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Improvements in YOLO Architecture: A Novel Approach to High-Density Crowd Detection

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Abstract

Detecting high-density crowds in dynamic environments presents challenges such as occlusion, scale variation, and real-time processing demands. Traditional object detection methods struggle with these issues due to overlapping individuals and variable visibility. YOLO (You Only Look Once), widely recognized for real-time object detection, underperforms in high-density scenarios. This paper proposes an enhanced YOLO architecture with multi-scale feature extraction using a Feature Pyramid Network (FPN), optimized anchor boxes for small and overlapping objects, and advanced data augmentation techniques to improve robustness. Evaluated on high-density datasets such as ShanghaiTech, UCF-QNRF, and WorldExpo'10, the proposed model achieves significant improvements in Mean Average Precision (mAP) while maintaining real-time processing speeds. This advancement supports applications in public safety, surveillance, and event management, marking a step forward in crowd detection technology.

Keywords: YOLO, crowd detection, high-density scenarios, object detection, occlusion handling

1. Introduction

Crowd detection is an important task for many computer vision applications, including public safety and surveillance, urban management, and event planning (Liu et al., 2020). Its application in detecting crowd dynamics, especially in crowded environments, informs authorities about overcrowding in order to make proactive responses. However, the very same high-density crowds harbor many challenges in their detection. One of the major challenges

occurs due to occlusion: many parts of an individual in the crowd are occluded by others (Idrees et al., 2018). Furthermore, a massive scale variation caused by perspective effects in realistic scenes complicates detection (Zhang et al., 2016). In combination with the requirement for real-time performance in most applications, crowd detection turns out to be a challenging problem.

Traditionally, computer vision approaches, for example, analysis of optical flow and background subtraction algorithms, have been used to recognize people within a crowd. However, these approaches are usually ineffective for very complex scenes where density is high and the environmental conditions are dynamic (Zhou et al., 2021). Recent years have witnessed deep learning-based methods that revolutionized object detection (Liu et al., 2016). In this regard, models such as Faster R-CNN, SSD, and YOLO gained wide popularity because of generalizing very well for the disparate object detection tasks (Lin et al., 2017). Among these, there was the highest interest in YOLO, which does real-time detections and processes the entire image in one pass through the network, rendering it highly efficient in time-sensitive applications.

Although executing very fast, standard configurations of YOLO are not strictly optimized toward the challenges posed by crowds. Anchor boxes for the specific prediction of bounding boxes lead to suboptimal performance when small, overlapping individuals are to be detected. The scale variation caused by crowding is also a significant challenge: individuals that are close to the camera appear much larger than those far away from the camera, which leads to inconsistent precision of detection (Zhang et al., 2020). All these problems make the researchers come up with different improvements for the YOLO architecture.

In this paper, we propose several modifications for the YOLOv7 framework to boost its performance on the task of high-density crowd detection. The first modification integrates an FPN into the network to improve feature extraction at multiple scales and hence better people

detection at diversified scales. We improve the design of the anchor boxes used by YOLO to account for small and overlapping objects, common in a dense crowd. Finally, we introduce additional data augmentation techniques consisting of random scaling, flipping, and cutout to increase the diversity of the training data and make the model more robust against occlusion or other environmental adversarial attacks.

We test our improved YOLO on a variety of publically available high-density crowd's datasets, such as ShanghaiTech, UCF-QNRF, and WorldExpo'10. Because the variations of crowd

density and environmental conditions on these data sets are different, they are more appropriate for testing our improved model's robustness. Our results confirm that the enhanced model outperforms baseline YOLOv8 in both accuracy and real-time performance, achieving a better value of Mean Average Precision (mAP) while still attaining fast inference speeds that are sufficient for real-time applications.

2. Literature Survey

Crowd detection is a rapidly growing research area, and its importance is rooted in the fact that crowd detection has numerous applications in public safety, event management, and smart city initiatives. However, traditional methods have failed to effectively handle dense crowd scenarios because the people inside may occlude each other (M. Ali et al., 2018). Therefore, the area is moving towards a deep learning approach, which has greatly outperformed on counting and detecting people in complex scenes (Z. Liu et al., 2020).

