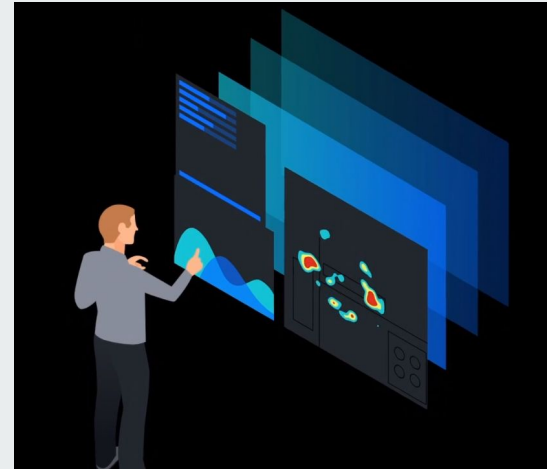


CROWD COUNTING AND MONITORING SYSTEM

Guided By : Prof. Swapnil G. Mali

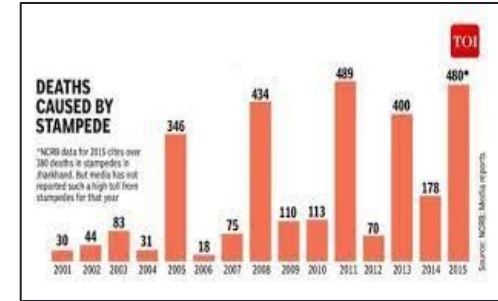
Group Members:

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111807079 - Mohit Bhaiyya
111807081 - Pranav Gandhe



INTRODUCTION :

- Population is Increasing.
- Monitoring and Analysis of Crowd.
- Detection and counting crowd levels.



Applications :

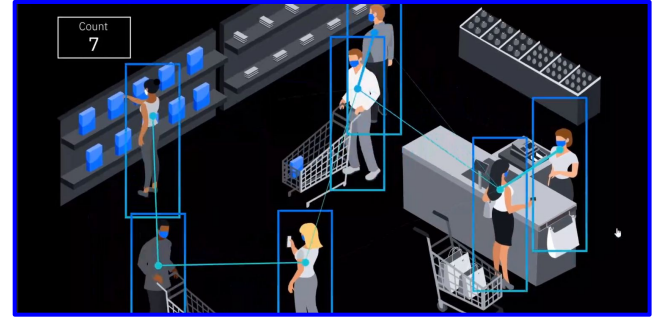
- Disaster management
- Safety and Health Monitoring
- Intelligence gathering and analysis
- Military Applications



Methodology and Implementation:

There are currently four methods we can use for counting the number of people in a crowd:

- 1) **Detection-Based Methods**
- 2) **Regression-based methods**
- 3) **Density estimation-based methods**
- 4) **CNN-Based Methods**



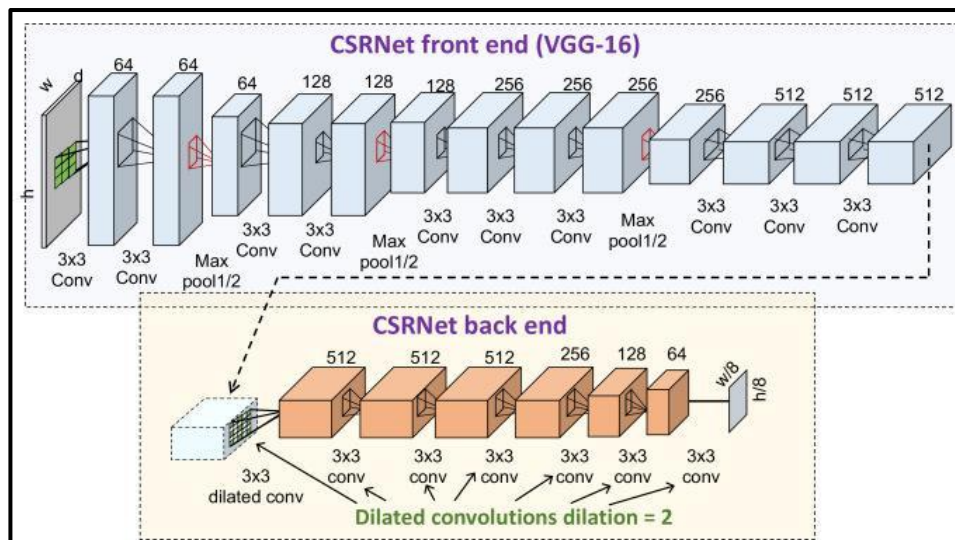
OUR IMPLEMENTATION:

We use a network for **Congested Scene Recognition** called **CSRNet**.

