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Automated Person Counting System for Video Surveillance

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Abstract: The paper presents an automated person counting system for video surveillance leveraging advanced deep learning techniques and computer vision. The system utilizes the YOLO (You Only Look Once) v3 model for efficient and accurate detection of persons in video frames. The YOLO model, pre-trained using COCO dataset, is employed to identify and locate persons within each frame by generating bounding boxes around detected individuals. To further refine the detection process, non-maximum suppression (NMS) is applied to eliminate redundant bounding boxes, ensuring each person is uniquely identified. Following detection, the VGG16 Convolutional Neural Network, trained using the famous ImageNet, is employed to extract deeper semantic features from respective detected person's region of interest (ROI). Identified features are essential for differentiating between unique individuals. The system processes video frames at specified intervals to balance computational efficiency and detection accuracy. To identify distinct individuals across the video, KMeans clustering is applied to the extracted features. The optimal number of clusters is determined empirically, representing the estimated number of unique individuals in the video. This clustering approach allows the system to compute the total number of distinct persons effectively. The implementation demonstrates a robust and scalable solution for automated person counting in surveillance videos, providing critical insights for security and monitoring applications. The system's ability to accurately detect and distinguish between individuals can enhance the effectiveness of surveillance operations, contributing to improved safety and situational awareness.

Keywords: YOLO v3, VGG16, KMeans, COCO dataset

I. INTRODUCTION

The increasing demand for sophisticated automated surveillance systems has surged in recent years due to their critical role in enhancing security and monitoring public spaces. Traditional methods of person counting and pedestrian tracking in video surveillance involve manual observation, which is labor-intensive, time-consuming, and prone to human error. To address these challenges, cutting-edge computer vision and deep learning techniques have emerged as potent tools for developing automated person counting systems.

The paper presents an automated person counting system designed to accurately detect and count individuals in video surveillance footage. The system leverages the YOLO (You Only Look Once) v3 model for real-time person detection. YOLO v3 is renowned for its speed and precision, making it an ideal choice for surveillance applications where timely and accurate detection is paramount. By employing a pre-trained YOLO v3 model on the COCO dataset, the system can effectively identify and localize persons within each frame of the video. To enhance the differentiation of detected individuals, the system integrates the VGG16 Convolutional Neural Network, which is pre-trained on ImageNet.

This network is utilized to extract deep features from the regions of interest (ROIs) corresponding to each detected person. These features, representing high-level attributes of individuals, are crucial for distinguishing between unique persons appearing in the video. To count the number of distinct individuals, KMeans clustering is applied to the extracted features. This clustering approach groups similar features together, allowing the system to estimate the number of unique individuals appearing in the video. The efficacy of the proposed method in identifying distinct persons makes it a valuable tool for various surveillance applications, from crowd monitoring to security management.

The introduction of this automated person counting system represents a significant advancement in the ground of video surveillance. By combining real-time object detection with sophisticated feature abstraction and clustering techniques, the system offers a robust and scalable solution for accurate person counting. This modernism not just enhances the efficiency and reliability of surveillance operations but also contributes to enhanced security and situational awareness in monitored environments.

II. LITERATURE REVIEW

The improvement of automated person counting systems in video surveillance has been extensively researched, with various methodologies leveraging innovations in computer vision and deep learning. This literature review explores significant contributions to the field, highlighting key approaches and their evolution [1]. Early person counting systems relied heavily on background subtraction and motion detection techniques [2]. These methods involved detecting changes between frames to identify moving objects, which are later classified as persons based on size, shape, and movement patterns [3]. While effective in controlled environments, these methods struggled with occlusions, dynamic backgrounds, and varying lighting conditions [4] [5]. The advent of machine learning techniques significantly enhanced person detection accuracy. Seminal work on face detection using Haar-like features and AdaBoost classifiers marked a significant advancement [6]. Subsequent improvements included Histogram of Oriented Gradients (HOG) and Support Vector Machines (SVM), as demonstrated in pedestrian detection framework [7]. These methods offered improved robustness but were computationally intensive and less effective in crowded scenes [8]. The general idea of deep learning revolutionized object detection. Convolutional Neural Networks (CNNs) became the foundation stone of modern detection frameworks, offering superior accuracy and generalization [9]. Among the pioneering models, Region-based CNN (R-CNN), combined region proposals with CNNs for precise localization. Fast R-CNN and Faster R-CNN further optimized this approach by integrating region proposal networks, significantly reducing computational overhead [10, 11].

