Trash Classification on Water Channels

Thesis – MS Computer Science

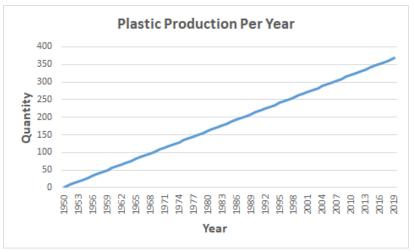
Abdul Wahab Amin

20030052

Motivation

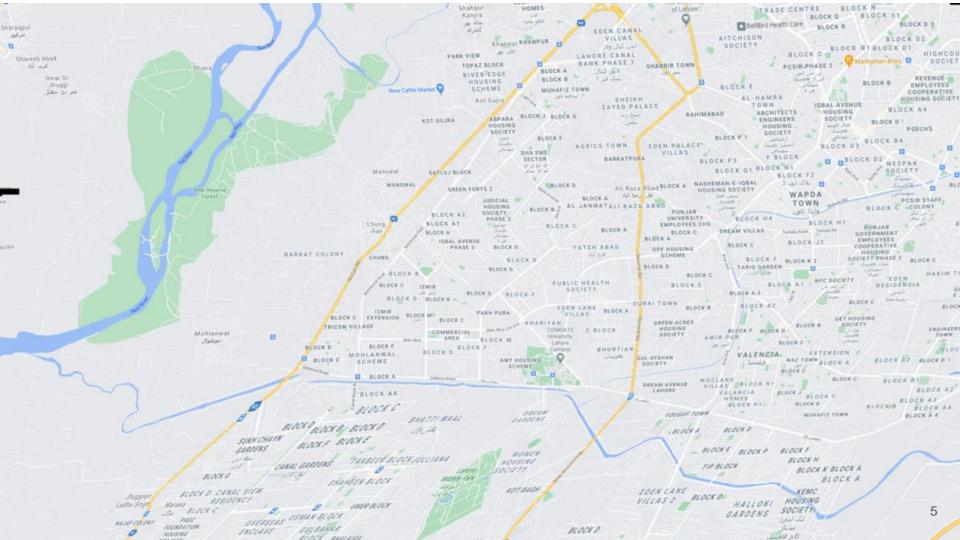
- 2 million tonnes of plastic produced in 1950
- 368 million tonnes of plastic produced in 2019
- 18,400% increase in plastic production
- 75% plastic ever produced is not recycled
- ~9704 tonnes of plastic

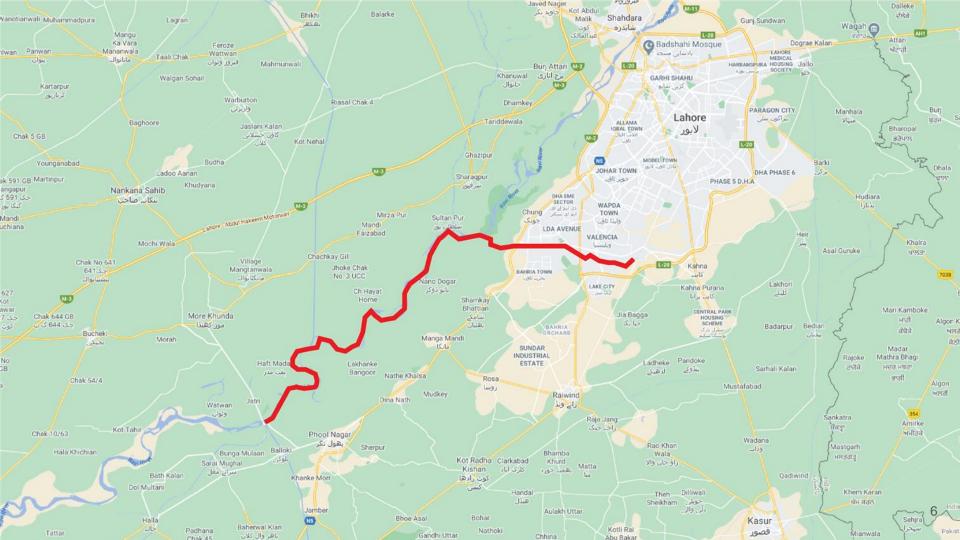




Where does the plastic go?









