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SMART CROWD MONITORING SYSTEM USING IOT-BASED YOLO-GHOST

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Internet of Things (IoT) devices offer an innovative, sophisticated, real-time surveillance solution for public spaces. However, due to instantaneous lighting changes and varying viewing angles, counting and tracking the people in crowded scenes is a challenging problem. To combat these issues, a novel YOLO-CROWD is proposed for an innovative crowd-monitoring system using YOLO-GHOST. Initially, an Internet Protocol (IP) based camera was used to monitor and capture crowds in a video sequence. The captured video sequences are converted into frames and passed to the server via the Internet. The recorded frames are given to the YOLO-GHOST classification module to perform people detection and counting. Finally, the detected output results are transferred to the surveillance monitoring center's server. The YOLO-CROWD technique is simulated by using MATLAB. The effectiveness of the proposed YOLO-CROWD technique is assessed using evaluation metrics such as accuracy, precision, recall, sensitivity, F1-score, and mean average precision. The experimental results show that the accuracy of the YOLO-CROWD has increased to up to 99.95 %, proving that its intended use is for accurate crowd detection. The detection accuracy of the proposed method is 84.9 %, 87.58 %, 93.91 %, and 97.72 % better than existing EABeD, LCDnet, CDEM-M, and Public Vision, respectively.

1. INTRODUCTION

Internet of Things (IoT) is a popular technology that has a wide-ranging impact on our lives, including social, commercial, and economic aspects. It converges with interpersonal organizations, allowing people and machines to collaborate and exchange data [1–3]. The IoT will promote using an object's unique identification and virtual representation as the foundation for the autonomous development of apps and services [4, 5]. An appropriate selection for security and emergency control is highly advantageous since automated surveillance systems immediately notice unusual and hazardous circumstances in crowded areas [6]. In environments, overcrowded streets, political events, airports, railway stations, or malls are used for safety, security, and statistical purposes. Real-time crowd monitoring systems (CMS) estimate a crucial video image analysis procedure for crowd surveillance, security, and control of the crowd's conditions [7].

Numerous locations, such as amusement parks, airports, hospitals, sports arenas, and entertainment events, are familiar places to observe large crowds or gatherings [8, 9]. A smart CMS is required to safeguard public safety, maintain high pedestrian numbers to prevent stampedes, offer improved emergency services during crowd-related emergencies, and maximize resource usage [10, 11]. Because of sudden changes in lighting, varying viewing positions and behaviors, partial or complete occlusion, intricate backgrounds, indoor and outdoor scenes, and a reduction in pixels per person as the number of persons per pitch rises. It becomes harder to count and follow the tracks of the audience as the stage expands. Figure 1 depicts the smart crowd monitoring [12, 13].

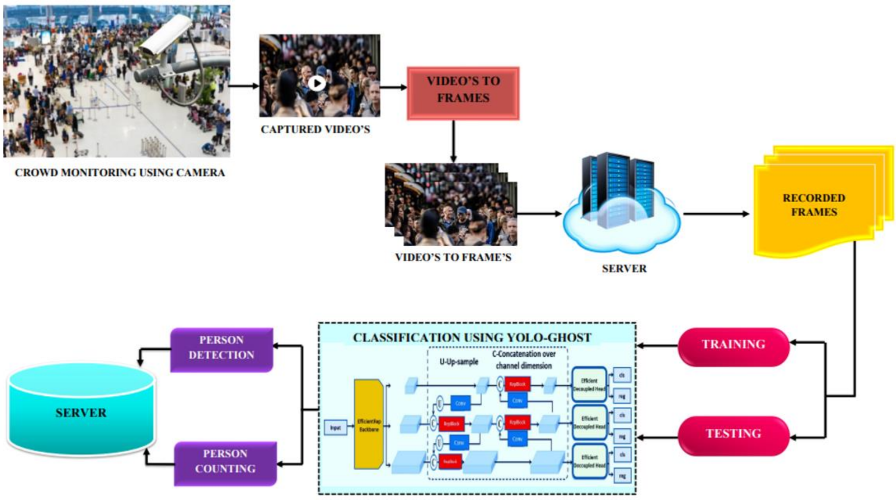

Fig. 1 – The overall proposed YOLO-SPEED methodology.