You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD) models represented a paradigm shift towards real-time object detection. YOLO model framed detection as a single regression problem, predicting bounding boxes and calculating class probabilities directly from complete images [12]. YOLO's unified architecture enabled real-time processing with competitive accuracy, making it suitable for surveillance applications. Similarly, Liu et al.'s SSD model offered real-time capabilities with multi-scale feature maps, enhancing detection of small objects [13]. Accurate person counting also hinges on effective feature extraction. Pre-trained deep learning architectures like VGG16, ResNet, and Inception have been extensively adopted for this purpose [14]. VGG16 model, known for its deep architecture and minimalism, has been widely used for feature extraction, capturing high-level semantic information crucial for distinguishing between individuals. These models, trained on large-scale datasets like ImageNet, provide robust feature representations transferable to various tasks [15].

To identify distinct individuals, clustering algorithms like KMeans have been employed. KMeans clustering, partitions data into discrete groups centered on feature similarity, making it suitable for grouping extracted feature vectors of individuals [16]. Despite its simplicity, KMeans requires the total amount of clusters to be predefined, posing challenges in dynamic scenarios. Advanced clustering methods, such as DBSCAN and hierarchical clustering, offer more flexibility but at increased computational costs [17]. Recent research integrates multiple methodologies to enhance performance. Chen et al. proposed combining YOLO for detection with Deep SORT for tracking, maintaining identities across frames in crowded environments [18]. Other approaches leverage hybrid models, incorporating conventional image processing techniques into deep learning, to address specific challenges like occlusions and varying densities [19].

The literature demonstrates a clear evolution from traditional image processing techniques to sophisticated deep learning models for individual person detection and counting. YOLO and VGG16 models, as utilized in this research, epitomize state-of-the-art advancements, offering real-time detection and robust feature extraction. Future research will likely focus on enhancing the adaptability and efficiency of these systems, exploring hybrid models, and leveraging advancements in edge computing and unsupervised learning for dynamic and real-time surveillance applications.

III. RESEARCH METHODOLOGY

The proposed methodology for the automated person counting system involves a comprehensive multi-stage process designed to ensure accurate detection and counting of individuals in video surveillance footage. Initially, video data is captured from a surveillance feed, with frames extracted at specified intervals to balance computational efficiency and temporal detail. For object detection, the YOLO v3 model, pre-trained on the COCO dataset, is utilized to detect persons within each frame. This involves converting frames into standardized blobs, running them through the YOLO network, and generating bounding boxes for detected persons with confidence scores above a defined threshold. To refine these detections, non-maximum suppression (NMS) is utilized to eliminate the redundant and overlapping bounding boxes, retaining only the most confident and non-overlapping detections.

Subsequently, the VGG16 model, pre-trained on ImageNet, is employed to extract deep features belonging to the regions of interest (ROIs) corresponding to each detected person. Each ROI is resized, preprocessed, and passed through the VGG16 network up to the 'block5_pool' layer to obtain a flattened feature vector representing high-level attributes of the individual. Subsequently, these feature vectors are collected and subjected to KMeans clustering to identify distinct individuals. The clustering process groups similar feature vectors together, with the integer number of unique clusters indicating the estimated number of distinct individuals in the video.

The final output consists of video frames marked up with bounding boxes around detected persons, saved to an output video file, and the printed count of distinct individuals. This methodology, combining real-time object detection, sophisticated feature extraction, and clustering techniques, provides a robust and scalable solution for automated person counting, enhancing the effectiveness of surveillance systems and contributing to improved security and situational awareness. Workflow of the recommended Automated person counting system can be seen in Fig. 1.

Algorithm:

1. Capture video data.
   - Let V be the video with frames {F1, F2, … , F_n}.
   - Set the frame interval k.

2. Object Detection via YOLO v3.
   - For each frame Fi (where i mod k = 0): Convert frame to a blob B:

     $$B = \text{blobFromImage}\ (Fi, 0.00392, (416, 416), (0, 0, 0), \text{True}, \text{False}) \qquad (1)$$

   - Pass blob B through YOLO network to get detections D:

     $$D = \text{YOLOv3}(B) \qquad (2)$$

   - Extract bounding boxes {B_j}, confidence scores {C_j}, and class IDs {ID_j} for persons:

     $$(B_j, C_j, ID_j) \text{ if } \quad C_j > 0.5 \quad \text{and} \quad ID_j = \text{'person'}$$

3. Non-Maximum Suppression (NMS):
   - Apply NMS to refine bounding boxes,
   - Define IoU (Intersection over Union) for bounding boxes B_i and B_j:

     $$\text{IoU}(Bi, Bj\,) = \frac{|Bi \cap Bj|}{|Bi \cup Bj|} \qquad (3)$$

   - Retain bounding boxes with the highest confidence scores that have IoU < threshold.