Microplastics

- Decomposed form of plastic
- Can be less than 100 nm in size
- Size of covid-19 is 60–140 nm
- Effect soil fertility by damaging the soil flora and fauna [1]
- Soil flora and fauna are responsible for nutrient recycling and organic matter Decomposition [2]



Thesis Aims

Thesis Aims

• Trash classification and localisation system based on deep learning

• Trash data analysis for identifying major pollutants

• Water flow measurement through visual sensor based on trash detection

Prior Work

Prior Work

- Trash identification
 - \circ Classification
 - Object Detection
 - Segmentation





Classification + Localization

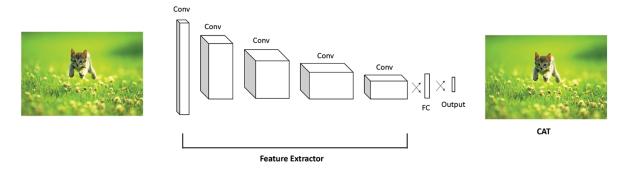






Prior Work: Classification

• Classify if an object is present in the image



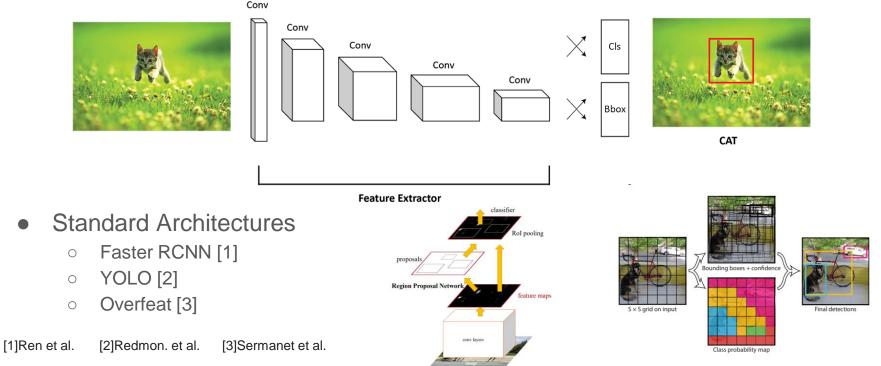
- Standard Architectures
 - DenseNet [1]
 - MobileNet [2]
 - Inception-v4 [3]
 - GoogLeNet [3]

[1]Huang, Gao, et al.

[3]Szegedy et al.

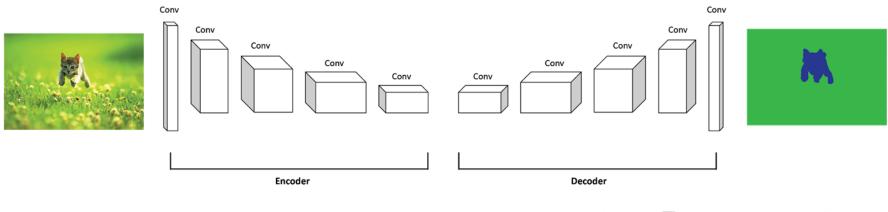
Prior Work: Object Detection

• Simultaneous localization and classification

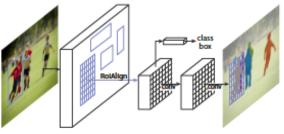


Prior Work: Segmentation

• Pixel-wise classification



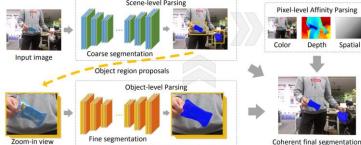
- Standard architectures
 - Mask R-CNN [1]



- Indoor Trash
 - TrashNet [1] 0
 - Classification of 6 trash categories
 - Inception-v4, DenseNet, MobileNet



- MJU-Waste [2] Ο
 - **RGBD** waste object segmentation





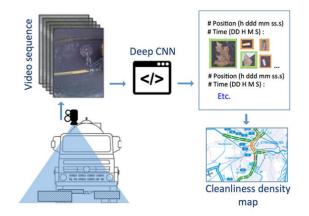
[1]Classification of TrashNet Dataset Based on Deep Learning Models

[2]Tao Wang, A Multi-Level Approach to Waste Object

Spatial

- Outdoor Trash
 - TACO [1]
 - Dataset the with the most diverse amount of backgrounds
 - Water Trash accounts for only 3% of the whole dataset
 - Annotated for segmentation
 - Mask R-CNN
 - Street [2]
 - Camera mounted on a sweeper truck
 - Uses a combination of GoogleNet and OverFeat
 - Cleanliness density map creation based on detected trash

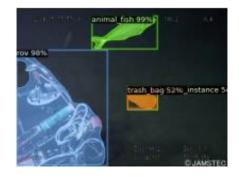




- Ocean Trash
 - Trash-det [1]
 - Autonomous underwater vehicles (AUVs)
 - Detection of plastic objects on ocean floor
 - YOLOv2, SSD etc.

