



COVID-19 Safe Distancing Measures in Public Spaces with Edge AI

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Government Technology Agency of Singapore (GovTech)



- Is a statutory board of the Government of Singapore, under the Prime Minister's Office
- **5 Capability Centres**, conducting **3 key activities**



ENGINEERING EXPERTISE in:

- Sensors & IoT (SIoT)
- Cybersecurity
- Data Science & AI
- Infrastructure
- Applications Design, Development, Deployment



TECHNOLOGY EXPERIMENTATION

- Generate key technologies for Whole of Government
- Establish key partnerships with industry players and research institutions

PRODUCT ENGINEERING & DEVELOPMENT



- Develop core technologies, standards and guidelines



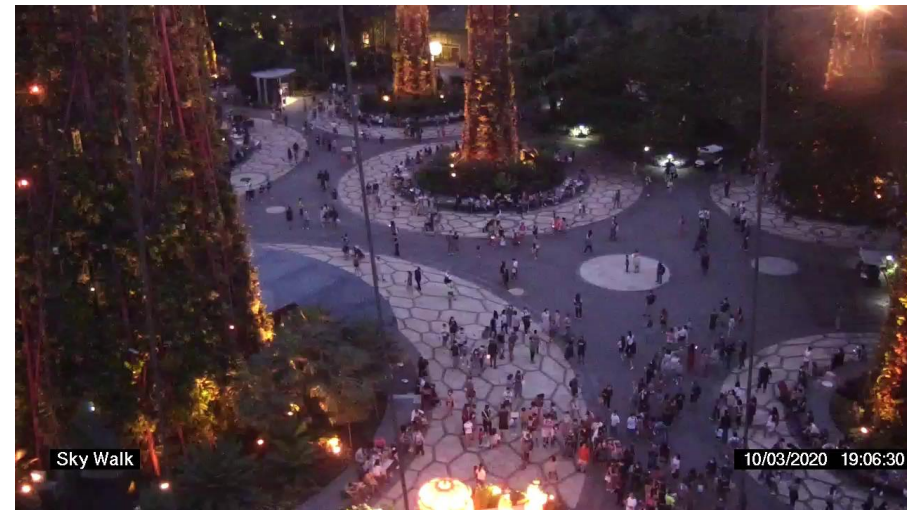
TECHNOLOGY ADVISORY & CONSULTANCY

- Provide technical consultation.
- Develop POCs and products

- Whether it's indoor environments (supermarkets, museums, etc.) or outdoors (parks), **crowd management** is a priority.
- By combining **edge AI** solutions with **cloud** connectivity, government agencies are equipped with information they need to **manage the crowd** effectively.
- Crowd counting deployments on the edge in **indoor** & **outdoor** environments are presented.



Indoors – Supermarkets, offices, museums

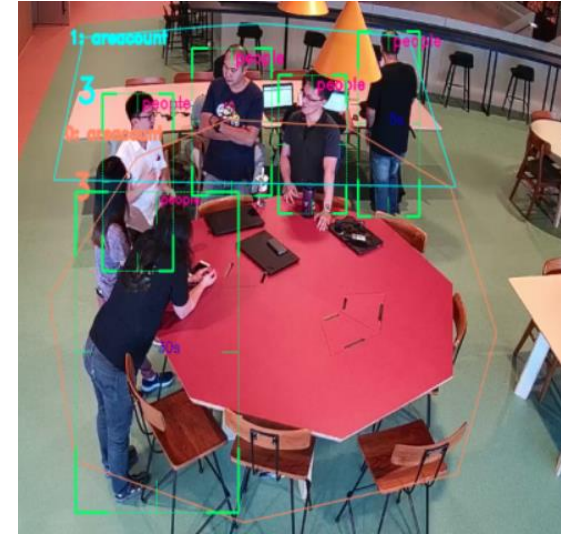


Outdoors - Parks

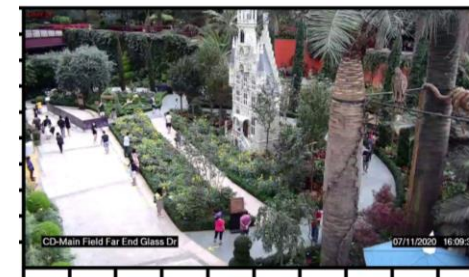
Key Approach in Indoor & Outdoor Visitor Counts



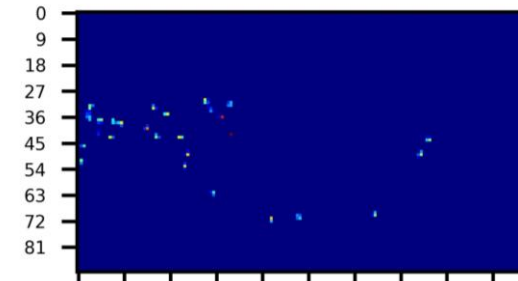
- Current state-of-the-art methods treat crowd counting as:
 - Detection-and-counting approach
 - Density map estimation
 - Where a deep neural network first produces a 2D crowd density map for a given input image, and...
 - ...estimates total size of the crowd by summing the density values across all spatial locations of the density map.
- For large crowds, the density map estimation approach is more robust than the detection-then-counting approach
 - as it is less sensitive to occlusion and clutter.
 - does not need to commit to binarized decisions at an early stage.