4. Feature Extraction Using VGG16
   - For each refined bounding box B_j: Extract ROI R_j from frame F_i: $R_j = F_i[B_j]$
   - Resize and preprocess ROI Rj:

     $$R_j\,' = \text{resize}\ (R_j, (224, 224)) \qquad (4)$$

     $$R'' = \text{preprocessInput}\ (R'\,) \qquad (5)$$

   - Pass R_j'' through VGG16 to get feature vector f_j:

     $$f_j = \text{VGG16}\ (R'') \qquad (6)$$

5. Clustering Using KMeans
   - Collect all feature vectors {fj} into a feature matrix F :

     $$F = [f1, f2, \dots , fm] \qquad (7)$$

   - Apply KMeans clustering to feature matrix F :
   - Define the number of clusters K.
   - Initialize cluster centroids {μ_k}K.
   - Assign each feature vector fj to the nearest centroid:

     $$C_j = \text{argmin}\ \|f_j - \mu^k\|^2 \qquad (8)$$

   - Update centroids based on assigned vectors:

     $$\mu_k = \frac{1}{|C_k|} \sum_{f_k \in C_k} f_i \qquad (9)$$

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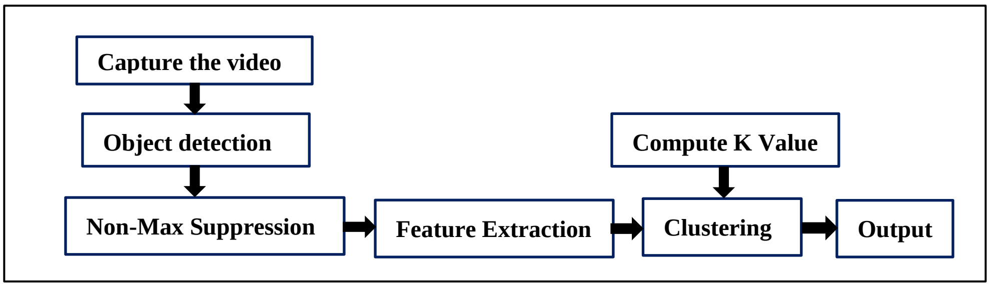
where C_k is the set of vectors assigned to cluster k. Iterate until convergence.

6. Output Generation
   - Annotate frames with bounding boxes.
   - Save annotated frames to an output video file.
   - Print the number of distinct individuals N :
   - N = number of unique c_j



- Fig. 1. Workflow of the recommended Automated person counting system

IV. RESULT AND DISCUSSIONS

The implemented automated person counting system underwent evaluation through a video dataset captured from a surveillance scenario, processing video frames at intervals to balance computational efficiency and accuracy. The system utilized the YOLO v3 model for object detection, demonstrating high accuracy in detecting and localizing individuals with bounding boxes. A confidence threshold of 0.5 was applied to ensure only reliable detections were considered. For feature extraction, the VGG16 model was employed, successfully capturing high-level attributes from the detected persons' regions of interest (ROIs), which were crucial for differentiation between individuals. KMeans clustering was then applied to group similar feature vectors, effectively identifying distinct individuals in the video. However, the accuracy achieved by the system was dependent on the choice of the k value in the clustering algorithm, with the current system achieving only 70% accuracy. The choice of 30 clusters provided a reasonable estimate of the numeral of unique persons, but there is a criterion to explore better clustering algorithms to improve accuracy. Consequently, the system's capability to differentiate between multiple persons was demonstrated, but further refinement is essential to enhance its performance.

V. CONCLUSION AND FUTURE AVENUES

The automated person counting system demonstrated effective performance in in identifying and tallying unique individuals in surveillance videos, leveraging state-of-the-art deep learning models specialized for task of object detection and feature extraction, combined with efficient clustering techniques, to achieve high accuracy and reliability. However, challenges such as computational load, occlusions, and the necessity for adaptive clustering remain. Subsequent efforts will prioritize integrating tracking algorithms like SORT or DeepSORT to maintain consistent identities across frames, implementing adaptive clustering methods to dynamically determine the optimal number of clusters, and exploring edge computing solutions to provide real-time processing capabilities directly at the surveillance site. These enhancements aim to further improve the system's robustness, scalability, and practical applicability, making it an invaluable tool for modern surveillance operations and enhancing overall security and monitoring efficiency.

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