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Variable Synergic Squeeze Convoluted Equilibrium Network Enabled Crowd Management in IoT

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Abstract: In IoT, Crowd counting is a difficult task, because of any sudden incidents people unites in a particular place. To count them effectively a crowd counting mechanism is needed. The crowd counting is help for public security. Several methods are proposed for crowd counting, but the existing methods does not provide high accuracy and high error rate. To overcome these drawbacks a Variable Synergic Squeeze Convoluted Equilibrium Network Enabled Crowd Management in IoT (VS^{2}CEN-CC-IOT) is proposed in this manuscript for crowd counting and crowd density detection. Initially, the images are taken from two datasets named ShanghaiTech and Venice dataset. Then the images are preprocessed using Gaussian filter based preprocessing. After preprocessing the discrete wavelet transform (DWT) is used for extracting the features. The extracted features are then given to Synergic Squeeze Convoluted Equilibrium Network (SSCEN) for detecting crowd count and crowd density. In this work, variable Equilibrium Optimization Algorithm (EOA) is applied to optimize the weight parameter of SSCEN. The simulation procedure is performed in PYTHON platform. The VS^2CEN-CC-IOT attains 0.8%, 1.3%, 1.5% higher accuracy, 13%, 3.3%, 8.2% higher Precision, 12%, 10%, 17% higher specificity , 8.2%, 3.3%, 6.9% higher F1-score and 0.12%, 0.06%, 0.07% lower mean absolute error (MAE), 0.2%, 0.25%, 0.1% lower root mean square error than the existing optimization approaches such as Arithmetic Optimization Algorithm(ADA), Chaos Game Optimization(CGO) and Gradient Based Optimizer(GBO) respectively.

Index Terms: Crowd Counting Detection, Crowd Density estimation, high and low density, SSCEN

1. Introduction

A modern technology paradigm known as the Internet of Things (IoT), which is also known as the Internet over Worldwide or a Corporate Internet, is envisioned as a vast worldwide system of mechanisms and gadgets that are capable of communication [1] Numerous everyday devices connected to the network in some way under the IoT model. The transition to a bidirectional network for information and communication is already obvious given the expansion of Wi-Fi and 4G-LTE wireless Internet connectivity [2] Internet of Things (IoT)Internet, billions of Wi-Fi-enabled devices such as smart TVs, smart sockets etc., being widely deployed in buildings [3] IoT services alter communication between routine equipment like house appliances, client devices, industrial controls, sensors, and any device possible [4]

Density maps record the amount and location of crowds at each pixel location [5] By integrating density maps, one can calculate the sum of persons in the crowd [6] To extract deep features from each overlapping-patches we divide the image into patches with overlaps. [7] By avoiding the traditional task of detecting and localizing individual object instances within the crowd density images [8,25] The deviation between the estimation and ground reality may be as small as viable [9] By using this technique, an increased accuracy range after processing hard samples more effectively

[10] Several deep learning-based crowd counting detections are proposed. But the existing methods provide an inaccurate detection result, overfitting issues and also very high computational time. To overcome these issues, some solutions need to be put forward to fix this problem. These are motivated to do this work.

In this manuscript, variable synergic squeeze convoluted equilibrium network enabled crowd management in IoT is proposed to detect crowd counting and crowd density valuation.

The key contributions of this manuscript are given below,

- In this manuscript, Crowd counting detection using Variable Synergic Squeeze Convoluted Equilibrium Network (VS^2CEN-CC-IOT) is proposed to for detecting crowd count and crowd density.
- Initially, input image is taken from two datasets named ShanghaiTech [15] and Venice [16].
- Then these input images are pre-processed using Gaussian filter based pre-processing method for removing noise and enhancing the input images. Then these preprocessed images are given to Feature extraction [17].
- At feature extraction, DWT method is used to extract the statistical features like Approximation features, Horizontal features, Vertical features and Diagonal features [18].
- The extracted features are given to the SSCEN for effectively detecting crowd count and crowd density.
- Then the weight parameter of SSCEN is optimized by means of EOA for minimizing the error rate [19-21] to accurately detecting the crow counting and crowd density estimation.
- The VS^2CEN-CC-IOT method is executed in PYTHON and the efficiency of the VS^2CEN-CC-IOT is analyzed several metrics like MAE, RMSE, accuracy, specificity, precision and F1 score.
- The outperforms of the proposed VS^2CEN-CC-IOT is likened with three existing approaches such as Arithmetic Optimization Algorithm (ADA) [22], Chaos Game Optimization (CGO) [23] and Gradient Based Optimizer (GBO) [24] respectively.

Remaining manuscript is organized as: Section 2 delineates the Literature survey. Section 3 illustrate the proposed methodology. Section 4 explains the outcomes and discussion. Section5 accomplishes this manuscript.

2. Literature Survey

A number of studies were previously suggested in the literature related to crowd counting and density. Among these, a few recent studies are expressed here,

In 2022, Li Z et al. [11] have proposed an effective CNN network called MSFFA, or Multi-Scale Feature Fusion and Attention was suggested. The three components of the illustrated network are the density map generators back-end, the multiscale joint optimization operators mid-end, and the low-level feature extractors front-end. While waiting, tough background scenes were exploited for important features using a global concentration mechanism module. According to experimental results, this technology performs better than several other cutting-edge approaches now in use, demonstrating its exceptional precision and stability. But this strategy required a lot of computation time.

In 2020, Bhangale U et al. [12] was presented a Multi-level feature combination-based locality-constrained longitudinal modifier network for detecting amount of people in a crowd. System employed an NVIDIAGPU processor to take advantage of the parallel computing framework in order to process video feed from a camera in a quick and flexible manner. The model receives significant training by being given many scenarios, such as overlapping heads, partial head visibility, partial head visibility, etc. This approach offers moderate accuracy but significant accuracy when predicting the head count in a dense population in a reasonable length of time.