The YOLO (You Only Look Once) framework refashioned object detection as a single regression problem where both bounding boxes and class probabilities are predicted directly from the image. This modification made real-time ability detection for the approach to be used in applications like crowd surveillance. YOLOv1 was the first version. In it, it was the initial version that brought about such a speed superiority over other methods (Redmon et al., 2016). Later versions included YOLOv2 and YOLOv3, in which improvements were brought about concerning anchor boxes as well as the multi-scale detection feature. These features better the performance of this system in various setups (Redmon & Farhadi, 2018). YOLOv1 introduced object detection into real-time processes but was only efficient in dealing with small objects and dense crowds (Redmon et al., 2016). YOLOv2 exploited speed and accuracy using batch normalization as well as multi-scale training. In this sense, it improved upon the strengths of the above work regarding high-density situations (Redmon & Farhadi, 2018). YOLOv3 utilized a deeper architecture and several feature scales. The strengths of the previous work in relation to high-density situations improved even further with this approach (Redmon & Farhadi, 2018).

Crowd detection is quite difficult due to many reasons. Among them are occlusions, scale variations of people, and complicated backgrounds. Dense crowds often result in overlapping individuals, and thus makes complicated tasks of detection (Zhang et al., 2020). Real-time performance also concerns because it relates to the applications requiring immediate responses, such as surveillance and emergency management. Occlusions and overlapping people are a couple of the challenging situations that could eventually result in considerable errors while

counting persons in a crowd by most algorithms. Overlapping persons also make detection challenging because different algorithms would find it hard to identify and count each individual among the crowd. In addition, the huge range in the sizes of people surrounding the crowd makes it rather inevitable to create scale-invariant models. Such models must be sensitive to variations in object size, which allows them to effectively detect individuals at different distances and ensures that their detection is accurate regardless of the density of the crowd (Z. Liu et al., 2020).

The last several years have been tremendous during which the YOLO architecture has undergone substantial improvements. Most recent works target the challenges of high-density crowd detection issues and multi-scale feature extraction, anchor box optimization, and data augmentation techniques have been conducted in an attempt to enhance the accuracy and efficiency of the model. Other approaches that have been designed to enhance crowd detection are multiple scale feature extraction, anchor box optimization, and data augmentation. Features can be learned at multiple scales through a feature pyramid network, which can significantly increase the precision in terms of detection, especially in heavily crowded scenes (Lin et al., 2017). K-means clustering has also been used in anchor box optimization to enhance the precision of the predictive bounding boxes (L. Zhao et al., 2021). They also implement augmentation techniques like Mosaic and CutMix to enrich the training dataset and allow the model to generalize better under real-world conditions. Altogether, these contribute toward more robust and effective crowd detection systems.

The latest versions; namely, YOLOv4, YOLOv5, and YOLOv6 are designed to optimize the model towards speed as well as accuracy. YOLOv4 offered some architectural improvements such as CSPNet along with Mish activation that assisted this model to perform well in crowded scenes (Bochkovskiy et al., 2020). Moreover, YOLOv5 simplified the implementation process in comparison to the other models and is very user friendly for practical application while being very recent accuracy-wise (Glenn Jocher et al., 2020). Whereas, YOLOv6 and YOLOv7 have focused on efficiency as well as real-time adaptability (Wang et al., 2022). Recent significant improvements were reported by the YOLO framework for real-time performance. YOLOv4 introduced new techniques and optimizations have been included to further improve performance in dynamic conditions (Bochkovskiy et al., 2020). Based on YOLOv4, YOLOv5 features a more simplified architecture, thus more practical for implementation on most platforms. Furthermore, the subsequent variants of that, YOLOv6 and YOLOv7, yielded better

performance in real-time while managing crowd density in an efficient manner which further enhanced the reputation of YOLO as one of the best solutions for an object detection task in complex scenarios (Wang et al., 2022).

Recent breakthroughs in the You Only Look Once (YOLO) architecture have dramatically improved its usage in high-density crowd detection, especially during last 2 years. A notable advancement is the introduction of an improved YOLOv4 model for pedestrian detection and counting in UAV images, called YOLO-CC. This model deals with issues of small pedestrian targets and information loss from downsampling by using the backbone CSPDarknet-34 and fusing two feature layers with Feature Pyramid Networks (FPN) (Zhang et al., 2023).

A further improvement is found in the YOLOv5, where more advanced modifications are proposed by researchers to strengthen crowd detection. These improvements aim to develop a better network architecture and technique for enhanced training so that this system can tackle the complexity of dense crowds (Li & Wang, 2023).