On the other hand, challenges in identifying crowd activity include low resolution with dynamic background, patterns in crowd behavior, individual separation, and random fluctuations in the crowd [14]. Therefore, effective descriptor extraction, including crucial information about motion and scene change and a dependable classifier, is

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needed for reliable crowd behavior identification [15]. To overcome these drawbacks, an innovative IoT-based smart crowd monitoring system called Yolo-crowd is developed [26–31]. The suggested Yolo-crowd approach makes the following primary contributions.

- At first, video footage of crowds was recorded and monitored using IP cameras. The video that has been recorded will be transformed into images and sent over the Internet to the server.
- The recorded frames are given to the Yolo-ghost classification module to perform people detection and counting.
- The counting module processes the coordinate data of the detected bounding box after the detection module uses it to identify people within the bounding box. Furthermore, the server receives and uses the detected outputs for the monitoring control center.
- The effectiveness of the proposed Yolo-crowd technique is assessed using evaluation metrics such as accuracy, recall, precision, F1-score, sensitivity, and mean average precision.

The following is the work structure presented in this paper: section 2 provides an overview of relevant research. Section 3 presents the deep learning-based Yolo-crowd detection model. Section 4 thoroughly explains the framework's outputs and performance assessment. Conclusions and future works are outlined in section 5.

2. LITERATURE SURVEY

Researchers developed many crowd analysis and monitoring methods, primarily based on front or side camera views and utilizing data about the head region. Several Deep Learning (DL) and Machine Learning (ML) techniques were developed, particularly to enhance IoT devices' intelligent crowd-monitoring systems. In this section, several related works are briefly explained below.

In 2021, Ahmed I. *et al*. [16] suggested a transfer learning-capable SSD-based Internet of Things crowd monitoring system. The proposed approach for crowd monitoring attains a 95% overall accuracy rate. Due to the comparable randomization of the various classifications, the system contains some categorization errors. In 2021, Xiao W. *et al*. [17] suggested deploying multiple drones in a secure blockchain-based crowd-monitoring system. The proposed technique applies an encryption algorithm and security protocol that ensure the security of each phase of the system, facilitating the drone team's cooperation in performing each surveillance operation. trustworthy.

In 2021, Rajendran L. and Shankaran R.S. [18], the big data concept renders real-time crowd surveillance with deep learning and artificial intelligence possible. The suggested method uses the data gathered to develop a framework for efficient crowd control or evacuation plans that reduce the possibility of dangerous situations and water spills. In 2022, Farooq M.U. *et al*. [19] suggested a deep learning technique based on motion patterns to identify different behaviors in a crowded area. In the FTLE domain, crowd-dominated motion is represented by LCS, and every unknown image is predicted to exhibit normal or unexpected behavior by combining CNN with supervised training.

In 2022, Choi H. *et al*. [20] suggested crowd computing and device-free localization using WiFi sensors and machine learning. Wi-CaL technique achieved positioning accuracy of 91.4 % and 98.1 %, with MAE values of 0.35 and 0.41, respectively. In 2022, Wang S. *et al*. [21] suggested a lightweight convolutional neural network and enhanced intelligence to estimate crowd density. Experiments are conducted to assess the accuracy and inference speed of the proposed approach using a public crowd image dataset.