In 2020, Fang Y et al. [13] have presented a Density map deterioration unit and Locality-Constrained Spatial Transformer (LST). By combining the low-level, middle-level, and high-level characteristics of the Convolutional Neural Networks, the density map for every frame is first estimated. It combines various regression density maps to estimate the density map for the following frame. to make it easier to calculate the effectiveness of video crowd-counting. Suggested method shows that the proposed method for crowd-counting is effective. But it did not give good accuracy.

In 2021 Zhou JT et al. [14] have presented a crowd counting with a local awareness IEEE Transactions on Pattern Analysis and Machine Intelligence. The locality-aware data partition (LADP) technique was offered as a way to categorize the training data. With the picture patches being upgraded adaptively based on the loss, LADP creates a more balanced data batch as a result. It was independent of the backbone network designs, which would improve the performance of such approaches. But the error rate was high.

2.1. Problem Formulation

From the above discussed methods several limitations are addressed such as inaccurate detection result, overfitting issues and also very high computational time. Due to these issues the detection accuracy was lowered. To overcome these limitations this research was motivated.

3. Proposed VS^{2}CEN-CC-IOT method

In this manuscript, a novel concept based on crowd density detection using a Variable Equilibrium Optimization Algorithm is proposed. Based on this concept, the area can be identified as high- and low-density of crowd. Fig. 1 shows the block diagram of VS^{2}CEN-CC-IOT and each block are explained detailly below.

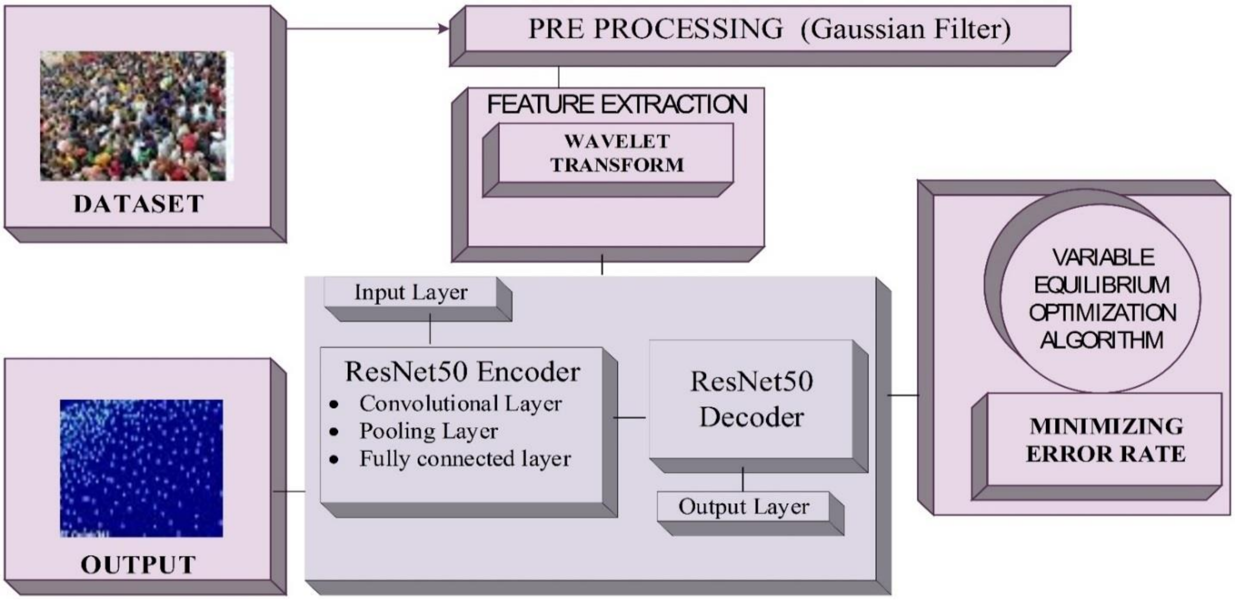

Fig. 1. Block Diagram of Proposed VS^{2}CEN-CC-IOT

3.1. Gaussian Filter Based Preprocessing

The fundamental approach for removing noise from images and improving their quality is called image pre-processing. Gaussian Filter is a low pass filter used for reducing noise (high frequency components) and blurring regions of an input image. At first, the crowd image is taken from the dataset, contains noise. For removing the unwanted noise from the image, Gaussian filter based preprocessing is applied in this VS^{2}CEN-CC-IOT. Gaussian filter is used to remove noises. The formula of Gaussian filter is given in (1).

$$G(X,Y)=\frac{1}{2\pi\sigma^2}e^{\frac{-X^2+Y^2}{2\pi\sigma^2}} \tag{1}$$

Here X indicates the distance from the parallel axis to the origin, the Y indicates the length between source and the perpendicular axis and the term σ indicates the standard deviation and it is applied to removing the noises from the image. The preprocessed image is then given to feature extraction.

3.2. DWT Based Feature Extraction

The aim of DWT is to represent the image in its compact and unique form. DWT can efficiently extract the important features from pre-processed images. Using DWT-based feature extraction, the preprocessed image is extracted, and the resulting images are divided into spatial frequency elements made up of the lower and upper sub-bands of wavelets.

The features that extracted are Approximation features (LL), it is in Low Low band, Horizontal features (LH) it is in Low High band, Vertical features (HL) it is in High Low band and Diagonal features (HH)it is in High High band and represented as in (2)-(5).

$$LL_{j+1}(e,d)=\sum_s\sum_t l_s^j l_t^j LL_j(e+s,d+t) \tag{2}$$

$$LH_{j+1}(e,d)=\sum_s\sum_t h_s^j l_t^j LL_j(e+s,d+t) \tag{3}$$

$$HL_{j+1}(e,d) = \sum_s \sum_t l_s^j h_t^j LL_j(e+s, d+t) \tag{4}$$

$$HH_{j+1}(e,d) = \sum_s \sum_t h_s^j h_t^j LL_j(e+s, d+t) \tag{5}$$

where $e = 1,2,....,M, d = 1,2,....,N$ and $'h','l'$ represents the low pass and high pass filters. After extracting these features the trained data is applied to synergic squeeze convoluted equilibrium network (SSCEN) for detecting the crowd count and crowd density estimation.