CSRNET Architecture:

The model architecture is divided into **two parts, front-end and back-end**.

1. Front End - VGG 16 (13 layers)
2. Back End - Dilated Convolution Layers



VGG 16

- Convolutional Neural Network
- Pre trained model

Key Features:

- 16 layers - Convolutional and Pooling layers
- 3 x 3 kernel for convolution
- 2 x 2 size of max pool
- Trained on ImageNet data
- About 138 million parameters

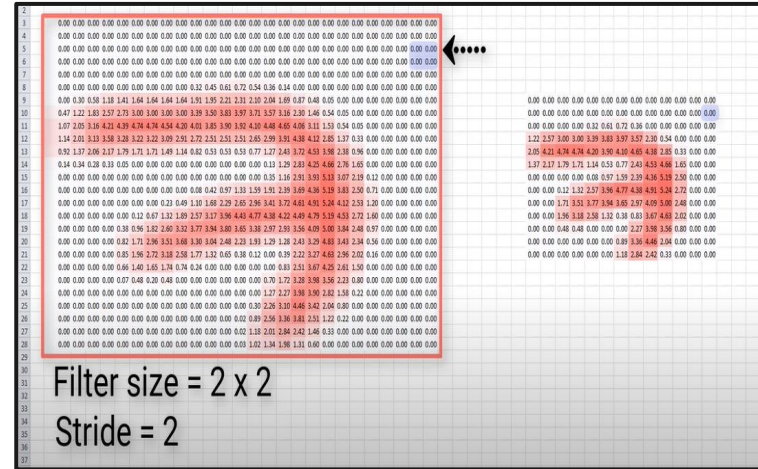
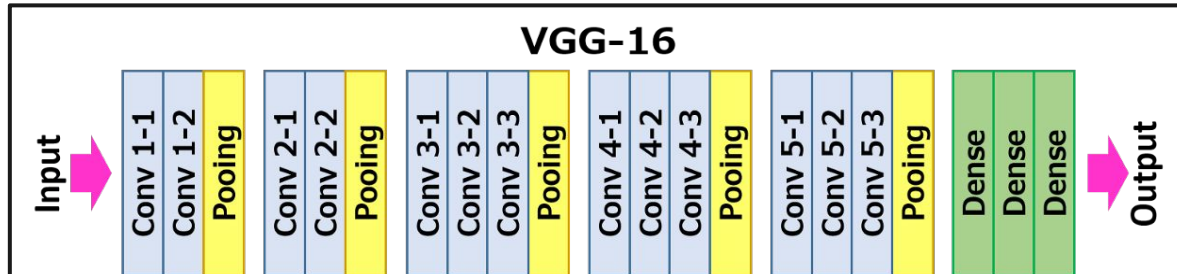


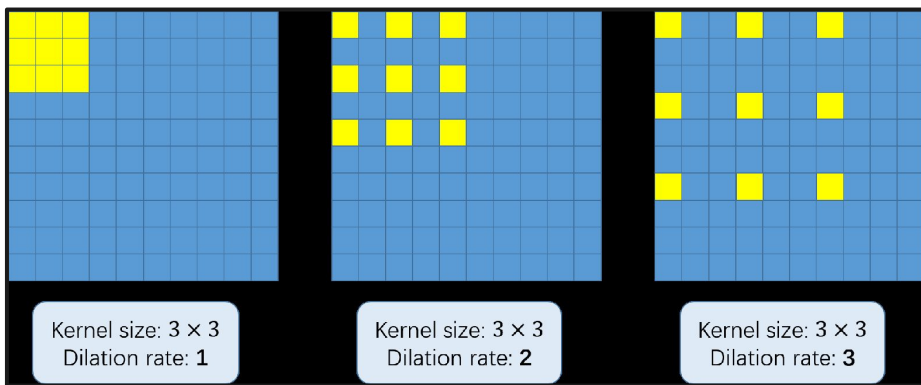
Fig: Max Pooling



Dilated Convolution :



Dilated Convolutions are a type of **convolution** that “inflate” the kernel by inserting holes between the kernel elements.