Table 1

Comparison table for the proposed and existing methods

Author	Proposed Method	Strength	Weakness
Ahmed, I. *et al*. [16]	IoT-based crowd monitoring system using SSD with transfer learning.	MobileNetV2 serves as base network for SSD person detection.	The system has certain misclassifications due to the similar randomization of different classes.
Xiao, W. *et al*. [17]	A blockchain-based secure crowd monitoring system using UAV swarm.	The technique ensures drone team surveillance security.	The suggested approach consists of limited performance.
Rajendran, L. and Shankaran, R.S., [18]	Bigdata enabled realtime crowd surveillance using artificial intelligence and deep learning.	The method develops crowd control plans, reducing danger and water spills.	The system accuracy is limited with illumination changes and in complex crowded scenes.
Farooq *et al*. [19]	In densely populated locations, motion patterns are used by DL systems to identify various actions.	In FTLE, LCS represents crowd motion, and a CNN predicts image behavior.	Unfortunately, because of overlap, the system produced a head detection error.
Choi, H. *et al*. [20]	ML-based localization, crowd counting, and device-free Wi-Fi detection.	ML and DL evaluate Wi-CaL, detecting static and dynamic crowd conditions.	The suggested approach was not able to detect human silhouettes clearly.
Wang, S. *et al*. [21]	Lightweight CNN and enhanced intelligence, estimate the density of the crowd.	A lightweight CNN crowd density model uses modified MobileNetV2 with dilated convolution.	In dense crowds, however, the accuracy of the model diminishes proportionately.
Y. Zhen *et al*. [22]	Efficient Adaptive Beacon Deployment Optimization.	The strategy reduces walking distance and optimization time pointedly.	However, random motion and overlap render this approach ineffective.
M.A. Khan *et al*. [23]	A lightweight crowd density estimation model for real-time video surveillance.	LCDnet achieves MAE 21.4% on DroneRGBT and CARPK datasets, close to MCNN's 10.1%.	However, the detection accuracy of the system degrades in a complex crowd.
X. Zhang *et al*. [24]	GIS and video surveillance form the basis of the crowd density mapping and estimating technique.	CDM achieves 86.29% classification accuracy.	However, the suggested approach consists of limited system accuracy.
Qaraqe, M., *et al*. [25]	An intelligent, secure surveillance system to recognize the behavior of crowds.	PublicVision uses Swin Transformer for secure video surveillance.	However, obtaining an exact trajectory in a multi-layered crowd is challenging.

In 2023, Zhen Y. *et al*. [22] suggested using adaptive beacon deployment to optimize indoor crowd monitoring. According to the findings, the proposed strategy, which relies on dense data collection, reduces both walking distance and optimization time by 90.2 % and achieves a detection range that is 26.4 % higher than that of the simulation-based method. In 2023, Khan M.A. *et al*. [23] suggested a lightweight crowd density estimation model for real-time video surveillance. The suggested LCDnet technique is evaluated by using the DroneRGBT and CARPK datasets and obtains an MAE of 21.4 %, which is close to the MCNN of 10.1 % and equal to the MCNN of 17.9 % and MAE of 13.1 %.

In 2023, Zhang X. *et al*. [24] suggested a crowd density estimation and mapping method based on surveillance video and GIS. According to the experimental results, the CDM's classification accuracy is 86.29 %, and CSSM's test accuracy is 96.70 %, enabling high-precision crowd extraction in massive crowd-ed scenarios. In 2024, Qaraqe M. *et al*. [25] suggested a secure surveillance system to recognize the behavior of crowds. The suggested PublicVision is an intelligent and secure end-to-end surveillance system that uses a Swin Transformer-based DL model for identification and analysis to provide video surveillance data to a distant center. According to related studies, many ML and DL methods have been applied to IoT devices' smart crowd-monitoring systems. To overcome these challenges, the Yolo-crowd technique is proposed to address this issue by using IoT devices for intelligent crowd surveillance.

3. **YOLO- CROWD METHODOLOGY**

This section proposes a deep learning-based Yolo-crowd system for intelligent crowd monitoring. This system efficiently detects and counts the number of people entering and leaving the venue. Fig. 1 depicts the overall block diagram of the proposed methodology.

3.1. CROWD MONITORING SYSTEM.

The recorded frames are given to the Yolo-ghost classification module to perform people detection and counting. This module accepts crowd-captured images with no restrictions on input image size. Before cropping and compression, the input image size was examined to ensure it was 600×600 pixels. The Visual Genome dataset is used to train the Yolo network. Recorded images are gathered over the Yolo V5 network and analyzed for human detection. By enhancing the network structure of Yolo V5, which is Yolo-ghost, the network structure is carried out for this research. The web's four components comprise the head, backbone, neck, and prediction. The Yolo-ghost model's architecture is depicted in Fig. 2.