Original Image



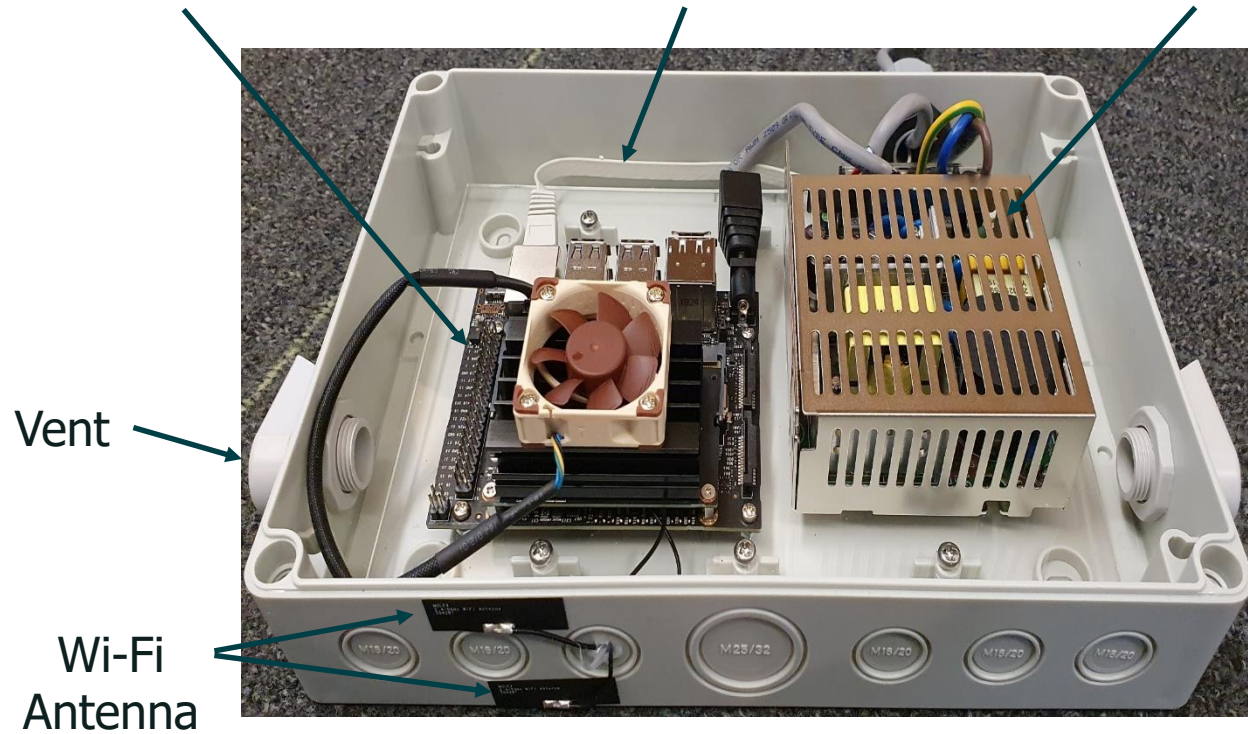
Density Map



People Counting in Indoor Environments - Hardware



Nvidia Jetson Nano Camera Data Cable AC-DC Power supply



Nvidia Jetson Nano Dev Kit



Aeon BOXER-8223AI NVIDIA Jetson Nano

One edge device can process up to 2 cameras.

People Counting in Indoor Environments - Software



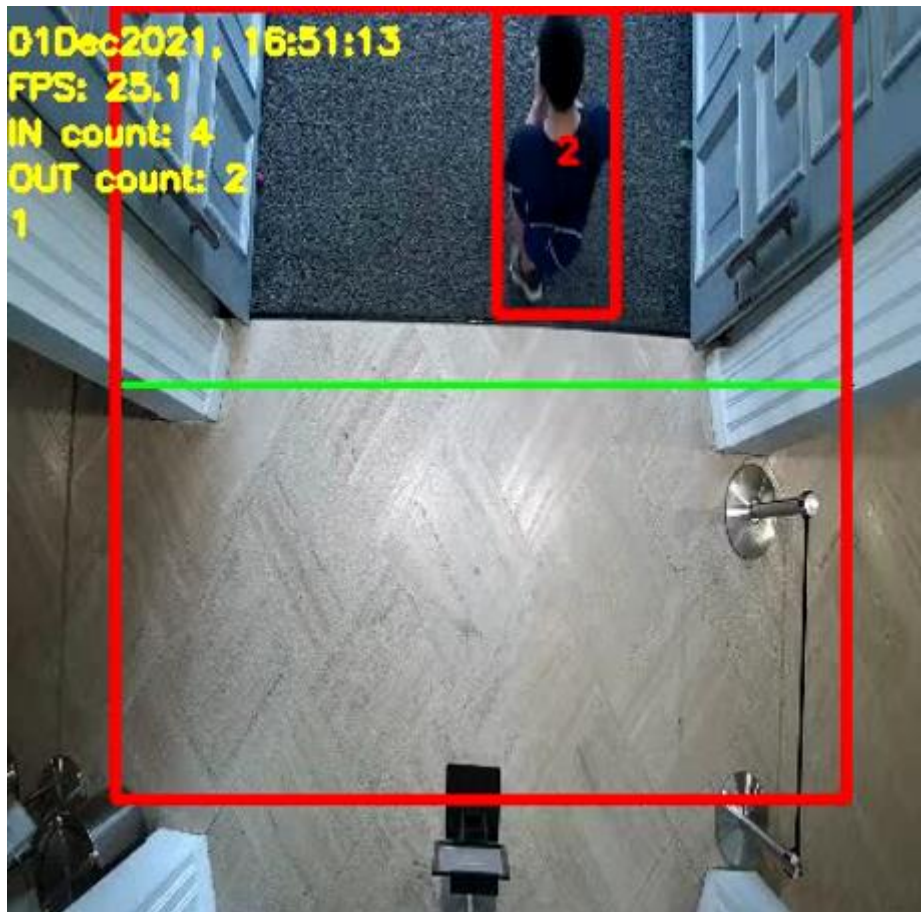
	Version 1	Version 2
Model	SSD-Mobilenet v2	PeopleNet
Pre-trained dataset	MS-COCO	Nvidia Proprietary
Initial Object Classes	80	3
Object class after transfer learning	1 (i.e. person)	1 (i.e. person)
Model optimization	TensorRT (FP16)	TensorRT (FP16)
DeepStream	No	Yes
Tracking	Simple Online and Realtime Tracking (SORT) https://github.com/abewley/sort	NvDCF tracker
Accuracy	86%	91%

Software Version	Model	TensorRT	FPS	CPU Usage	GPU Usage	RAM Usage (Gb)
Version 1	SSD Mobilenet v2	No	17	49% (avg.)	70% (avg.)	2.9 / 4.0
	SSD Mobilenet v2	Yes	23	35% (avg.)	50% (avg.)	2.7 / 4.0
Version 2	Nvidia PeopleNet	Yes	25	40% (avg.)	50% (avg.)	2.7 / 4.0

People Counting Indoors



- Transfer learning with custom dataset can achieve detection accuracy > 91%.
- (Almost) a solved problem!