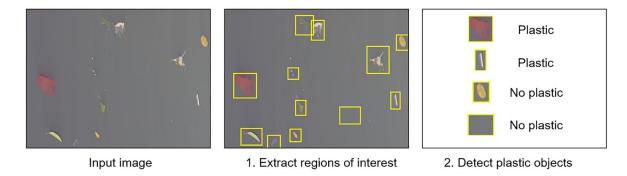
- Trashcan [2]
 - Autonomous underwater vehicles (AUVs)
 - Segmentation of floating and ocean floor plastics
 - Faster R-CNN, Mask R-CNN





- River Trash
 - River Plastics [1]
 - Plastics and non-plastics
 - Detection using Inception v2
 - Segmentation using Faster R-CNN
 - Only contains top-view of trash objects





Prior Work: Dataset Comparison

Dataset	Type	# images	# classes	# instances	annot. type	Availability
TrashNet	Indoor	2500	6	2500	Classification	Public
VN-trash	Indoor	5904	3	5904	Classification	Public
MJU-Waste	Indoor	2475	1	2475	Mask	Public
Street	Road	469	6	1421	BBox	Private
TACO	Multi	1500	60	4784	Mask	Public
YOLOTrash	Multi	3974	4	5535	BBox	Private
Trash-det	Marine	5720	3	-	BBox	Private
TrashCan	Marine	7212	22	12480	Mask	Private
River Plastic	Rivers	1272	1	14892	Mask	Private

Summary of Prior Work: Trash Analysis

- Majority of the work has been done on street trash
- River channels have been explored for plastic/non-plastic detection
- Hardly no work has been done on water channels
- No public data available on water trash







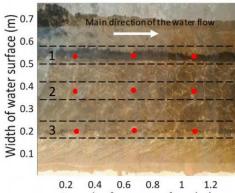






Prior Work: Water Flow Analysis

- Water flow measure through dense optical flow [1]
 - Camera placement is parallel to water stream
 - Used rectangular box for mapping pixel coordinates to real world dimensions
 - Divided whole area into multiple regions and applied optical flow to get displacement of particles
- Real-Time, Inexpensive, and Portable Measurement of Water Surface Velocity through Smartphone [2]
 - Measurement of water flow through objects
 - Detecting objects through rgb color variation
 - Works at a specific phone height and velocity limits
 - Not deployable



Length of water surface (m)

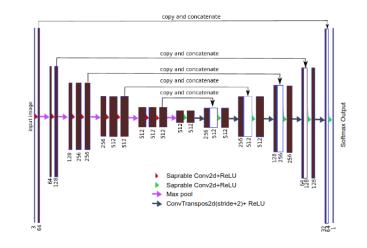
Our Prior Work

- Segmentation
- Separable Convolution in U-Net
- Novel Loss function for Water and Trash Imbalance problem

$$CB_{ipw}(p,y) = \frac{\sum_{i=1}^{C} n_i}{n_c} (\sum_{j=1}^{C} (1-p_i) log(p_i)),$$

• 2x improvement in processing time with 10x reduction in model parameters

Model	Parameters (Millions)	Accuracy	F1-Score	FPS
UNet	31	0.99	0.99	8
UNET+Sep	3.9	0.986	0.987	14





Problem Formulation/Statement

Problem Formulation/Statement

The problem can be formulated as:

- Dataset Collection & Annotation
 - Data collection from multiple sites
 - Class-wise annotation of trash objects
- Automatic Quantification Fine Grained Detection & Classification
 - Deep learning system for trash detection and classification
- Trash Class Distribution Analysis
 - Detailed analysis on major water channel pollution contributors
- Water Flow Measurement
 - Measuring water flow through trash detection

Dataset Collection & Annotation

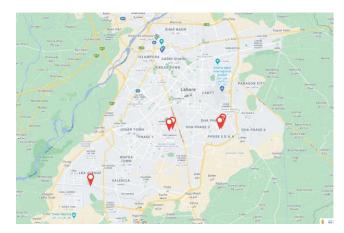
Dataset Collection

- Two datasets collected
- Trash Classification Dataset (TCD)
 - Image dataset
 - Deep Learning system for trash detection
- Trash Flow Rate Dataset (TFD)
 - Video Dataset
 - Trash Class Distribution Analysis
 - Water Flow Analysis

Dataset Collection (TCD)

• 7 Sites

City	Location	Water Channel	GPS Co	ordinates
			Latitude	Longitude
Lahore	LUMS	Rohi Nala	31.478224	74.413272
Lahore	Alfalah Town	Rohi Nala	31.472700	74.409738
Lahore	Alfalah Town	Rohi Nala	31.480270	74.414445
Lahore	Liaquatabad	Rohi Nala	31.470839	74.332759
Lahore	Liaquatabad	Rohi Nala	31.473074	74.337413
Lahore	Defence Raod	Hudiara Nala	31.397972	74.211921
Sheikhupura	Shah Khalid Town	SKP Drain	31.667509	74.265385