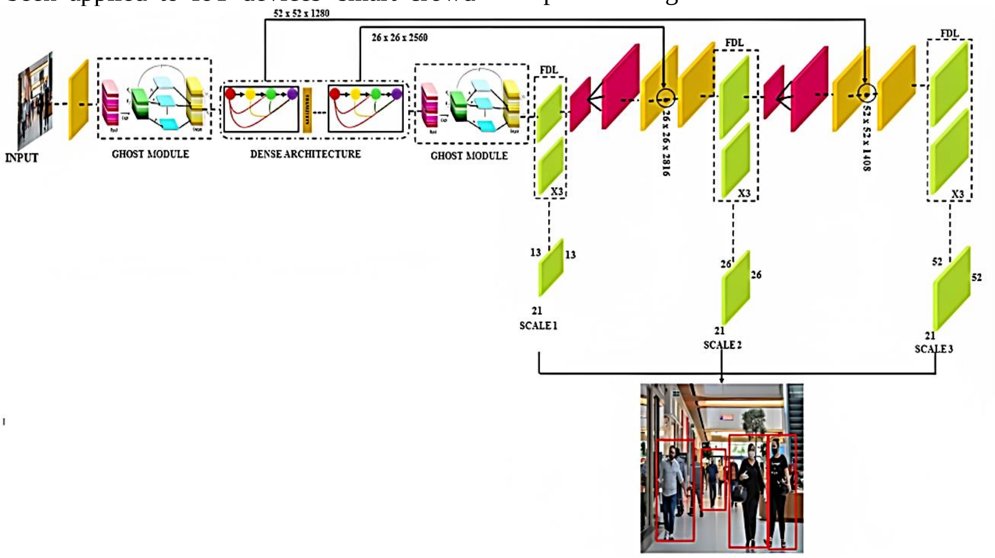

Fig. 2 – Architecture of Yolo-ghost.

The adaptive anchor framework modified the network settings. It independently determined the value of dark anchor frames by identifying numerous anchor frames and continuously updating the difference between detected and labeled frames. Ghost convolution builds the Focus, SPP, and BottleneckCSP backbone networks. To address the issue of non-overlap between the predicted and labeled boxes, the bounding box loss function during detection is set to LoU Loss.

3.2. PERSON DETECTION PROCESS USING YOLO-GHOST

The CSP bottleneck mostly integrates feature maps at various scales and extracts deep semantic information from images for semantic data enrichment. Feature maps are inserted at the top and bottom of the network after CSP mixing to reflect changes in gradients. The following equation 1 is given below

$$y = F(x_0) = x_k = H_k(x_{k-1}, H_{k-1}(x_{k-2}), H_{k-2}(x_{k-3}), \ldots, H_1(x_0), x_0). \quad (1)$$

The k^{th} layer is an operator function, and H_k typically consisting of an activation function and a convolution layer.

$$y = M\left(x_{0'}, T\left(F\left(x_{0''}\right)\right)\right), \quad (2)$$

where x_0 can be divided into two parts along the channel. The slope is truncated by function *T*, and the two portions are mixed by function *M*, which is used to obtain an information-rich feature map.

3.3. GHOST CONVOLUTION

In this module, virtual convolution uses only one region of the feature map to prevent redundancy in the feature map generated by normal convolution. The input function is shown by $X \in R^{c \times h \times w}$, the height and width of the map objects are indicated by *H* and *W*, and the channel number of the input function tag is indicated by *C*. The working of the conventional convolution is described by

$$Y = X * f + b. \tag{3}$$

X represents a feature map with an output channel in the above equation. The following equation is described by

$$Y' = X * f' + b. \tag{4}$$

The output feature is represented by $Y' \in R^{h' \times w' \times m}$, and the size of this convolutional layer is represented by $f' \in R^{c \times k \times k \times m}$. Comparing the output feature map to a standard convolutional layer, there are *m*, *n* less channels

$$y_{ij} = \phi_{i,j}(y_i') \ . \tag{5}$$

In eq. (5), where y_i stands for m feature maps of Y', indicates the linear transform class that represents the creation of redundant feature maps. To produce s feature maps, each feature map in Y' goes through a small linear transformation called $\phi_{i,j}$ (*j* = 1, 2,..., *s*). The detection module uses a bounding box to find persons.