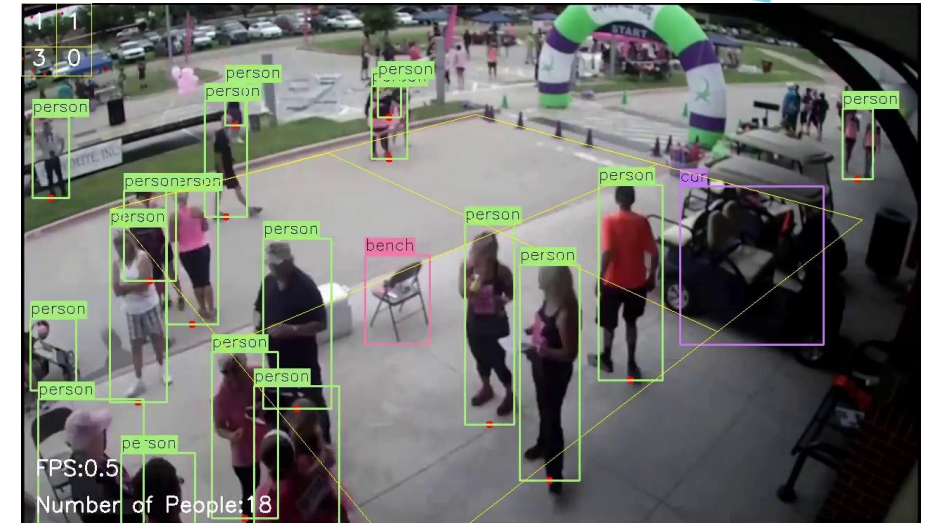
Crowd Counting in Outdoor Environments



Crowd Counting in Outdoors



- A challenging computer vision problem due to:
 - Heavy occlusion
 - Perspective distortion
 - Scale variation
 - Diverse crowd distribution



Crowd Density Methods – MSFANet & DM-Count



- Crowd counting algorithms predict a density map from a crowd image. Summation of the density map is the crowd count.
- Each training image contains multiple people, each person is annotated by a dot.
- MSFANet crowd counting method
 - Combination of multi-scale-aware modules and dual path decoder
 - Predicts density maps and attention maps for highlighting crowd regions in input image.
 - Uses a Gaussian kernel to smooth each annotated dot.
 - Is trained on L2 pixel-wise loss.
 - Sensitive to the choice of variance in the Gaussian kernel.
- DM-Count crowd counting method
 - Considers density maps and dot maps as probability distributions.
 - Loss composed of optimal transport (OT) loss, total variation (TV) pixel-wise loss & counting loss (CL).



Multi-Scale Feature Adaptive Network (M-SFANet) – Data Preprocessing



Convolve the head annotation with Gaussian kernel (G) which has fixed standard deviation (σ).

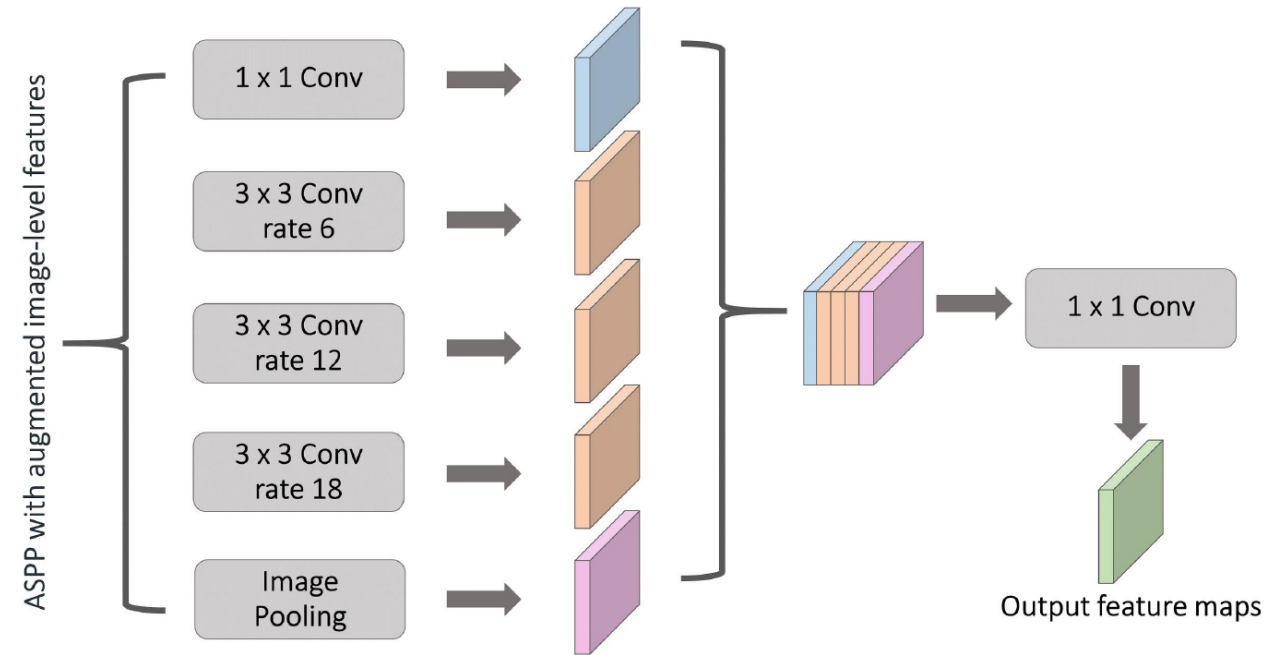
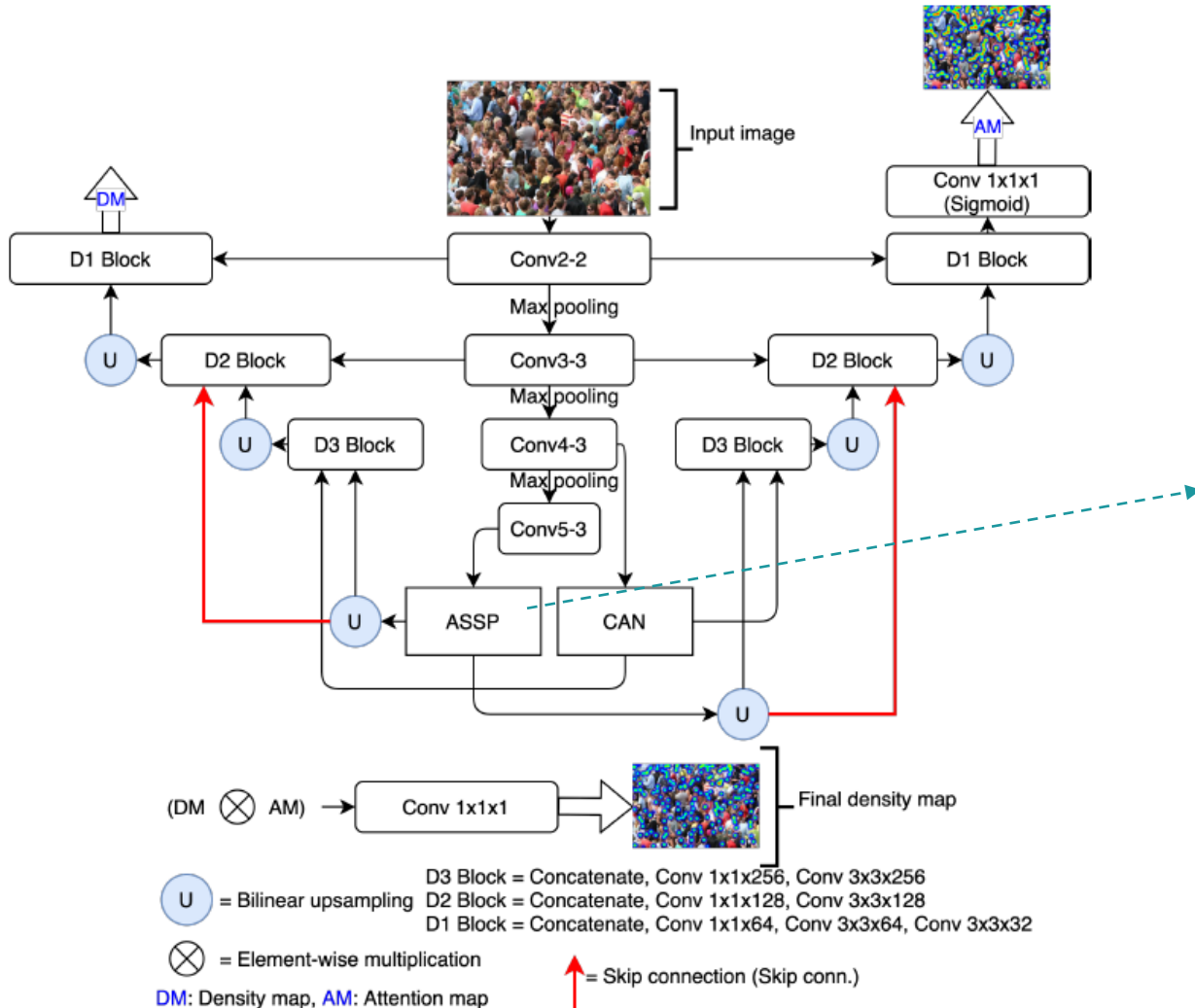
Assuming a head annotation at pixel x_i , represented as $\delta(x - x_i)$,