3.3. Synergic Squeeze Convoluted Equilibrium Network (SSCEN) for crowd count detection and crowd density estimation

The extracted features are given to SSCEN. A convolutional neural network with 50 layers deep is called ResNet-50. Density map estimation, which uses a CNN-based approach, estimates the density map of crowd images and integrates it to provide the final count. With the help of this ResNet50-CNN, the crowd size and density are estimated.

- ***Input Layer***

A neural network's input layer is made up of artificial input neurons that provide information into the system for processing by those neurons at higher layers. Random training is used for the input layer. The photos in this example are 32 by 32 pixels in size. We must apply the feature reduction principle before moving the data to the following layer.

- ***Compressed by Wavelet Transform***

For the wavelet transform and the Haar basis model to effectively handle the high dimensional data, we used them in this feature reduction idea. The transformations incorporate these filters to provide subtracted input coefficients. The feature reduction equation is given in (6).

$$x' = \begin{bmatrix} a \\ v \end{bmatrix} x \begin{bmatrix} a \\ \overline{v} \end{bmatrix}^T = \begin{bmatrix} ax \\ vx \end{bmatrix} \begin{bmatrix} a^T v^T \end{bmatrix} = \begin{bmatrix} axa^T & axv^T \\ vxa^T & vxv^T \end{bmatrix} \tag{6}$$

Here a and v are two filters that applied for feature reduction Learning complexity and learning time can be decreased as a result of this transition into the DCNN. The CNN architecture is scaled down together with the number of features in this procedure.

- ***Convolutional layer***

The structural foundation of the CNN is a convolutional layer. There are a number of filters whose settings must be explained during training. An activation map is created after each filter convolves with the image.

- ***Pooling Layer***

After the convolutional layer, a pooling layer is a new layer that is added. Specifically, once a nonlinearity has been added to a convolutional layer's feature mappings. Pooling layers, like convolution layers, can maintain translation invariance because they take into account neighboring pixels. The maximum and average pools are two of the most used methods for pooling.

- ***Fully connected Layer***

Neural networks that are fed forward are the Fully Connected Layer. Fully Connected Levels are the last few layers of the network. Before being sent into the fully connected layer as the input, the productivity from the previous pooling or convolutional layer is flattened.

- ***ResNet 50***

ResNet model outperforms competing models in image classification, demonstrating that it successfully extracted visual features. It makes logical to use sigmoid instead of SoftMax because the task at hand is binary image categorization, and sigmoid achieves fine by binary categorization. For multi-class categorization, SoftMax works well. The mathematic expression of sigmoid activation is given in (7)

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{7}$$

Here, x represents the dot product of every neuron values through the weight. Hence the weight parameter of SSCEN is optimized by EOA. By optimizing, the weight parameter the error rate is minimized and it increases the detection accuracy.

3.3.1. Variable Equilibrium Optimization Algorithm for Optimizing Weight Parameter of SSCEN to Minimize Error Rate

In this manuscript, the variable equilibrium optimization algorithm (EOA) approach has introduced for minimizing the error rate of SSCEN. In EOA, every solution with its concentration acts as a search agent. To finally arrive at the equilibrium state, the search agents at random change their concentration in relation to the best-yet solutions, or equilibrium candidates. The key goal of the EOA is to decrease the error rate by optimizing the weight parameters of the SSCEN. Fig. 2 depicts the EOA flow diagram. The detailed step by step procedure of EOA is given below,

Step 1: Initialization

To optimize the weight parameters of the SSCEN, first initialize the EOA 's starting variables. Initial EOA variables are based on the first order differential equation, and their weight is equivalent to the sum of the sum of candidates incoming the system and the number of candidates existing it. and its initialization equation is given in (8).

$$Variables\ \frac{dc}{dt} AC_{equilizer} - AC + H \tag{8}$$

where C is represented as the concentrations of the variable for detecting the crowd count, $C_{equilizer}$ is represented as the concentration at an equilibrium state, H is represented as the number of crowd entering into the state, A is represented as the number of flow rate with every A^{th} iteration.

Step 2: Random generation

After initialization randomly generate the exploration, and exploitation phase for attaining best solution. In this, the initial concentration of the equilibrium optimizations is built by using the number of particles and the dimensions with random generations and its equation is given in (9).

$$C_F^{initialization} = C_{\min imization} + random_F \left(C_{\max imization} - C_{\min imization}\right) i = 1,2,...,m \tag{9}$$

where $C_F^{initialization}$ is represented as the initial concentration of the vector with F^{th} particle, $C_{\max imization}$ and $C_{\min imization}$ is represented as the maximum and minimum variables of the variable equilibrium optimization for attaining best solution, $random_F$ is represented as the random vector with interval [0,1], and the m is represented as the amount of the particles of the population.