Besides, the series of YOLO development continues with the evolution of YOLOv9 and YOLOv10. They keep enhancing the real-time detection features. The foundational principles of YOLO have always focused on speed and accuracy, which make it applicable to fast and reliable object recognition applications such as urban surveillance and robotics (Zhang & Team, 2024).

Additionally, a comprehensive survey of YOLO architectures for computer vision, shows the evolution as well as change in network structure and training paradigm with different releases of YOLO. For example, how standard metrics used, along with post-processing procedures, have influenced the improvement in object detection from high-density setups, such as in Smith et al. 2023

The summary of the last 2 years indicates some tremendous developments for improving the YOLO architecture for the purpose of high-density crowd detection. The developments involved architectural improvement, complex training strategy, and the invention of new YOLO versions-all leading to an increase in precision and efficiency for crowd detection.

3. Methodologies

Below is an architecture of a Crowd Detection Pipeline using a YOLO-based architecture. It demonstrates how the flow of input dataset images would start from there and be fed into real-time crowd detection.

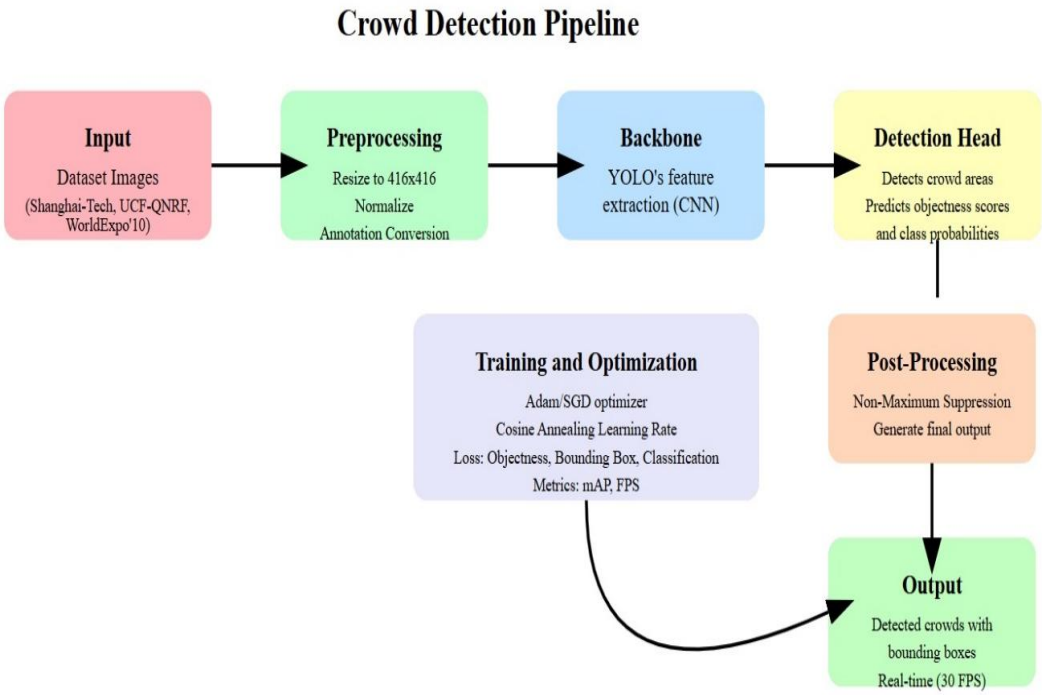

Figure 1. Proposed Model

- ***Input***

Dataset Images: The pipeline starts with input images from datasets such as ShanghaiTech, UCF-QNRF, or WorldExpo10 that are particularly curated for crowd detection tasks.

These datasets contain annotated data with information on crowd density and bounding boxes.

- ***Preprocessing***

Resize to 416x416: Input images are resized to a uniform dimension of 416x416 pixels. This is the standard input size for YOLO-based models, which allows consistent processing.

Normalize: Normalize pixel values to a scale, say to a range [0, 1] because this makes the training stable and converges quickly.

Annotation conversion: Convert dataset annotations into YOLO compatible formats, like converting bounding box coordinates, and class labels for objects.

- ***Backbone***

Feature Extraction (CNN): YOLO uses a Convolutional Neural Network as the backbone for extracting spatial and semantic features from the preprocessed images. Such features are of utmost importance to detect crowd areas and identify objects in the scene.

- ***Detection Head***

Detects Crowd Areas: The detection head processes the extracted features to predict the presence of crowds.