$$\text{density map, } D(x) = \sum_{i=1}^N \delta(x - x_i) * G_{\sigma}(x)$$

where N = total number of headcounts.

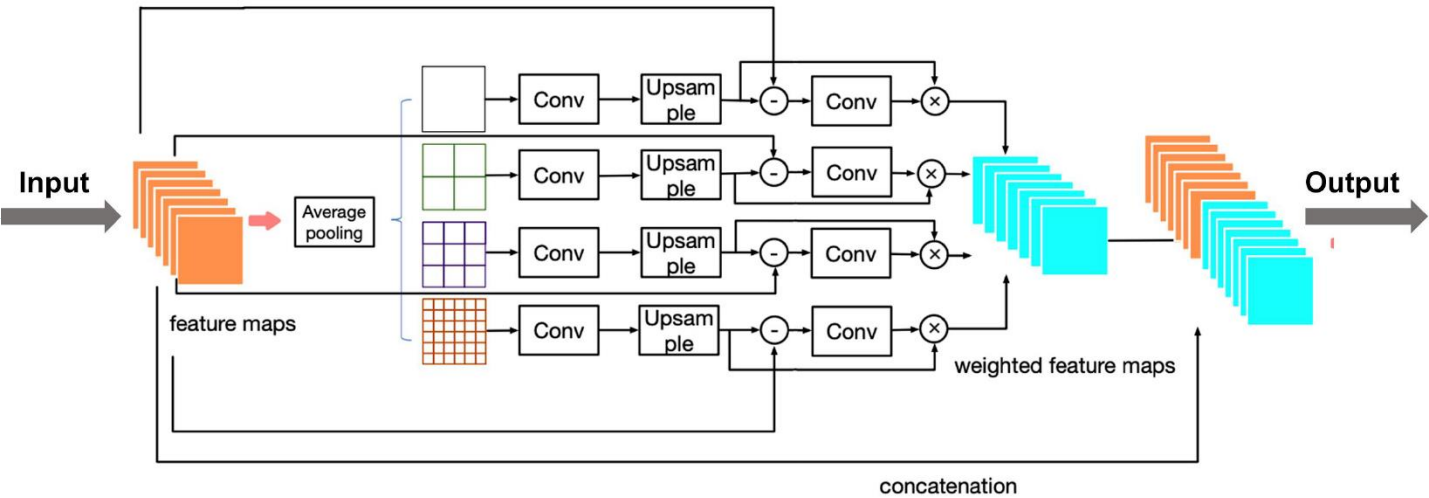
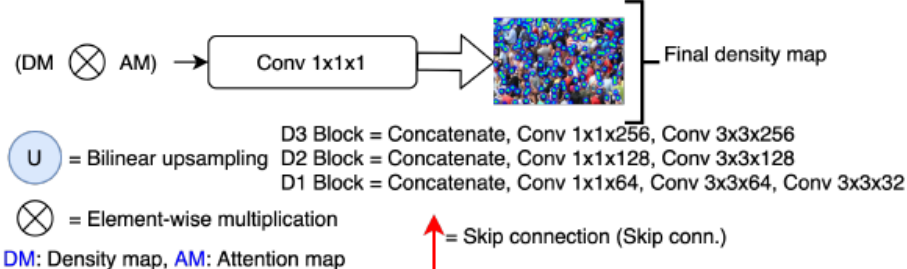
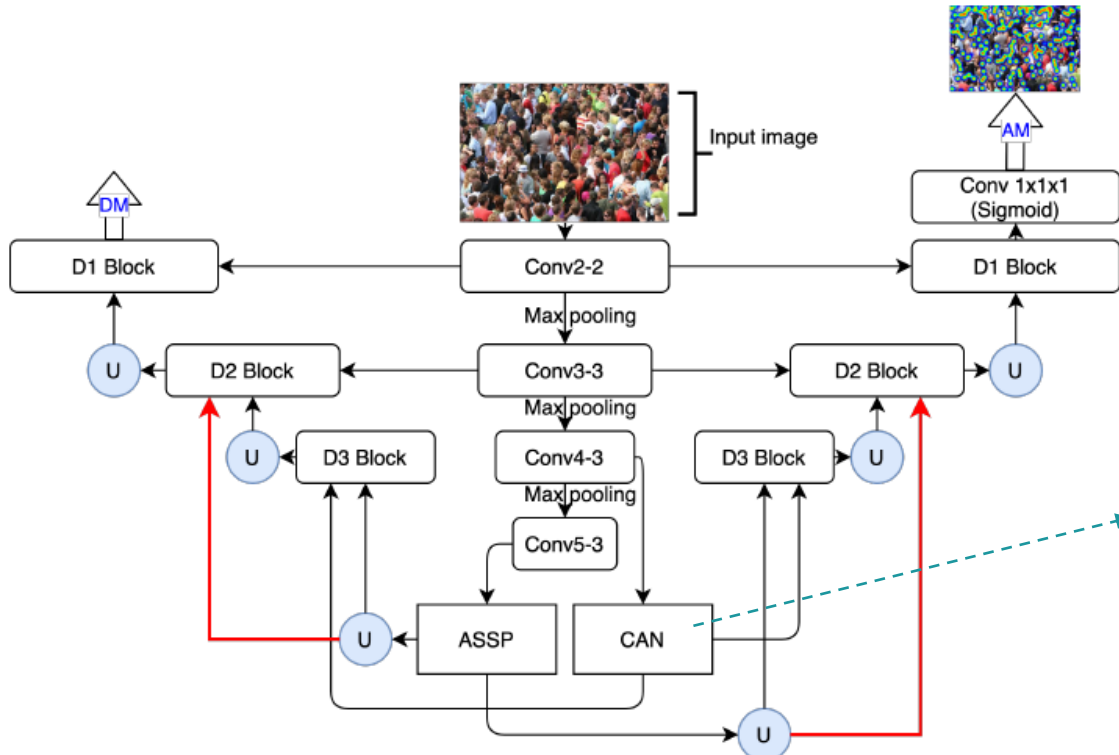
$$\text{attention map, } A(i) = \begin{cases} 0 & \text{if } 0.001 > D(i) \\ 1 & \text{if } 0.001 \leq D(i) \end{cases}$$

