvement over others concerning accuracy, efficiency, and adaptability. Besides taking into consideration such metrics as length, and customers' reorientation brings the added advantage in terms of optimization of the resource use and customer satisfaction. In conclusion, the established queue management system proficiently integrates accuracy, speed, and adaptability, rendering it an effective instrument for monitoring and managing queues in real-time within fluctuating environments.

CONCLUSION

The current study demonstrates the effectiveness of a YOLO-based real-time system that can detect and manage queues intended for public service. Building on deep learning and computer vision technologies, the system promotes an accurate, scalable and reliable procedure for dynamic detection of people and management of queues in various settings, such as retail facilities, transportation facilities, and government facilities. The results show high improvements in performance, as reflected by a mean Average Precision (mAP) of 96.2%, a precision of 96.5%, and a recall of 95.0% [1] [12]. The system's capabilities for real-time processing contribute to minimal latency, resulting in immediate and actionable feedback. These advancements have the potential to significantly enhance customer experience through the reduction of wait times and optimization of resources.

FUTURE WORK

As the current system efficiently oversees real-time queue operations, room for further improvement exists:

- **Occlusion Handling**: Future releases would be able to experiment with much more complex strategies for resolving occlusion issues in very dense or cluttered scenes, like using multi-view cameras or 3D depth information.
- **Incorporation of Thermal Cameras**: The incorporation of thermal imaging technology into the system could

significantly enhance detection performance in low-light or night-time environments.

- **Expanse to Complex Spaces**: The system could be adapted for extensive and complex environments, such as airports, stadiums, or large public events, where different queues tend to merge and fluid crowd dynamics are quite important.
- **Predictive Analytics**: The predictive analytics can be merged into the system, in which it can predict queue patterns based on historical data that can make the resource distribution smarter and the operational strategy much better.
- **Real-time Alerts and Recommendations**: The creation of a notification system delivering immediate alerts and suggestions for queue redirection or personnel deployment has the potential to enhance operational efficiency and customer satisfaction. In conclusion, the proposed system offers a robust framework for intelligent queue management, while further developments shall focus on increasing its applicability and longevity, ensuring that it remains responsive to the increasing needs of dynamic and complex environments.

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