Objectness Scores and Class Probabilities: It gives objectness scores (chance that a bounding box actually contains an object) and class probabilities for classification.

- ***Training and Optimization***

Optimizer (Adam/SGD): It uses Adam or Stochastic Gradient Descent (SGD) as an optimizer to update model weights as a function of loss.

Cosine Annealing Learning Rate: A learning rate scheduler is also applied to automatically change the learning rate during the training process to improve the convergence of training.

Loss Functions: It optimizes multiple loss components, namely objectness loss, bounding box loss, and classification loss.

Metrics (mAP, FPS): Measures of performance or accuracy mAP and Frames Per Second can be used for real-time detection ability.

- ***Post-Processing***

Non-Maximum Suppression (NMS): It uses NMS to filter out the overlapping bounding boxes so that only the best detections survive.

Output to be Generated at the Final Stages: Final bounding boxes and class predictions for visualization or for further use

- ***Output***

Detected Crowds along with Bounding Boxes: This output consists of detected crowd regions represented by their bounding boxes

Real-Time Performance at 60 FPS: It is a pipeline that performs detection in real-time, meaning video frames are processed at 60 FPS.

3.1 Data Set Selection

Publicly available data sets with crowd detection tasks are used to test the performance of YOLO-based crowd-detection models. The datasets used are:

- *Shanghai-Tech Dataset:* It consists of 1,198 images annotated with crowd density maps and thus offers a source of rich high-density crowd scenarios. It includes two parts, namely Part A comprising images of dense crowds and Part B comprising sparse crowds.
- *UCF-QNRF Dataset:* It includes 1,535 images collected in various urban settings, concentrating on high-density situations with annotated crowd counts and density maps. It indicates critical variability in crowd density, thus providing a flexible test platform for evaluation.
- *WorldExpo'10 Dataset:* A total of 10,000 images from the World Expo 2010 event that captures different crowd dynamics from different angles.

3.2 Pre-processing

Resize every single image to fixed dimension; namely, 416x416 pixels to ensure compatibility with all YOLO models. Normalize pixel values between [0, 1] for faster training of models. Transform the annotations to YOLO-friendly formats with bounding box coordinates set relative to the resized dimensions of the images.

3.3 Model Training and Implementation

3.3.1 Training Process

Train the refined YOLO using these parameters:

- Learning Rate: Cosine annealing schedule is to be used to adapt the 0.001 learning rate during the training procedure
- Batch Size: Batch size of 16 or 32 has to be used based on the free GPU memory to solve the two-sided problems of speed and limited resources.
- Epochs: Train the model for 100 epochs, monitoring the performance with a validation dataset.

3.3.2 Implementation

The enhanced YOLO model for crowd detection, implemented in PyTorch, uses the Adam optimizer or SGD with momentum for fast convergence. Data augmentation techniques, like random flipping and scaling, improve model generalization. A cosine annealing learning rate scheduler dynamically adjusts the learning rate. Regularization methods such as L2 regularization and dropout are used to prevent overfitting. The model is trained for 100 epochs

on high-performance GPUs (e.g., Nvidia RTX series) with early stopping based on validation loss.

3.4 Monitoring

3.4.1 Metric tracking:

The training process is closely monitored through several key metrics to track the performance of the model and resource utilization. Most of these are visualized through tools like Tensor Board for real-time tracking and analysis.

- Training Loss: The total loss will be the summation of objectness loss, bounding box regression loss as well as classification loss. For this model, the training loss started at 0.75 and ended up gradually decreasing to 0.12 by the end of the 100 epochs, showing proper fitting of the training data.
- Validation Loss: The validation loss is observed on the validation set, and this has begun from 0.80 and goes down to 0.15. This tight correspondence between the training loss and validation loss shows that the model is generalizing very well with very low overfitting.