M-SFANet Architecture (1)



Atrous spatial pyramid pooling (**ASPP**) with augmented image-level features

M-SFANet Architecture (2)

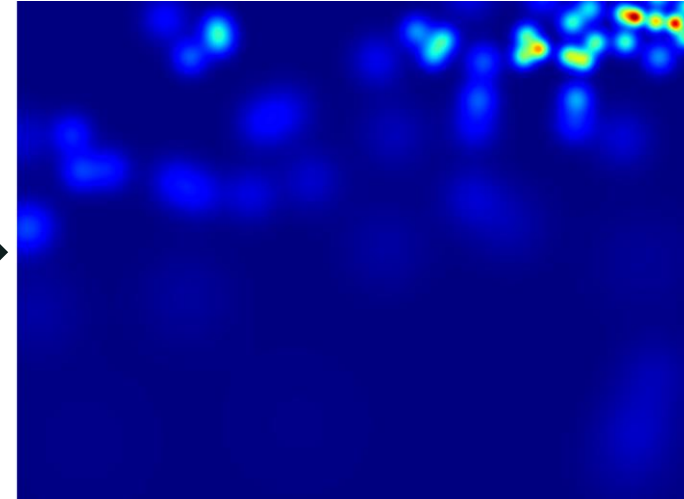


Context-aware module (CAN)

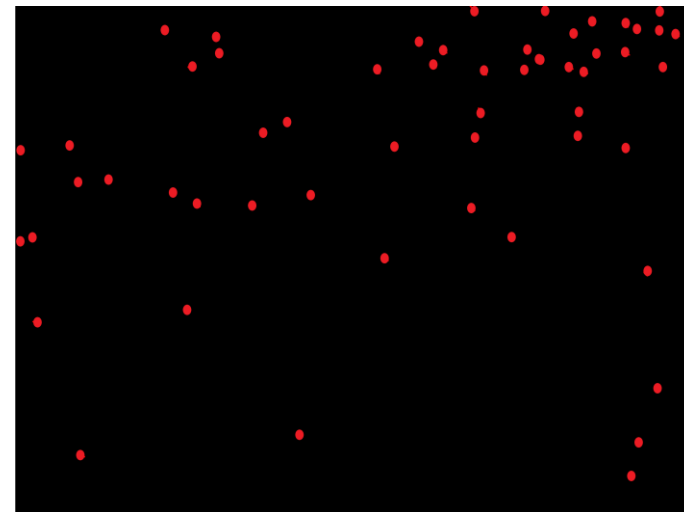
Crowd Counting in Outdoors – DM Count Estimation



Predicted Density Map



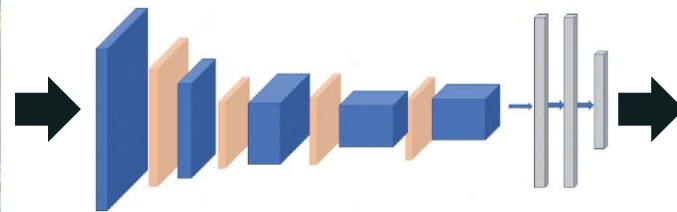
How to measure discrepancy for training?



Annotations (Ground Truth Count = 54)



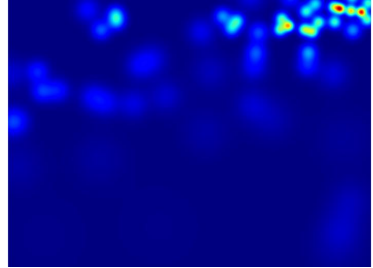
Input Image



VGG19 model

- Almost all previous work converts the sparse point annotation into dense ground truth maps.
 - Each point is replaced by a gaussian blob.
- DM-Count paper shows that imposing Gaussians to annotations hurts generalization performance.