Step 3: Fitness function for optimizing SSCEN weight parameters:

In this, the fitness function of the EOA is used for optimizing the weight parameters of SSCEN classifier. The weight parameters of SSCEN is $\sigma(x)$, here $\sigma(x)$ is represented as the weight parameter which is optimized for reducing error rate. The fitness calculation of EOA is mentioned in (10),

$$FitnessFunction = \left\{ \min\left(\sigma(x) = \frac{1}{1+e^{-x}} \right) \right\} \tag{10}$$

Step 4: Updating the exploration phase of EOA

The exploration phase of the variable equilibrium optimizer is used to improve the accuracy for accurately detect the crowd count and crowd density estimation with high accuracy by varying the volume of the equilibrium with interval [0,1] and its equation is given in (11).

$$EOA_{Accuracy} = e^{-\delta(T-T_0)} \tag{11}$$

where T is represented as the time, δ is represented as the optimization parameter for improving accuracy and the search speed is increased. The time T is known as the number of repetitions and the time reduces with the number of repetitions and its equation is given in (12).

$$T = \left(1 - \frac{A_{iteration}}{Max\_A_{iteration}}\right)^{\left(\mu_2 - \frac{A_{iteration}}{Max\_A_{iteration}}\right)} \tag{12}$$

where $A_{iteration}$ and $Max\_A_{iteration}$ is represented as the current and the extreme number of repetitions and $Max\_A_{iteration}$ is represented as the constant value with optimizing parameter represented as error rate and the error parameter is optimized in exploitation phase.

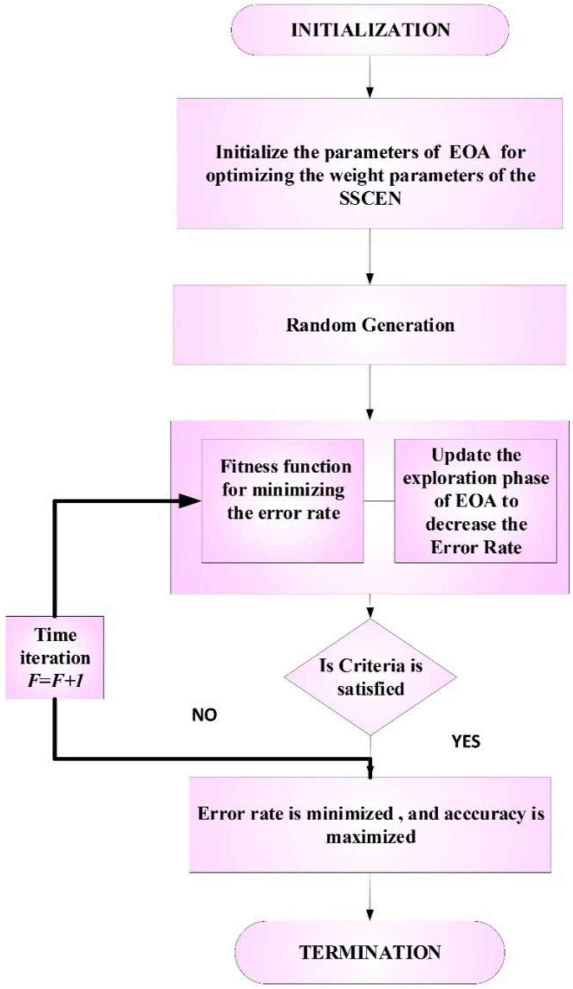

Fig. 2. Flow chart of variable equilibrium optimization

Step 5: Updating the exploitation phase of EOA to decrease the error rate (μ)

In this, the exploitation phase is utilized to decrease the error rate of the SSCEN for accurately detect the crowd count and its equation is given in (13)

$$T_0 = \frac{1}{\delta} In\left(-\mu_2 sign\left(random_{vector} - 0.5\left[1 - e^{-\delta T}\right]\right)\right) + T \tag{13}$$

where δ and μ are the constant values for improving accuracy and to reduce the error rate, there (13) reduces the error rate.

Step 6: Termination

Here, the EOA is used for optimizing the weight parameter $\sigma(x)$ to minimize the error rate. In this, the proposed VS^2CEN-CC-IOT method the crowd count and crowd density are estimated accurately. Thus, accuracy is improved. Until met the termination conditions, the algorithm iterates the step 5 to 3 till the criteria time iteration $F = F + 1$ is met.

4. Results and Discussion

In this section a variable synergic squeeze convoluted equilibrium network enabled crowd management in IoT was discussed. Here the detection of crowd counting and crowd density approximation was proposed. The evaluation metrics are accuracy, specificity, f-measure, MAE and MSE are analyzed. And the VS^2CEN-CC-IOT is compared with three optimization approaches such as Arithmetic Optimization Algorithm (AOA), Chaos Game Optimization (CGO) and Gradient Based Optimizer (GBO) respectively

4.1 Dataset Description

In this manuscript the input data is taken from two datasets named ShanghaiTech and Venice. ShanghaiTech contains part A and part B. The dataset has total 1,198 images and 330,165 annotations. From this dataset, 50% is utilized for training and 50% is used for testing. On the Venice dataset, Crowd outperforms the other approaches in terms of state-of-the-art performance. Strong transfer learning capabilities along with the extraction of low to complex characteristics are what resulted in the lowest error. Additionally, scaling up dense feature extraction and propagation to high-level layers improves the capacity to access scale-varying information.

4.2 Performance Metrics

The proposed VS^2CEN-CC-IOT is estimated using, Accuracy, precision, specificity, f1-score, MAE and RMSE.

TP' (True Positive)- positive is predicted correctly.

FN' (False Negative)- positive is predicted incorrectly.

TN' (True Negative)- Negative is predicted correctly.

FP' (False Positive)- Negative is predicted incorrectly.

$$Accuracy = \frac{TP' + TN'}{TP' + FP' + FN' + TN'} \times 100\% \tag{14}$$

$$\Pr ecision = \frac{(TP')}{(TP') + (FP')} \tag{15}$$

$$Specificit\,y = \frac{TN'}{TN' + FP'} \times 100\% \tag{16}$$

$$F1 - score = 2 \times \frac{(\Pr ecision) \times (\operatorname{Re} call)}{(\Pr ecision) + (\operatorname{Re} call)} \tag{17}$$

4.2.1 MAE (Mean Absolute Error)

Equation (18) is used to calculate MAE,

$$MAE = \frac{1}{N} \sum_{i=1}^{N} | C_i - C_i^{CT} | \tag{18}$$

where N represents the entire count; C_i and C_i^{CT} are the predicted density map and factual density map of the crowd counting.