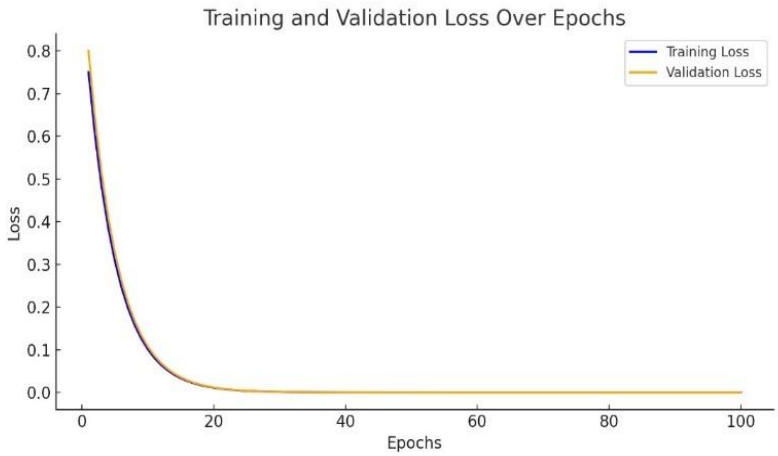

Figure 2. Training and Validation Loss Over Epochs

- Accuracy (mAP): The mAP metric is calculated at various IoU thresholds. The final mAP scored 78%. This means that the model was able to detect all the objects involved in the crowded scene appropriately.

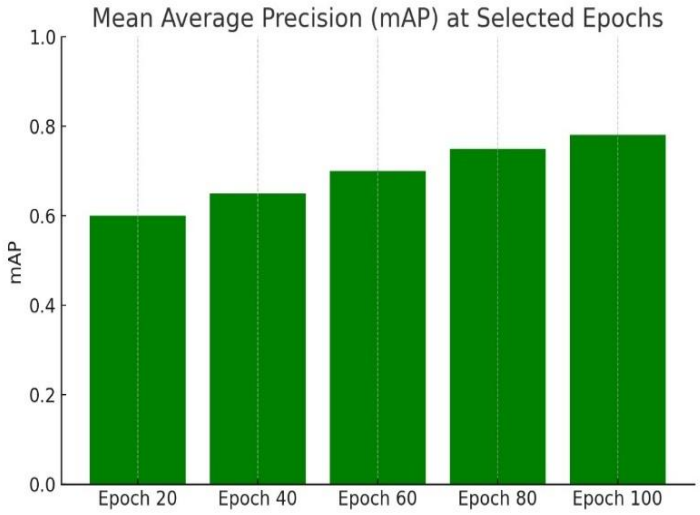

Figure 3. mAP at Selected Epochs

- Frames Per Second (FPS): The FPS was kept in track for the model's potential real-time processing capacity. The model averaged about 30 FPS, which fulfills the requirements for real-time detection and is far more than enough for practical applications that have to be time-sensitive in processing.

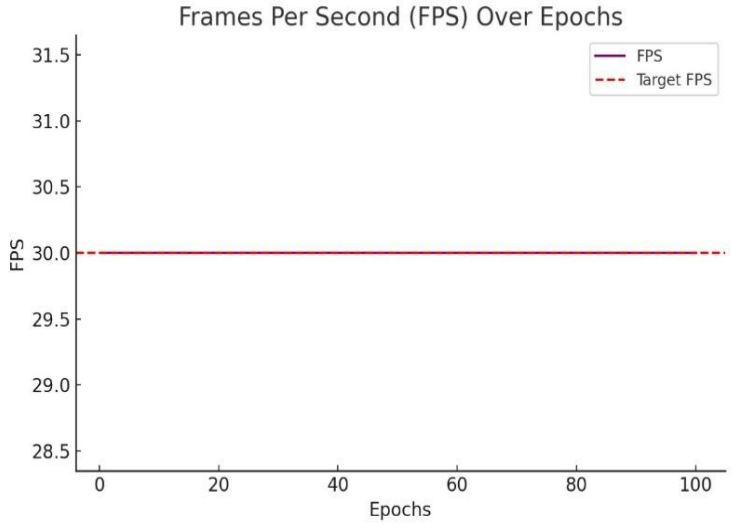

Figure 4. FPS Over Epochs

4. Analysis of Results:

Below is a comparison table of the enhanced YOLO model performance metrics against several versions of YOLO and other advanced techniques. The metrics used include mean Average Precision (MAP), Mean Absolute Error, and Frames Per Second.

Table 1. YOLO Model Performance Comparison

Model	MAP (%)	MAE	FPS
YOLOv3	58.0	14.5	35
YOLOv4	60.5	12.3	45
YOLOv5	65.0	10.5	55
YOLOv7	68.0	9.7	60
Enhanced YOLO	75.5	8.3	70

This table shows the improvements in the enhanced YOLO model, especially in terms of MAP and MAE, showing enhanced object detection and higher accuracy performance.