The basic concept of using dilated convolutions is to enlarge the kernel without increasing the parameters.

- if the dilation rate is 1, we take the kernel and convolve it on the entire image.
- If the dilation rate is 2, the kernel extends as shown in the above image. It can be an alternative to pooling layers.

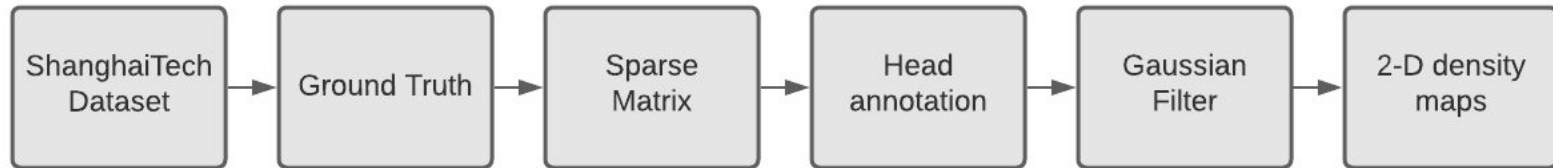
Dataset :

- ShanghaiTech Dataset - 1198 Crowd Images.
- Part A - High Density Crowd - 482 Images.
- Part B - Sparse Density Crowd - 716 Images.

	Number of frames	Resolution	Minimum number of persons	Maximum number of persons	Total number of persons	Average crowd count
Part A	482	different	33	3139	241677	501.4
Part B	716	768*1024	9	578	88488	123.6

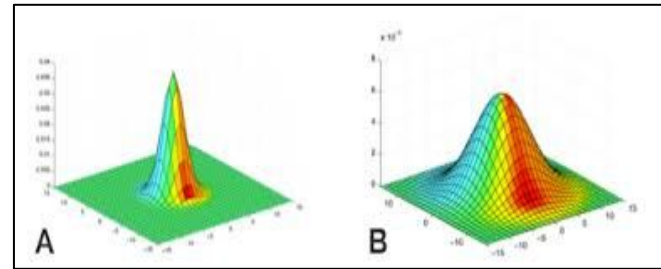


Data Preprocessing :



Further Process:

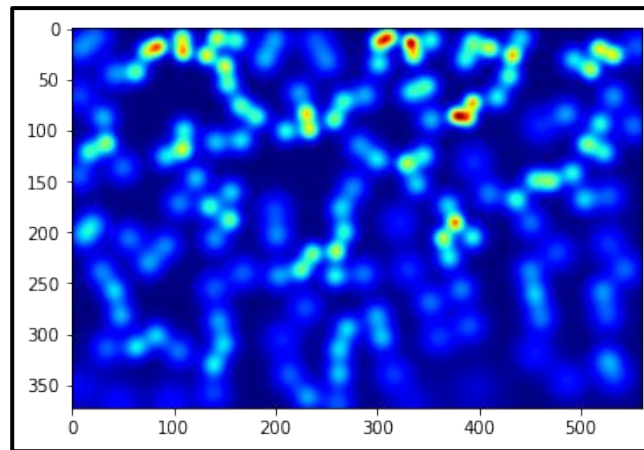
- To convert this to a continuous density function, we convolve this function with a Gaussian kernel G so that the density is $\mathbf{F(x) = H(x) * G(x)}$.
- The average distance between the head and its nearest ' k ' neighbors is calculated.



$$F(x) = \sum_{i=1}^N \delta(x - x_i) * G_{\sigma_i}(x), \quad \text{with} \quad \sigma_i = \beta \bar{d}^i$$


(where $F(x)$ is the density function)

A image and its conversion into density map.