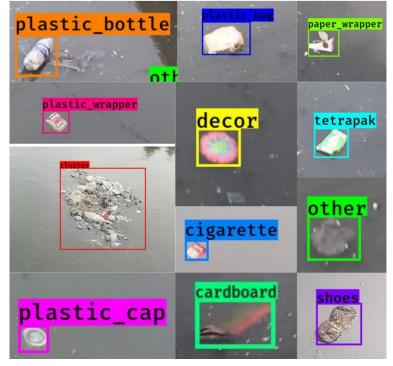




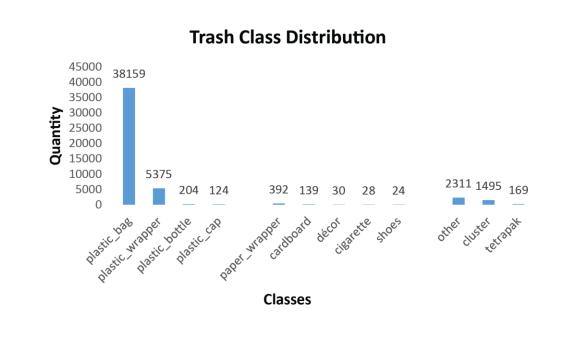
Dataset Annotation (TCD)

- Trash/Non-Trash
 - Single Class, 13,500 Images, 48,450 instances
- Trash
 - 3 Super-classes, 12 classes,
 13,500 images, 48,450 instances

Plastic	Non-plastic	Hybrid
Plastic Bag	Shoes	Tetrapak
Plastic Wrapper	Decor	Cluster
Plastic Bottle	Cigarette	Other
Plastic Cap	Paper Wrapper	
	Cardboard	



Data Distribution (TCD)



Dataset Collection (TFD)

• 2 Sites

City	Location	Water Channel	GPS Coordinates	
			Latitude	Longitude
Lahore	Liaquatabad	Cantonment Drain	31.470839	74.332759
Lahore	Defence Raod	Hudiara Drain	31.397972	74.211921

- ~49 hours of video data collected
 - Liaquatabad 24 hours
 - Defence Road 25 hours

Location	Water Channel	Date	Starting Time	Video Time
Liaquatabad	Cantonment Drain	03-17-21	15:00	$1 \text{ hr } 47 \min$
Liaquatabad	Cantonment Drain	03-18-21	15:00	2 hr 6 min
Liaquatabad	Cantonment Drain	03-20-21	15:00	2 hr 8 min
Liaquatabad	Cantonment Drain	03 - 31 - 21	07:00	7 hr 57 min
Liaquatabad	Cantonment Drain	04-01-21	07:00	$4~{\rm hr}~57~{\rm min}$
Liaquatabad	Cantonment Drain	04-03-21	07:00	$4~{\rm hr}~51~{\rm min}$
Defence Raod	Hudiara Drain	03-17-21	11:00	$2~{\rm hr}$ 24 min
Defence Raod	Hudiara Drain	03-18-21	11:00	$2~{\rm hr}$ 54 min
Defence Raod	Hudiara Drain	03-20-21	11:00	$2~{\rm hr}$ 56 min
Defence Raod	Hudiara Drain	03-24-21	07:00	$4 \text{ hr } 1 \min$
Defence Raod	Hudiara Drain	03 - 25 - 21	07:00	$3~{\rm hr}$ $55~{\rm min}$
Defence Raod	Hudiara Drain	03 - 27 - 21	07:00	$3~{\rm hr}$ $37~{\rm min}$
Defence Raod	Hudiara Drain	03-31-21	15:00	$2~{\rm hr}$ 47 min
Defence Raod	Hudiara Drain	04-01-21	15:00	$2~{\rm hr}$ 54 min



Dataset Annotation (TFD)

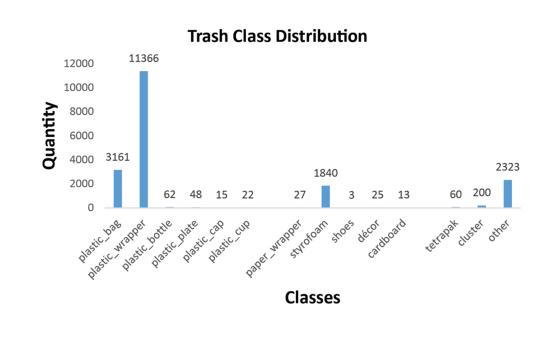
- Camera calibration data for trash flow rate
- Trash
 - 3 Super-classes, 14 classes
 - 19,165 unique instances

Plastic	Non-plastic	Hybrid
Plastic Bag	Shoes	Tetrapak
Plastic Wrapper	Decor	Cluster
Plastic Bottle	Styrofoam	Other
Plastic Plate	Paper Wrapper	
Plastic Cap	Cardboard	
Plastic Cup		





Data Distribution (TFD)



Automatic Quantification

Fine Grained Detection & Classification

Trash/Non-Trash Detection Challenges



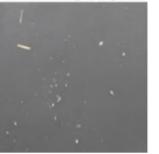
(a) Deformed object



(f) Color variation



(b) Sub-merged objects



(g) Micro-particles of trash



(c) Reflection of flying bird



(h) Pile of trash



(d) Reflection of buildings







(e) Object in Reflection



(j) Air bubbles

Trash/Non-Trash Detection Challenges

- Variable Object Sizes (COCO Standard)
 - Deformed objects cause intra-class variance