3.4. GHOST CONVOLUTION

A list of objects is generated to count all the people, and data is organized for each bounding box found in the count list. The same procedure determines how many individuals are arriving and leaving the scene. Two virtual routes, A1 and A2, are established for the scenario. The bounding box information is recorded in the output list when you connect the scene and pass through A1, but it will be recorded in the exit list when you leave the scene and pass through A2. The detection and counting of people are shown in Fig. 3.

Fig. 3 – Person detection and counting.

Two lines A1 and A2, represented by green lines, are utilized for counting. A pink rectangle that crosses A1 and A2 serves as a representation of the two detected bounding boxes. Yolo-ghost is a deep learning technique that is used to detect persons. Video sequences were randomly transformed into video frames to create training and testing samples. This module counts each identified bounding box and records the person detection information. Two predetermined ROI lines, A1 and A2, are used to count people entering and exiting the field. The incoming object list is updated with information about the bounding box identified through A1. In contrast, the server is updated with information about the bounding box detected traveling through A2.

4. **RESULT AND DISCUSSION**

This section used the Visual Genome dataset to assess the experimentation. The training data is sent to Yolo-ghost in the first step for classification, and the same video clip from the first stage is used for the tests in the second stage. The remaining section defines many metrics to gauge a device's overall performance.

4.1. DATASET DESCRIPTION

The Visual Genome collection consists of 108,077 annotated images of scene graphs with seven essential elements, including objects, properties, relationships, scene graphs, area descriptors, area charts, and QA pairings. An average of 35 objects make up each image, and 26 different characteristics and actions can be used to relate the components. The dataset is processed before being split into 80 % training, 10 % validation, and 10 % testing.

4.2. PERFORMANCE METRICS

Accuracy is a significant criterion to consider while assessing the model's performance. The accuracy of Yolo-ghost can be assessed using the equation.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}\,, \tag{6}$$

$$P = \int_0^1 P(R)\,\mathrm{d}R, \tag{7}$$

$$\text{mAP} = \frac{\sum_{i=1}^{N} AP_i}{N}. \tag{8}$$

The *P*, *R*, and *N* denote accuracy, recovery rate, and overall entries. For various models, variable processing speeds result from different hardware configurations.

4.3. PERFORMANCE ANALYSIS

Figures 4 demonstrate that the proposed Yolo-crowd model maintains high accuracy throughout the training and testing phases.

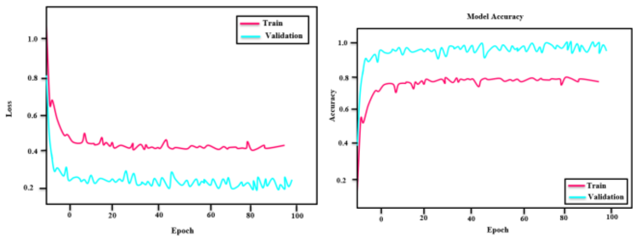

Fig. 4 – Loss curve and accuracy curve for the Yolo-crowd model.

The model's sensitivity, accuracy, specificity, and resilience form the basis of its effectiveness. The results reveal that the Yolo-crowd classifier achieves a 99.69 % accuracy rate. Therefore, the proposed Yolo-crowd method is highly suitable for crowd surveillance.

4.4. COMPARATIVE ANALYSIS

The proposed model can recognize trained deep-learning patterns with accuracy, as demonstrated by the comparison experiment, which is presented in Fig. 5. Regarding overall detection performance, the proposed strategy surpasses existing crowd detection methods.