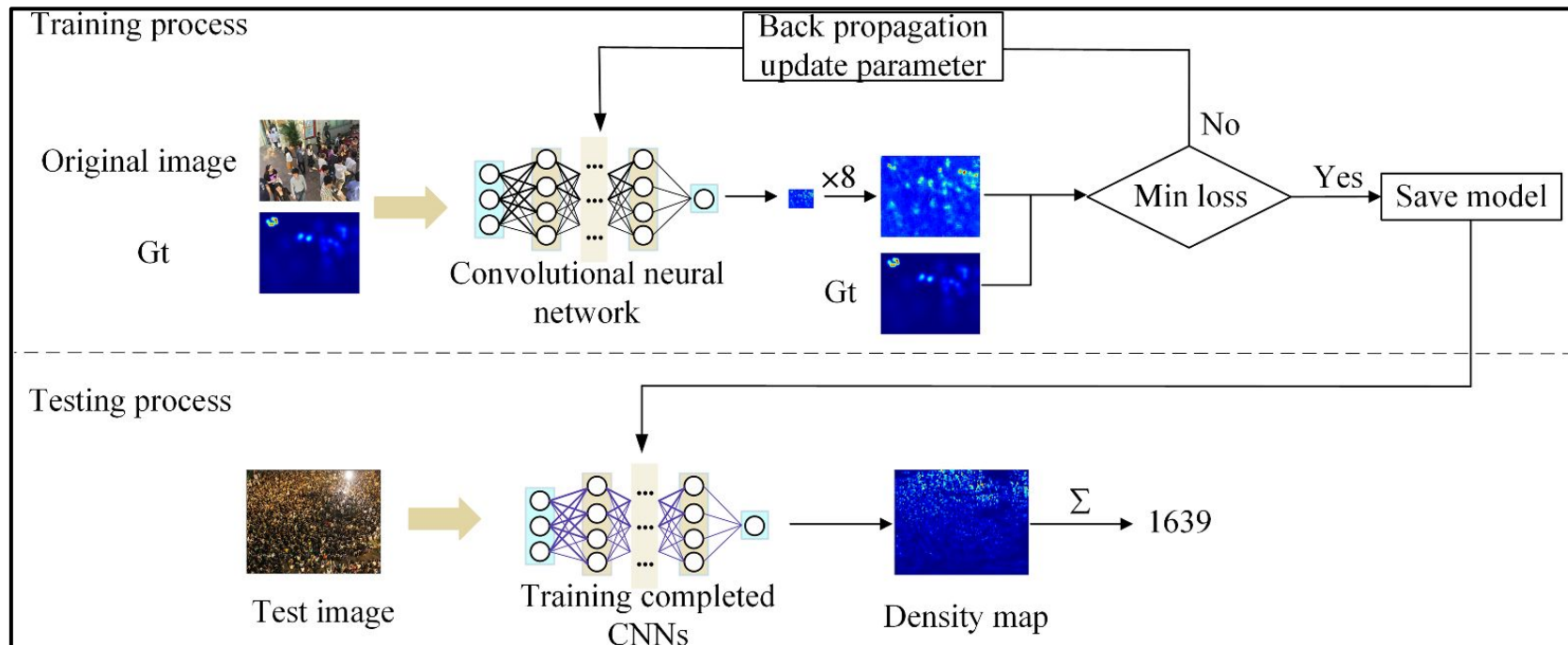
Model and Training Details:

- Optimizer - Stochastic Gradient Descent (SGD)
- Learning Rate - $1e-7$
- Number of epochs - 400
- Batch size - 1
- Momentum - 0.95
- Euclidean distance : Measure of difference between the ground truth and the estimated density map generated

$$L(\Theta) = \frac{1}{2N} \sum_{i=1}^N \| Z(X_i; \Theta) - Z_i^{GT} \|_2^2$$


Loss Function

where, N = size of training batch and
Z(Xi ; Θ) = output generated by CSRNet with parameter Θ.
Xi = input image
Zi^(GT) = ground truth result of the input image Xi .