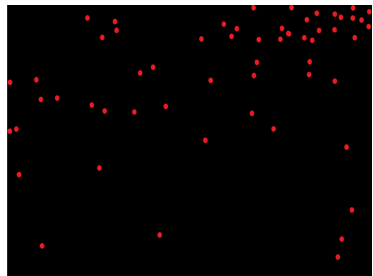
DM-Count Loss



Predicted density map



Source distribution



Sparse annotations



Target distribution

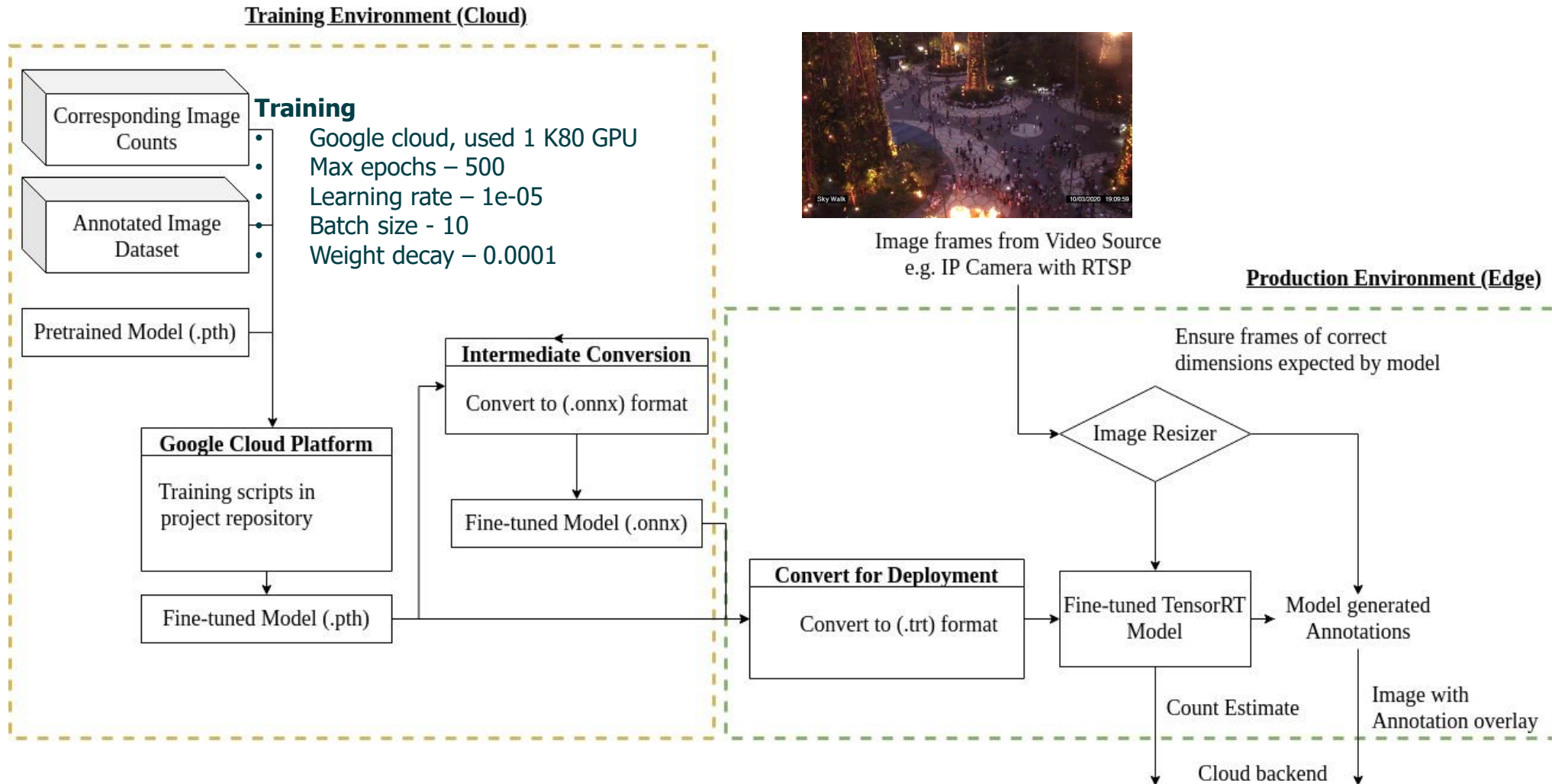
Distribution distance

- DM-Count considers density map as distributions.
- Use of Optimal Transport (OT) to compute the distance between density maps.

$$\text{Total loss, } l(\mathbf{Y}, \hat{\mathbf{Y}}) = l_C(\mathbf{Y}, \hat{\mathbf{Y}}) + \lambda_1 l_{OT}(\mathbf{Y}, \hat{\mathbf{Y}}) + \lambda_2 \|\mathbf{Y}\|_1 l_{TV}(\mathbf{Y}, \hat{\mathbf{Y}})$$

- Counting loss (l_C): absolute loss between ground truth and predicted counts
- The Optimal Transport loss (l_{OT}): The OT similarity measurements provide valid gradients that can train a network if the source distribution does not overlap with the target distribution.
- Total Variation loss (l_{TV}): Improve stability when optimising the OT loss with the Sinkhorn algorithm.