4.2.2 RMSE (Root Mean Square Error)

Here (19) is used to calculate RMSE,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} | C_i - C_i^{CT} |^2} \tag{19}$$

where N represents the entire count of images C_i and C_i^{CT} are the predicted density map and factual density map of the crowd counting.

4.3 Performance Analysis of Proposed VS2CEN-CC-IOT Method

Fig. 3 shows the performance examination of VS^2CEN-CC-IOT. (a) shows the high-density estimation using VS^2CEN-CC-IOT method the input image is taken from ShanghaiTech A dataset, (b) shows the low-density estimation using VS^2CEN-CC-IOT method the input image is taken from ShanghaiTech dataset and (c) shows the high-density estimation using VS^2CEN-CC-IOT method the input image is taken from Venice dataset.

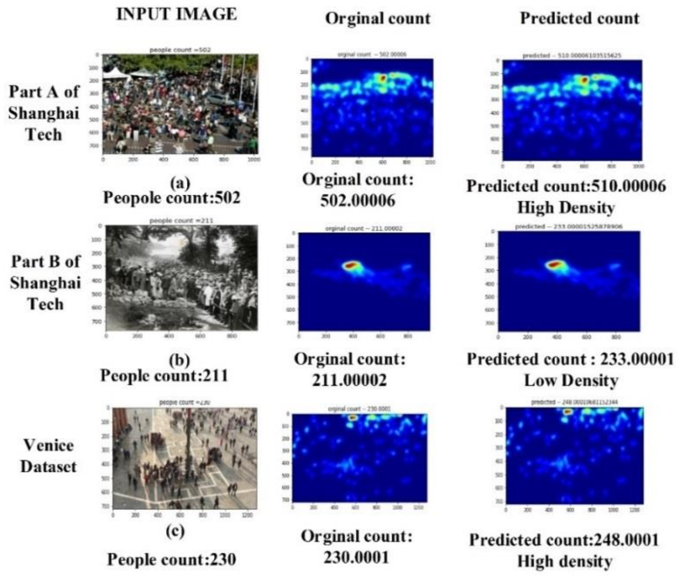

Fig. 3. Performance analysis of proposed VS^{2}CEN-CC-IOT method for crowd density estimation

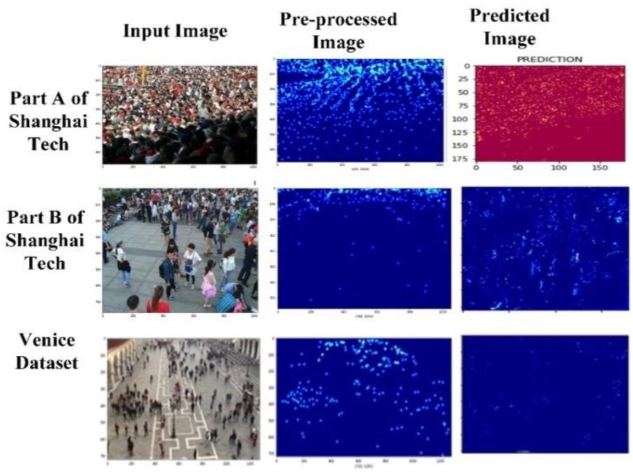

Fig. 4. Performance analysis of proposed VS^{2}CEN-CC-IOT method for crowd counting with ShanghaiTech and Venice datasets

4.4 Performance Analysis of Proposed VS2CEN-CC-IOT Method for Crowd Counting with Small Number of People

Fig. 5 demonstrate the performance analysis of proposed VS^{2}CEN-CC-IOT with small number of people. The analysis shows that the proposed method accurately predict the crowd count with small number of people.

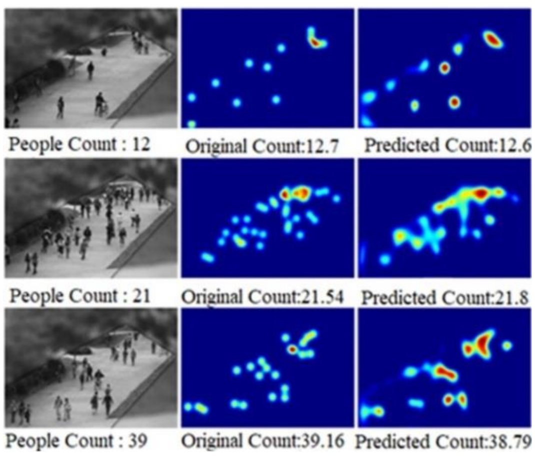

Fig. 5. Performance analysis of proposed VS^{2}CEN-CC-IOT method for crowd counting with small number of people

4.5 Performance Analysis of VS2CEN-CC-IOT with Various Optimization Methods

In this section, Figs. 6-14 illustrate the performance like accuracy, precision, specificity, f1-score, MAE and RMSE for crowd counting and crowd density are analyzed. Then the effectiveness of the VS^{2}CEN-CC-IOT is compared with ADA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively.