Size	No. of Objects	Area (pixels)
Small	11,214	area $\leq 32^2$
Medium	32,078	$32^2 < \text{area} \le 96^2$
Large	5,158	area > 96^2
Total	48,450	area $> 7^2$

Fine-grained Detection & Classification Challenges

• Texture and Geometrical similarity



Existing object detectors fail to localize and classify in these challengings cases

- What is attention?
 - How does the human visual system work? 0





Wake up the red

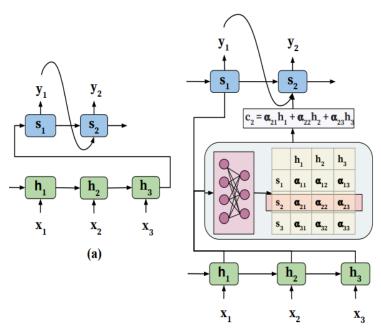






Improving simultaneous localization and classification via Attention

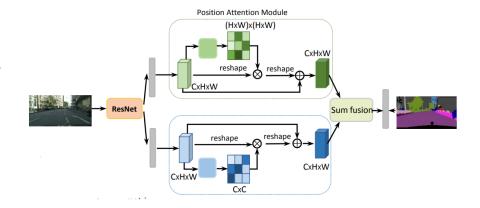
- Attention for machine translation*
 - Encoder-Decoder network
 - Attention as relative importance



*Chaudhari, Sneha, et al. "An attentive survey of attention models."

- Attention for image classification*
- Comparison of the second secon

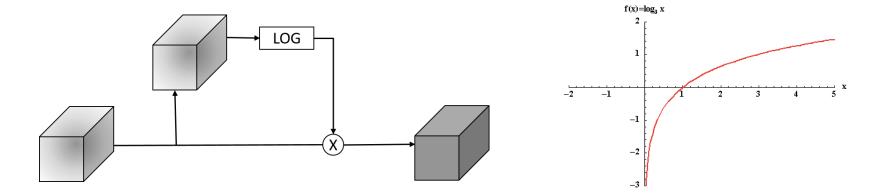
Attention for image segmentation**



*Jetley, Saumya, et al. "Learn to pay attention." **Fu, Jun, et al. "Dual attention network for scene segmentation."

• Log Attention Module (LAM)

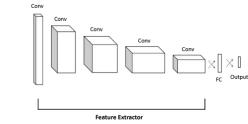
$$f_{i+1} = f_i \times \log(ReLU(f_i) + 1)$$



Methodology: Introducing Attention in Yolo-v3

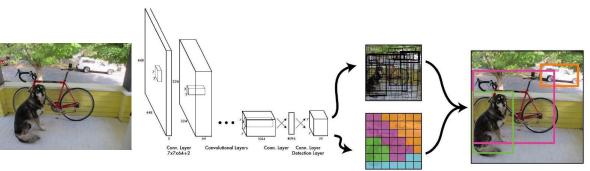
• Sliding Window Detection







• YOLO: You Only Look Once



Methodology: Introducing Attention in Yolo-v3

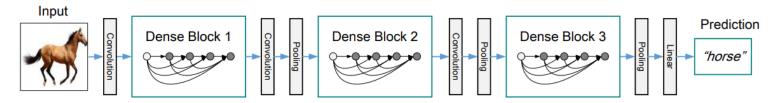
• 4 Log Attention Modules (LAM)

Type	Size	Times	Output
Convolutional	$3 \ge 3$		256x256
Convolutional	$3 \ge 3$		128x128
Convolutional	$1 \ge 1$		$128 \ge 128$
Convolutional	$3 \ge 3$	1x	$128\ge 128$
Residual			$128 \ge 128$
Convolutional	$3 \ge 3$		$64 \ge 64$
Convolutional	$1 \ge 1$		64 x 64
Convolutional	$3 \ge 3$	2x	$64 \ge 64$
Residual			$64\ge 64$
Convolutional	$3 \ge 3$		$32 \ge 32$
Convolutional	$1 \ge 1$		32 x 32
Convolutional	$3 \ge 3$	8x	$32 \ge 32$
Residual			$32 \ge 32$
Convolutional	$3 \ge 3$		16 x 16
Convolutional	1 x 1		16 x 16
Convolutional	$3 \ge 3$	8x	$16 \ge 16$
Residual			$16\ge 16$
Convolutional	$3 \ge 3$		8 x 8
Convolutional	$1 \ge 1$		8 x 8
Convolutional	$3 \ge 3$	4x	8 x 8
Residual			8 x 8