Evaluation Metric:

- **Mean Absolute Error** - average difference between the actual data value and the value predicted by the model.

$$MAE = \frac{1}{N} \sum_{i=1}^N |C_i - C_i^{GT}|$$

- Dense Crowd Dataset:

```
[14] print("Mean Absolute Error :",mae_avg)
      print("Mean Absolute Percentage Error :", (mae_avg/avg)*100, "%")

Mean Absolute Error : 65.96636728140024
Mean Absolute Percentage Error : 15.36797194376203 %
```

- Sparse Crowd dataset:

```
[ ] print("Mean Absolute Error :",mae_avg)
     print("Mean Absolute Percentage Error : ", (mae_avg/avg)*100, "%")

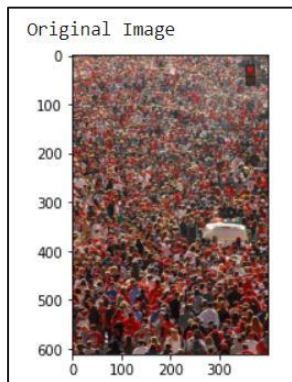
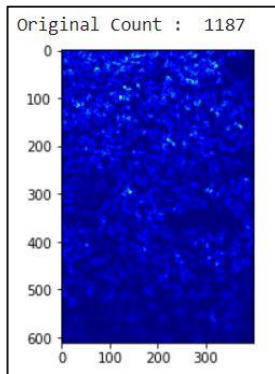
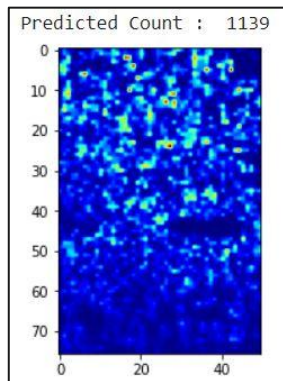
Mean Absolute Error : 10.549921805345559
Mean Absolute Percentage Error : 8.792767923155468 %
```

Result :

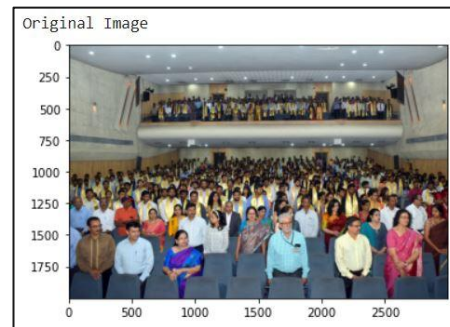
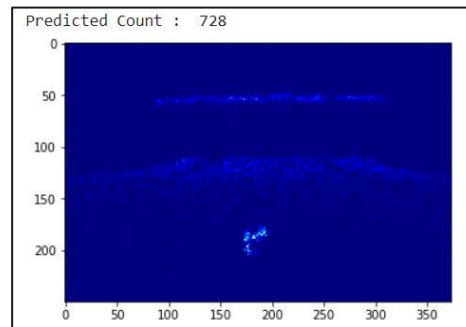
Dense Crowd :



1)

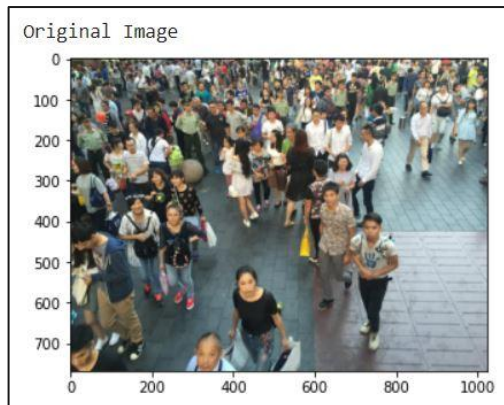
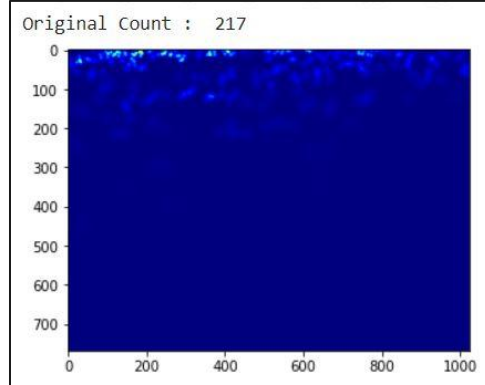
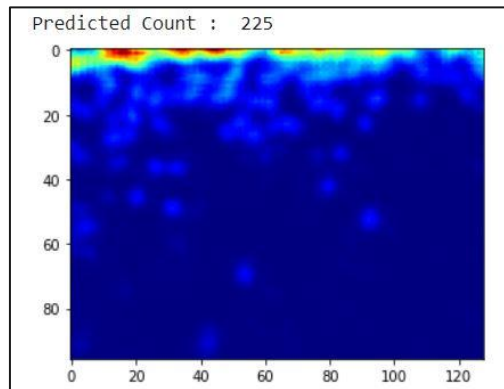