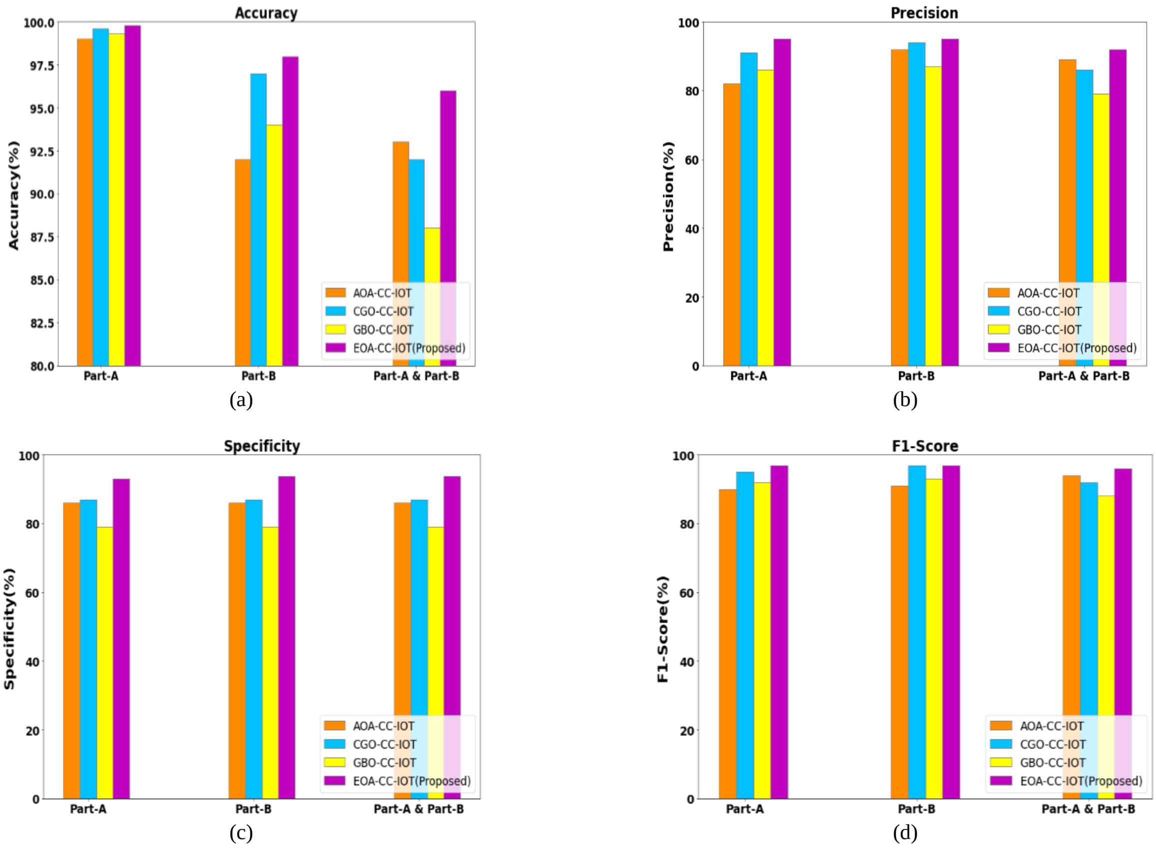

Fig. 6. Classification analysis of (a) Accuracy, (b) Precision, (c) Specificity, (d) F1-score

Fig. 6(a) illustrates the accuracy of VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. For part A in Shanghai Dataset the accuracy of the VS^{2}CEN-CC-IOT method attains 0.8%, 1.3% and 1.5% higher than the existing method. At part B of Shanghai dataset, the VS^{2}CEN-CC-IOT method attains 4.8%, 1.1% and 3.5% higher than the existing method. For both part A and B in Shanghai dataset the VS^{2}CEN-CC-IOT method attains 2.4%, 3.8% and 8.3% higher. Fig. 6(b) explains the precision of VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as ADA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. For part A in Shanghai Dataset the precision of the VS^{2}CEN-CC-IOT method attains 13%, 3.3% and 8.2%higher than the AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. At part B of Shanghai dataset, the precision of the VS^{2}CEN-CC-IOT method attains 2.2%, 1% and 8.2% higher than the existing method. For both part A and part B in Shanghai dataset the precision of the VS^{2}CEN-CC-IOT method attains 12%,14% and 19% higher than the existing method.

Fig. 6(c) shows the specificity of VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively.For part A in Shanghai Dataset the specificity of the VS^{2}CEN-CC-IOT method attains 12%, 10% and 17% higher than the existing method. At part B of Shanghai dataset, the specificity of the VS^{2}CEN-CC-IOT Shanghai dataset the specificity of the VS^{2}CEN-CC-IOT method attains 12%, 10% and 17% higher than the AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. Fig. 6(d) shows the F1-score of VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively.For part A in Shanghai Dataset the F1-score of the VS^{2}CEN-CC-IOT method attains 8.2%, 3.3% and 6.9% higher than the existing method. At part B of Shanghai dataset, the F1-score of the VS^{2}CEN-CC-IOT method attains 4.6%, 2.2% and 3.4% higher than the existing method. For both part A and part B in Shanghai dataset the F1-score of the VS^{2}CEN-CC-IOT method attains 3.3%, 6.9% and 9.5% higher than the existing method.

Fig. 7 shows the MAE analysis of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. For part A in Shanghai Dataset the MAE of the proposed method attains 0.12%, 0.06% and 0.07% lower than the existing method. At part B of Shanghai dataset, the MAE of the VS^{2}CEN-CC-IOT method attains 0.6%, 0.1% and 0.5% lower than the existing method. For both part A and part B in Shanghai dataset the MAE of the proposed method attains 0.7%, 0.6% and 0.1% lower than the AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. Fig. 8 shows the RMSE of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. For part A in Shanghai Dataset the RMSE of the VS^{2}CEN-CC-IOT method attains 0.1%, 0.1% and 0.1% lower than the existing method. At part B of Shanghai dataset, the RMSE of the VS^{2}CEN-CC-IOT method attains 0.2%, 0.25% and 0.1% lower than the existing method. For both part A and part B in Shanghai dataset the RMSE of the VS^{2}CEN-CC-IOT method attains 0.2%, 0.1% and 0.1% lower than the existing method.