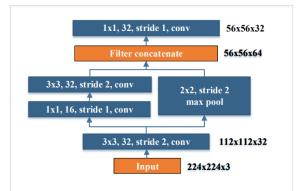
Type	Size	Times	Output
Convolutional	$3 \ge 3$		256x256
Convolutional	$3 \ge 3$		128x128
Convolutional	$1 \ge 1$		128 x 128
Convolutional	$3 \ge 3$	1x	$128 \ge 128$
Residual			$128 \ge 128$
LAM			128 x 128
Convolutional	$3 \ge 3$		$64 \ge 64$
Convolutional	$1 \ge 1$		64 x 64
Convolutional	$3 \ge 3$	2x	$64 \ge 64$
Residual			$64 \ge 64$
LAM			64 x 64
Convolutional	$3 \ge 3$		$32 \ge 32$
Convolutional	1 x 1		32 x 32
Convolutional	$3 \ge 3$	8x	$32 \ge 32$
Residual			$32 \ge 32$
LAM			32 x 32
Convolutional	$3 \ge 3$		16 x 16
Convolutional	1 x 1		16 x 16
Convolutional	$3 \ge 3$	8x	$16 \ge 16$
Residual			$16 \ge 16$
LAM			16 x 16
Convolutional	$3 \ge 3$		8 x 8
Convolutional	1 x 1		8 x 8
Contonational			
Convolutional	$3 \ge 3$	4x	8 x 8

Methodology: Introducing Attention in PeleeNet

- PeleeNet
 - A variant of densenet*



- Densenet41
- Stem Block for better feature expression
- Dynamic Number of Channels in BottleNeck Layer
- Residual Connections for fine-grained features



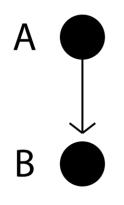
Methodology: Introducing Attention in PeleeNet

• 2 L	og Attention	Modules	(LAM)
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Type	Size	Times	Output
Stem Block			$56 \ge 56 \ge 32$
Dense Layer		3x	$56 \ge 56 \ge 128$
Convolutional	$1 \ge 1$		$56 \ge 56 \ge 128$
Average Pool	$2 \ge 2$		$28 \ge 28 \ge 128$
Dense Layer		4x	$28 \ge 28 \ge 256$
Convolutional	$1 \ge 1$		$28 \ge 28 \ge 256$
Average Pool	$2 \ge 2$		$14 \ge 14 \ge 128$
Dense Layer		8x	$14 \ge 14 \ge 512$
Convolutional	$1 \ge 1$		$14 \ge 14 \ge 512$
Average Pool	$2 \ge 2$		$7 \ge 7 \ge 512$
Dense Layer		6x	7 x 7 x 704
Convolutional	$1 \ge 1$		$7 \ge 7 \ge 128$

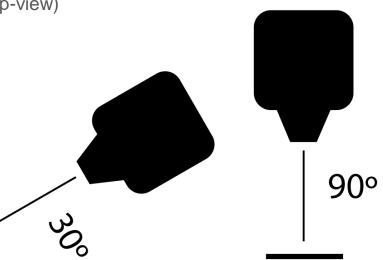
Type	Size	Times	Output
Stem Block			$56 \ge 56 \ge 32$
Dense Layer		3x	$56 \ge 56 \ge 128$
LAM			$56 \ge 56 \ge 128$
Convolutional	$1 \ge 1$		$56 \ge 56 \ge 128$
Average Pool	$2 \ge 2$		$28 \ge 28 \ge 128$
Dense Layer		4x	$28 \ge 28 \ge 256$
LAM			$28 \ge 28 \ge 256$
Convolutional	$1 \ge 1$		$28 \ge 28 \ge 256$
Average Pool	$2 \ge 2$		$14 \ge 14 \ge 128$
Dense Layer		8x	$14 \ge 14 \ge 512$
Convolutional	$1 \ge 1$		$14 \ge 14 \ge 512$
Average Pool	$2 \ge 2$		$7 \ge 7 \ge 512$
Dense Layer		6x	7 x 7 x 704
Convolutional	$1 \ge 1$		$7 \ge 7 \ge 128$

- Water flow measurement through object detection
- Steps:
 - Calculating vertical distance travelled by trash object
 - Divide vertical distance by time taken to travel between point A and B to get water flow



- Pixel to Pixel real world distance?
 - Take image of an object with known dimension (top-view)
 - Map pixel dimensions to real world dimensions
 - Dataset does not contain top-view
 - Videos with slight tilt or perspective



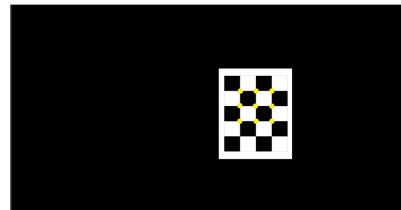


- Orthogonal projection of tilted image through Homography
 - Checkerboard Pattern Used (Checker dimensions = 4 inches)
 - Orthogonal image creation for calculating transformation



- Orthogonal projection of tilted image through Homography
 - 9 corresponding points from both images





• Orthogonal projection of tilted image through Homography

$$\begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} \Leftrightarrow \mathbf{x}_2 = H\mathbf{x}_1$$