The Yolo-ghost model prevents false positives and missed detections, providing high accuracy and real-time detection capabilities. The commonly used Yolo V3 and Yolo V4 approaches were selected for comparison. Detection accuracy is evaluated using mAP while running speed is assessed using FPS.

Figure 6 illustrates the crowd detection results achievable with this method. The effectiveness of existing techniques has been evaluated, and the proposed deep learning-based crowd-detection method demonstrates both effectiveness and accuracy.

Fig. 5 – Results of experiments using Yolo-crowd.

Fig. 6 – Crowd detection results of existing Yolo with proposed Yolo-ghost.

Performance metrics such as F1-score, mAP, recall, specificity, precision, and accuracy underscore the proposed approach's success, as depicted in Table 2.

Table 2

Performance comparison of YOLO-CROWD method

Class	Accu-racy	Speci-ficity	Preci-sion	F1-Score	Recall
EABeD	84.90	73.43	82.11	86.65	82.41
LCDnet	87.58	88.10	84.40	87.30	85.70
CDEM-M	93.91	93.99	94.45	95.54	88.97
PublicVision	97.72	94.22	95.17	96.82	96.67
Proposed	99.95	95.39	98.20	99.11	98.99

Figure 7 shows that the proposed approach outperforms other methods. It achieves an accuracy of up to 99.95 %, compared to 84.9 % for EABeD, 87.58 % for LCDnet, 93.91 % for CDEM-M, and 97.72 % for PublicVision representing improvements of 16.09 %, 13.8 %, 3.75 %, and 2.23 %, respectively.

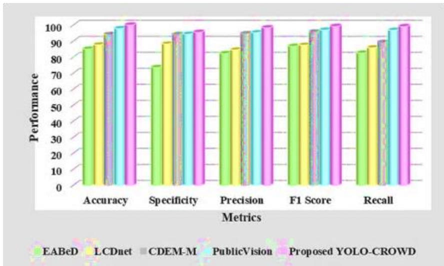

Fig. 7 – Performance of the proposed with the existing method.

The proposed approach also achieves the highest F-measure of 99.11 %, significantly higher than the existing methods.

Table 3

Comparison of mAP

Methods	EABeD	LCDnet	CDEM-M	Proposed
mAP	85.55	90.45	95.62	99.72
Frames per seconds	10	15.5	25	30.2

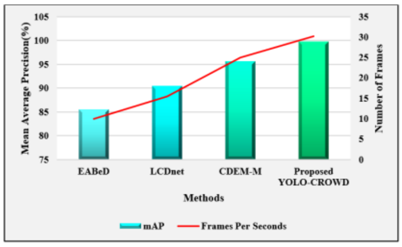

Fig. 8 – Mean average precision.

The comparison of mAP is depicted in Table 3. As shown in Fig. 8, the proposed Yolo-crowd increases mAP to 99.72 % and improves FPS by 13.5 %. This technique significantly enhances detection speed and accuracy compared to EABeD, LCDnet, and CDEM-M. Evaluating FPS and mAP across various networks reveals that the sproposed approach offers excellent accuracy and speed stability.

5. CONCLUSION

This paper proposed a Yolo-crowd approach developed for detecting and counting people using an IoT-based smart crowd-monitoring system. Using the real-time Visual Genome dataset, the proposed Yolo-crowd's performance was validated and compared to the Yolo-ghost deep learning model. The Yolo-crowd technique is simulated by using

MATLAB. According to the simulation results, a comparison is made between the proposed Yolo-crowd approach and the existing approaches such as EABeD, LCDnet, CDEM-M, and PublicVision in terms of accuracy, precision, recall, sensitivity, F1-score, and mean average precision. The experimental results demonstrate that the accuracy of the Yolo-crowd has increased up to 99.95 %, proving that its intended use for accurate crowd monitoring in real-time is due to the minimal time complexity. The detection accuracy of the proposed method is 84.9 %, 87.58 %, 93.91 %, and 97.72 % better than existing EABeD, LCDnet, CDEM-M, and PublicVision, respectively. The study will track the analysis of behavioral patterns using various data sets in the future.

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