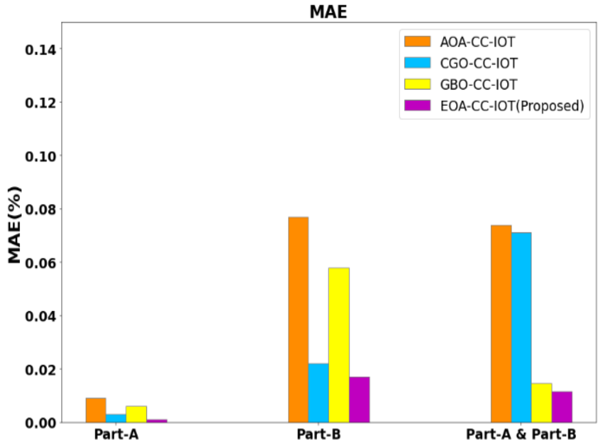

Fig. 7. MAE analysis

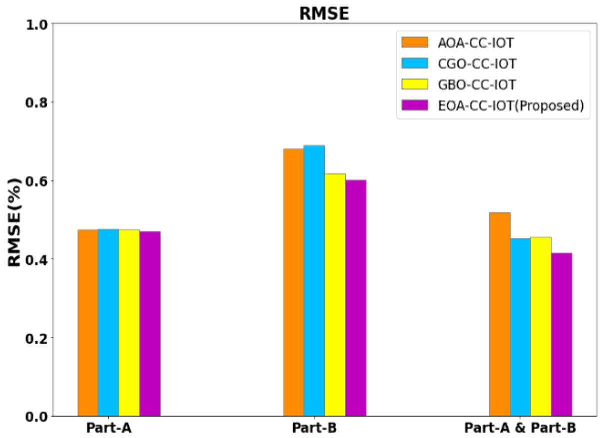

Fig. 8. RMSE analysis

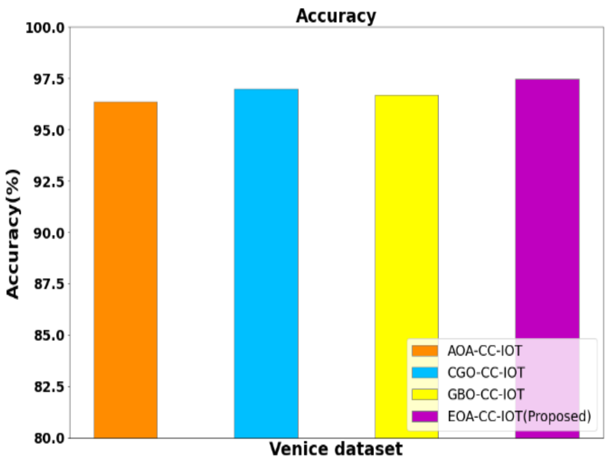

Fig. 9. Accuracy analysis using Venice dataset

Fig. 9 shows the accuracy analysis of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 1.15%, 0.62% and 1.57% higher accuracy than the AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. Fig. 10 shows the precision of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is compared with optimization methods such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 0.52%, 0.42% and 0.63% higher precision than the existing methods.

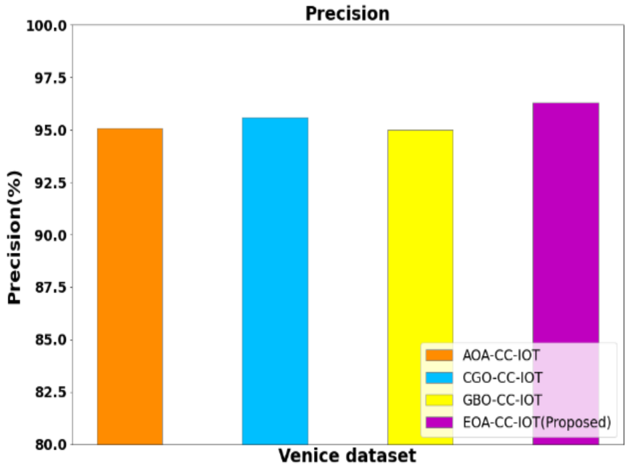

Fig. 10. Precision analysis using Venice dataset

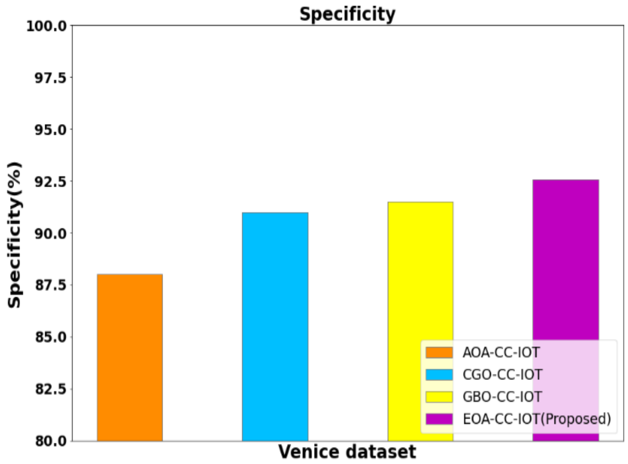

Fig. 11. Specificity analysis using Venice dataset

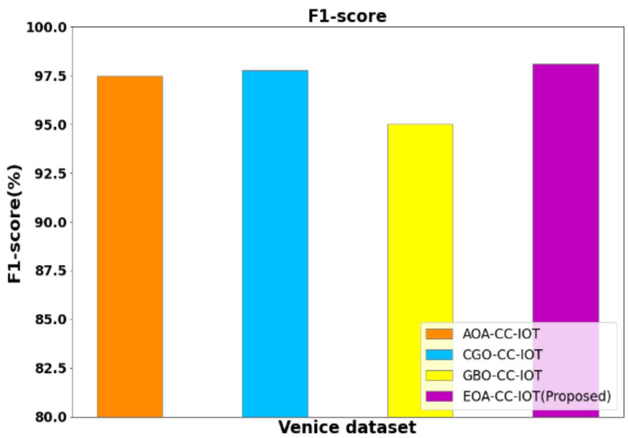

Fig. 12. F1-Score analysis using Venice dataset

Fig. 11 shows the specificity of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 4.68%, 1.77% and 1.21% higher specificity than the AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. Fig. 12 shows the F1-score of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 0.61%, 0.41% and 5.72% higher F1-score than the existing methods.