In inhomogenous coordina ($x'_2 = x_2/z_2$ and $y'_2 = y_2/z_2$),

$$x_{2}' = \frac{H_{11}x_{1} + H_{12}y_{1} + H_{13}z_{1}}{H_{31}x_{1} + H_{32}y_{1} + H_{33}z_{1}}$$
$$y_{2}' = \frac{H_{21}x_{1} + H_{22}y_{1} + H_{23}z_{1}}{H_{31}x_{1} + H_{32}y_{1} + H_{33}z_{1}}$$

• Orthogonal projection of tilted image through Homography

$$z_1 = 1$$

$$x'_2(H_{31}x_1 + H_{32}y_1 + H_{33}) = H_{11}x_1 + H_{12}y_1 + H_{13}$$

$$y'_2(H_{31}x_1 + H_{32}y_1 + H_{33}) = H_{21}x_1 + H_{22}y_1 + H_{23}$$

$$\mathbf{a}_x^T \mathbf{h} = \mathbf{0}$$

 $\mathbf{a}_y^T \mathbf{h} = \mathbf{0}$

• Orthogonal projection of tilted image through Homography

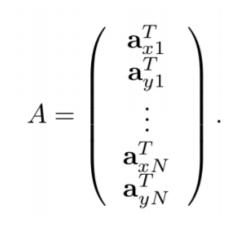
$$\mathbf{h} = (H_{11}, H_{12}, H_{13}, H_{21}, H_{22}, H_{23}, H_{31}, H_{32}, H_{33})^{T}$$

$$\mathbf{a}_{x} = (-x_{1}, -y_{1}, -1, 0, 0, 0, x'_{2}x_{1}, x'_{2}y_{1}, x'_{2})^{T}$$

$$\mathbf{a}_{y} = (0, 0, 0, -x_{1}, -y_{1}, -1, y'_{2}x_{1}, y'_{2}y_{1}, y'_{2})^{T}.$$

• Orthogonal projection of tilted image through Homography

 $A\mathbf{h} = \mathbf{0}$ 2Nx9 9x1



Results & Analysis

Experimental Setup

Dataset

- Split (TCD)
 - Training 12500 samples
 - Testing 1000 samples

Algorithms

- Yolo-v3*
- Yolo-v3-Tiny*
- PeeleNet**
- Yolo-v3+Attn
- PeeleNet+Attn

Evaluation Metrics

• Precision

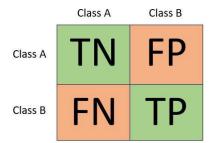
$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

• Intersection over union (IoU)

$$IoU = \frac{Area(P \cap G)}{Area(P \cup G)}$$

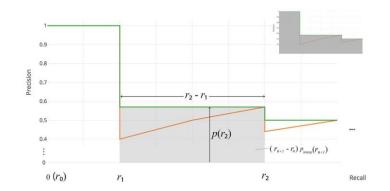


Evaluation Metrics

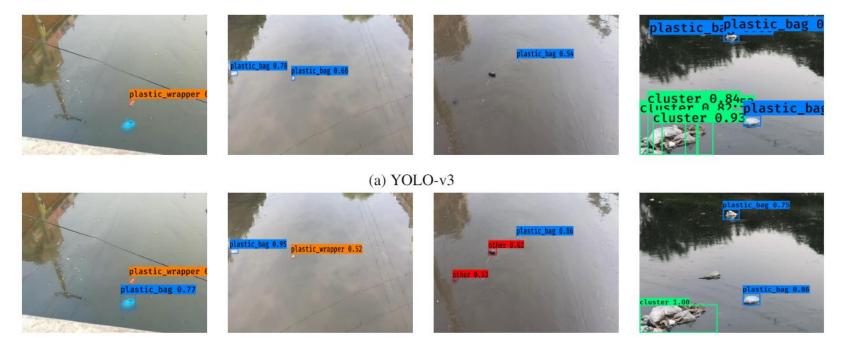
• Average Precision (AP)

$$\mathrm{AP} = \int_0^1 p(r) dr$$

- Three different object sizes
 - Small
 - Medium
 - Large



Qualitative Results



(b) YOLO-v3+Attn

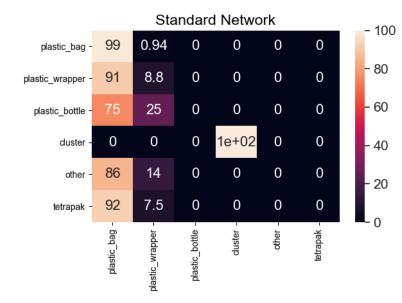
Size	No. of Objects	Area (pixels)
Small	11,214	area $\leq 32^2$
Medium	32,078	$32^2 < area \le 96^2$
Large	5,158	area > 96^2
Total	48,450	area $> 7^2$