People Counting Outdoors - Workflow



Crowd Counting Outdoors – Hardware & Software



AAEON Boxer-8253AI

- Nvidia Jetson Xavier NX
- 8GB LPDDR4x
- Storage option: 16GB eMMC and 64GB MicroSD
- GbE PoE/PSE LAN x 2
- Quectel EP06: LTE-A Cat 6 module with Mini PCIe form factor

Model	DM-Count	MSFANet
Dataset	UCF QNRF, Custom	UCF QNRF, Custom
Framework	Pytorch 1.2	Pytorch 1.2
Model optimization	TensorRT (FP16)	TensorRT (FP16)

Model	Accuracy (%)	Latency (sec)
DM-Count	92.10	3.467
M-SFANet	88.99	8.841

Pytorch Model on Nvidia Jetson Xavier NX

Model	Accuracy (%)	Latency (sec)
DM-Count	91.08	0.380
M-SFANet	86.46	0.637

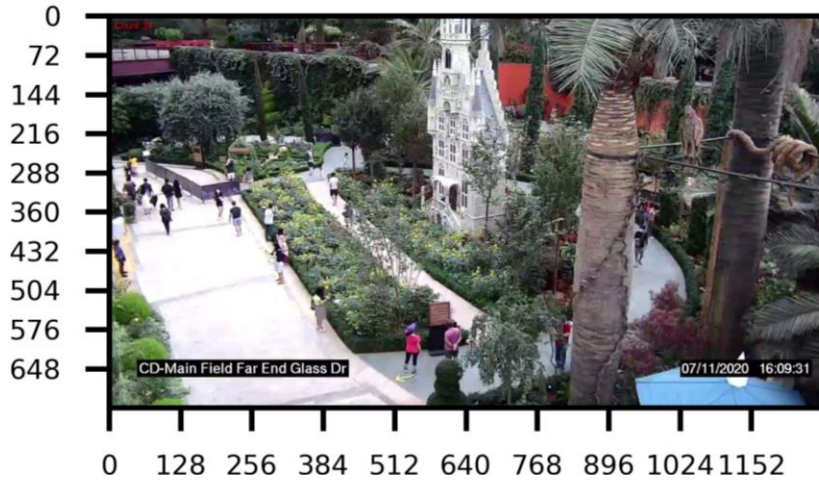
TensorRT (FP-16) on Nvidia Jetson Xavier NX