2)

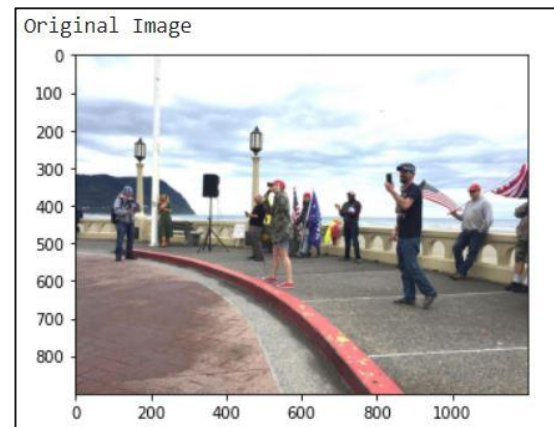
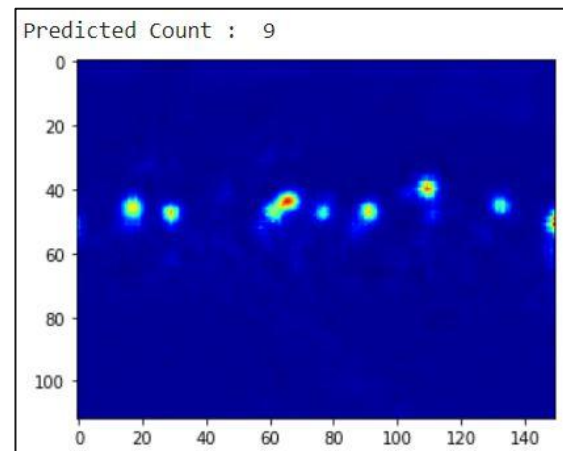


Sparse Crowd :

1)



2)



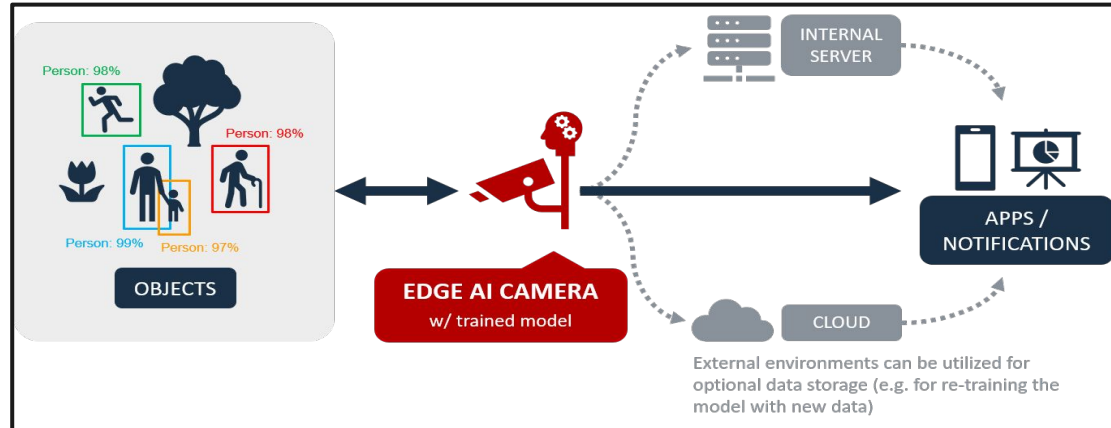
Conclusion:



- Effective approach for real time crowd counting using CSRnet is presented.
- Deep learning enables the system to perform in versatile environments and continuously learn from new inputs.
- Proposed methodology achieves crowd count predictions almost as good as ground truth values.
- Model A and Model B perform well on dense crowds and sparse crowd respectively.
- The density map generated by both models are accurate enough to depict the varied density of the crowd.
- CSRNet achieves low value of Mean Absolute Error (MAE).

Future Scope:

- We can train model on a huge dataset containing both dense and sparse crowd images.
- Hyperparameter tuning.
- Different backbone architectures instead of VGG 16 such as Resnet, inception,xception.
- Edge Cameras and Edge Computing



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