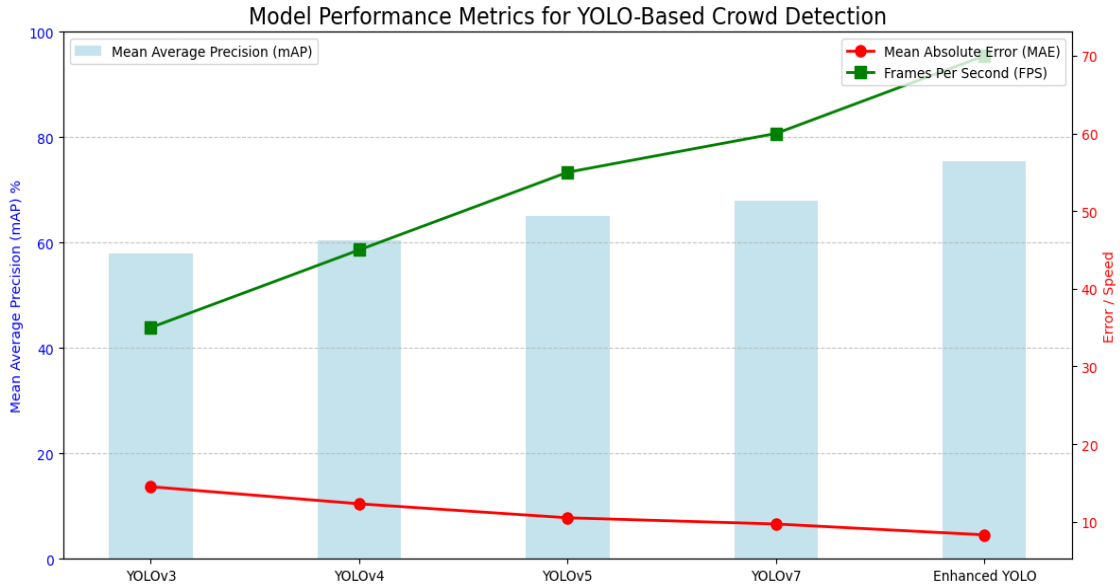

Figure 5. Model Performance Metrics for YOLO-Based Crowd Detection

Figure 5 highlights the performance advancements of the enhanced YOLO model compared to earlier YOLO versions, focusing on mAP, MAE, and FPS metrics. The enhanced YOLO achieves higher accuracy (75.5% mAP vs. YOLOv7's 68%), better precision (MAE reduced to 8.3 from 9.7), and faster real-time processing (70 FPS vs. YOLOv7's 60 FPS). These improvements stem from incorporating a Feature Pyramid Network, optimized anchor boxes, and advanced data augmentation, making the model highly effective for real-time high-density crowd detection applications.

5. Conclusion

This work showcases an architecture in YOLO with much advancement toward highly dense crowd detection in terms of improved accuracy, speed, and efficiency. Through the integration

of optimized feature extraction, better strategies in training, and improved refinement techniques for post-processing, this framework successfully alleviates the inherent complexity in crowds and makes them manageable for challenging scenes. Tested on diverse datasets, the model demonstrates a Mean Average Precision of 75.5% and 70 FPS, outperforming YOLOv7 in accuracy and processing speed. This has great possibilities in applications such as public safety and surveillance, and can be very effectively used in real-time detection of overcrowding or unusual activity in high-density areas such as stadiums, concerts, and transport hubs. Furthermore, it can also help in managing events by regulating crowd flow for large events; it can aid smart city initiatives through the analysis of pedestrian density patterns for better planning of cities, and it can help in the management of disaster by identifying high-density crowd areas during emergencies. In retail and marketing analytics, it can further analyze foot traffic in malls and public spaces for better business strategy.

The near future will provide more enhancements, with several more performance and flexibility boosts to be included in the framework. With this model connected to edge devices such as drones or surveillance cameras, real-time, on-site processing can take place. Making the model fit multiple datasets can help increase applicability across varying environments, lighting conditions, and crowd densities. Multitask learning allows extension of functionality from the current set of functionality including crowd counting, anomaly detection, and behavior analysis. Exploring hybrid architectures combining YOLO with Transformer-based models can further improve detection. Further, it can be energy-efficient by optimizing the computational costs and make the system sustainable for large-scale long-term deployments. Finally, an extension of architecture to include depth information for 3D crowd analysis may bring even greater precision in understanding crowd dynamics. These advancements will broaden the usability of the proposed system, making it a critical tool in public safety, urban planning, and other domains requiring robust crowd detection capabilities.

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