Fig. 13 shows the MAE analysis of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 0.003%, 0.002% and 0.004% low MAE than AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods. Fig. 14 shows the RMSE analysis of crowd counting and crowd density using VS^{2}CEN-CC-IOT approach. Here the VS^{2}CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. Venice data set provides 0.1%, 0.2% and 0.1% low RMSE than the ADA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT methods.

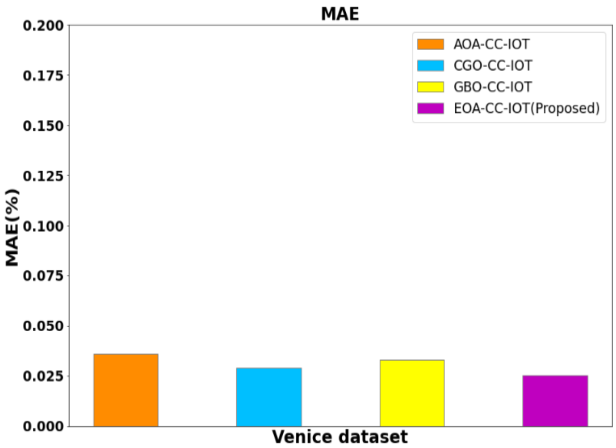

Fig. 13. MAE analysis using Venice dataset

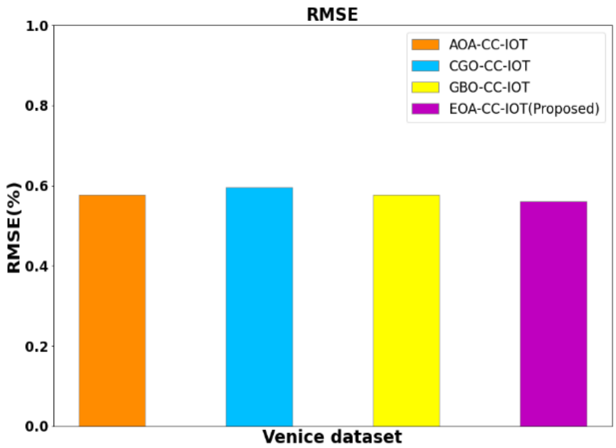

Fig. 14. RMSE analysis using Venice dataset

4.6 Comparison of ShangahaiTech and Venice Datasets

The presentation of the VS^{2}CEN-CC-IOT is likened with existing optimizations like AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively methods. Fig. 15 illustrates the Comparison of ShangahaiTech and Venice datasets of VS^{2}CEN-CC-IOT method with existing optimization methods.

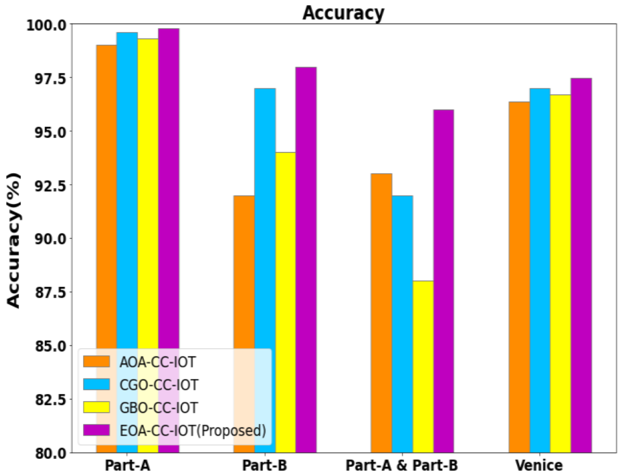

Fig. 15. Accuracy analysis comparison of ShangahaiTech and Venice datasets

Fig. 15 shows the Accuracy analysis comparison of ShangahaiTech and Venice datasets of proposed VS^2CEN-CC-IOT approach. Here the VS^2CEN-CC-IOT method is likened with optimization approaches such as AOA-CC-IOT, CGO-CC-IOT and GBO-CC-IOT respectively. For ShanghaiTech Dataset the accuracy of the proposed method attains 2.64%, 6.01% and 12.13% higher than the existing method. Venice data set provides 0.30%, 1.24% and 1.56% higher accuracy than the existing methods.

5. Conclusion

Here, Variable Synergic Squeeze Convoluted Equilibrium Network optimized with variable equilibrium optimization algorithm is successfully implemented for accurately detect the crowd count and crowd density estimation. The VS^2CEN-CC-IOT is implemented in PYTHON platform. The Error rate of SSCEN is enhanced by means of Variable Equilibrium Optimization Algorithm. The proposed VS^2CEN-CC-IOT method attains better accuracy, sensitivity, specificity, precision, recall and the proposed method minimized the error rate. And the proposed VS^2CEN-CC-IOT method is likened with the existing approaches such as Arithmetic Optimization Algorithm (AOA), Chaos Game Optimization (CGO) and Gradient Based Optimizer (GBO) respectively. Therefore, the performances demonstrate that the proposed VS^2CEN-CC-IOT method achieved improved performance by means of high accuracy and decreased error rate compared with the existing techniques. Following are a list of promising directions for future work:

- Addressing Diversity in crowd's analysis in crowds is definitely still one of the major areas where significant improvements can be made. Future research may aim to enhance the performance of the classifiers when using a combination of expert approaches.
- Localization aspect of crowd analysis is important and directly helps to support applications other than counting. Although the dense detection approach has significantly improved localization, the bounding box sizing performance still has to be enhanced.

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