Crowd Counting Outdoors – Results

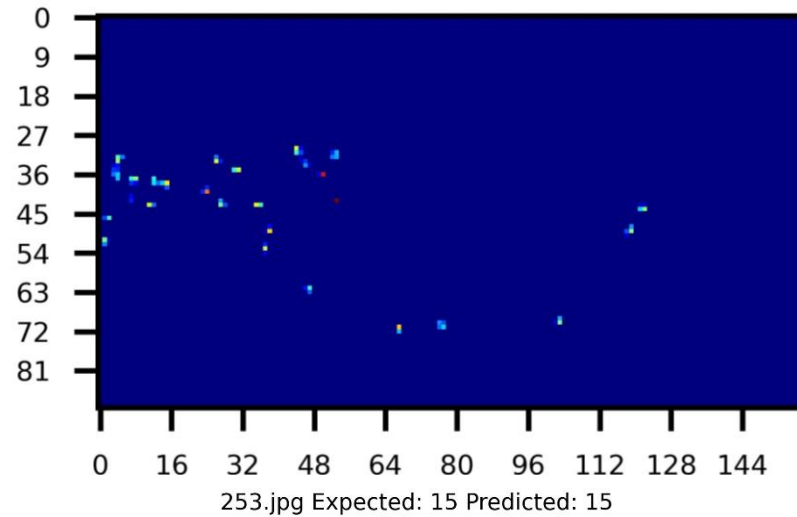


96.jpg Expected: 26 Predicted: 27

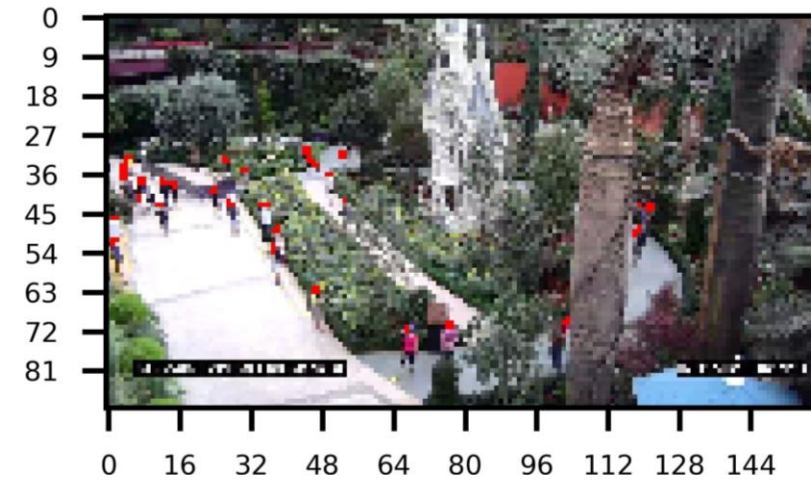
Original Image



Density Map



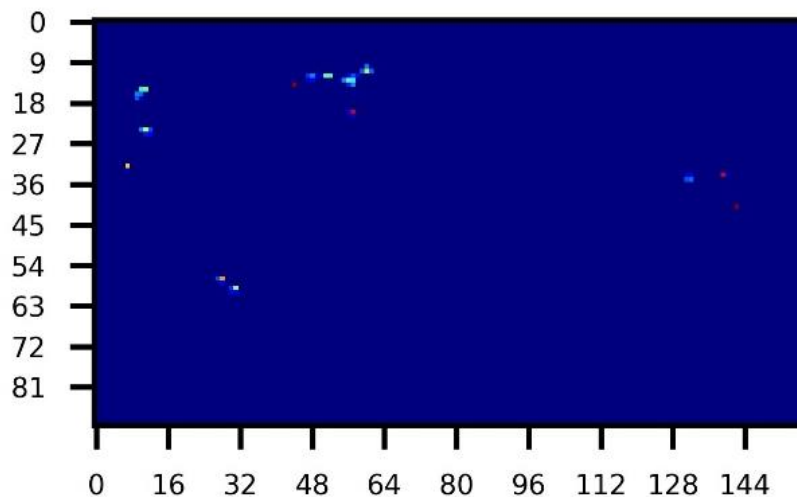
Superimposed Image



Original Image



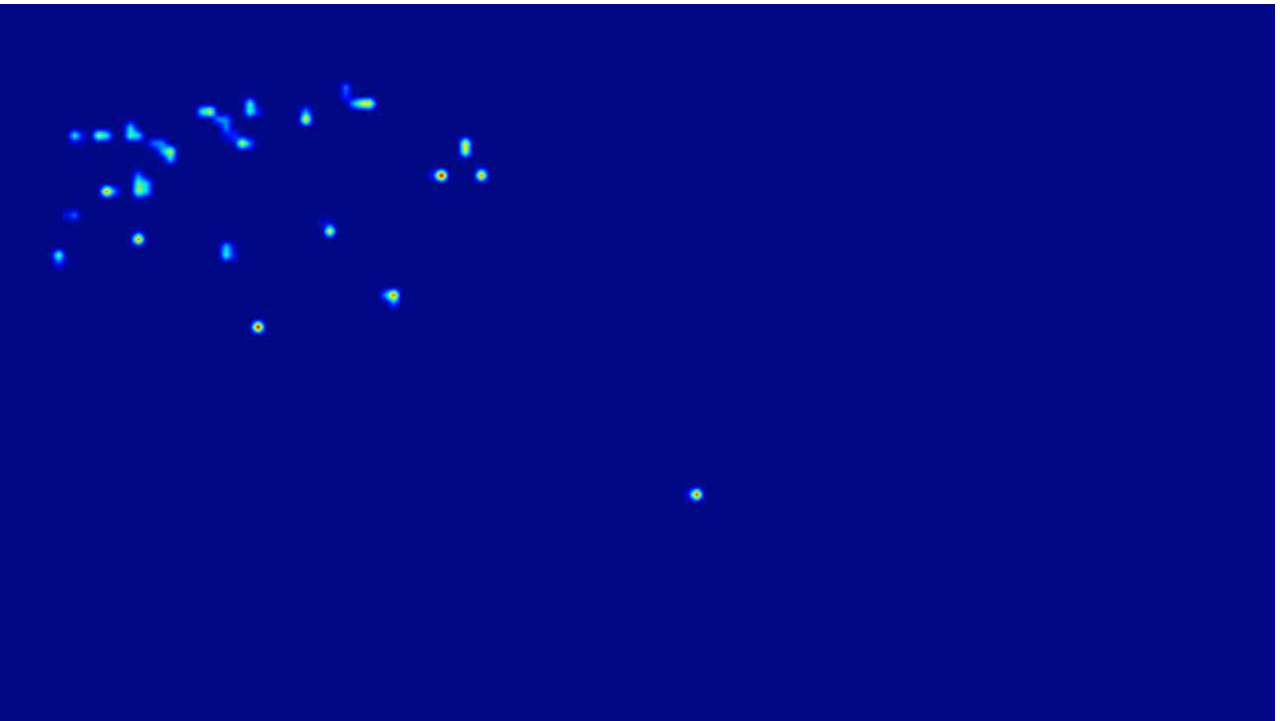
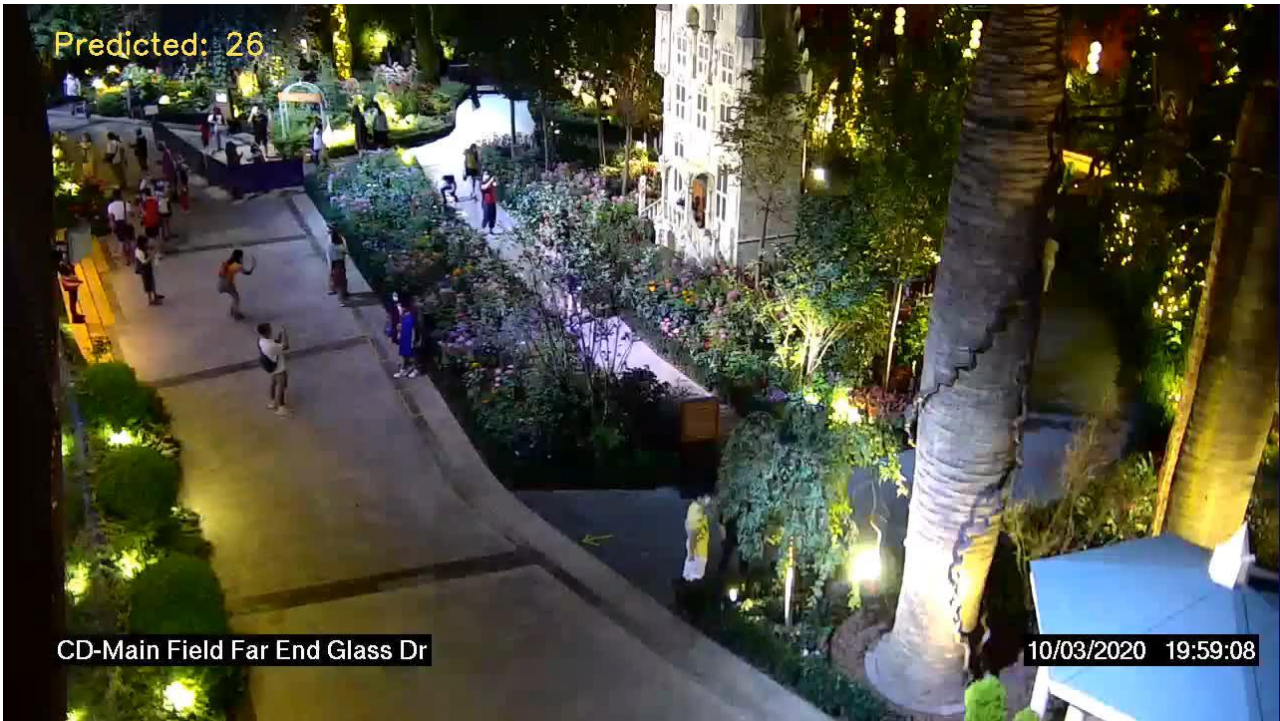
Density Map



Superimposed Image



Crowd Counting in Outdoors – DM-Count Results



- Accurate people counting:
 - For indoor environments, is almost a solved problem, when there are less/no occlusions.
 - For outdoor environments, is a challenging problem due to:
 - Heavy occlusion
 - Perspective distortion
 - Scale variation
 - Diverse crowd distribution
 - DM-Count performed well even with occlusions, providing accurate counts.

Sensors & IoT Department

<https://www.tech.gov.sg/capability-centre-siot>

Government Technology Agency of Singapore (GovTech)

<https://www.tech.gov.sg>

M-SFANet for Count Counting (original paper and code)

<https://arxiv.org/abs/2003.05586>

<https://github.com/Pongpisit-Thanasutives/Variations-of-SFANet-for-Crowd-Counting>

Distribution Matching for Count Counting (original paper and code)

<https://arxiv.org/abs/2009.13077>

<https://github.com/cvlab-stonybrook/DM-Count>