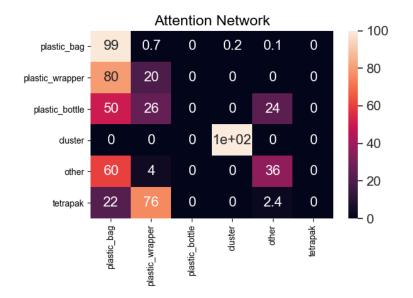
Object Detection Analysis

Model	#Param	AP^S	AP^M	AP^{L}	mAP
YOLO-v3 [20]	61.5M	3.4	7.4	10.5	21.7
YOLO-v3-Tiny	8.6M	0.7	2.4	7.4	7.8
PeleeNet [25]	4.8M	3.0	10.3	21.0	26.0
YOLO-v3+Attn	61.5M	3.6	21.4	10.8	31.5
PeleeNet+Attn	4.8M	3.4	10.4	26.6	26.5

Object Detection Analysis

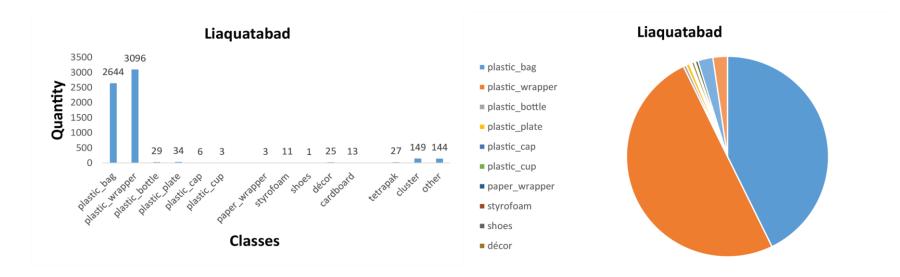
• Plastic bag occupies most of the predictions.





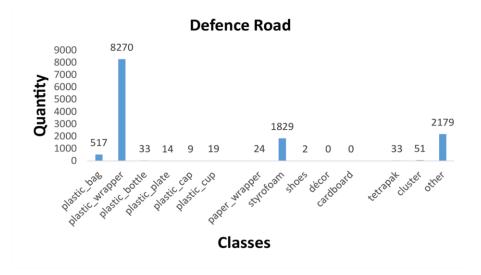
Trash Class Distribution Analysis (TFD)

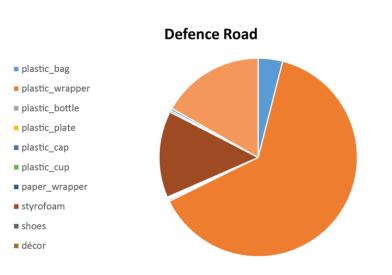
• Liaquatabad (Cantonment Drain)



Trash Class Distribution Analysis (TFD)

• Defence Road (Hudiara Drain)



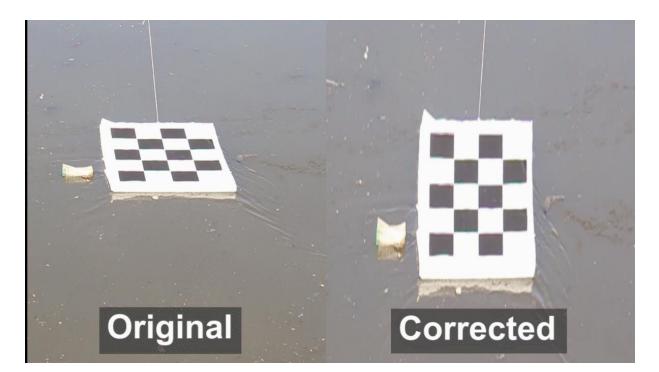


Trash Class Distribution Analysis (TFD)

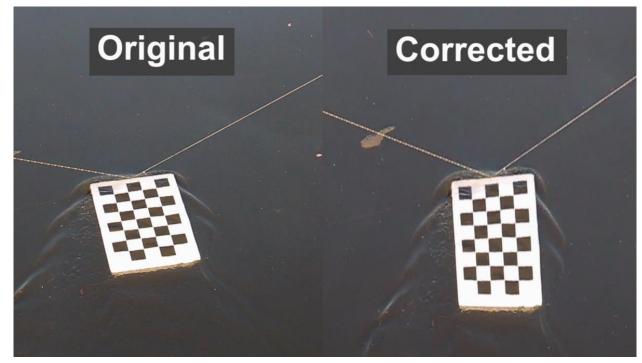
• ATOPH (Average Trash Objects Per Hour)

Site	Drain	ATOPH
Liaquatabad	Cantonment Drain	260
Defence Road	Hudiara Drain	508

• Liaquatabad site (Cantonment Drain) after applying Homography



• Defence Road site (Hudiara Drain) after applying homography



• Water Flow Calculation For Liaquatabad

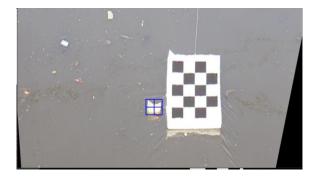
Checker dimension = 4 inches = 0.1016 m

Checker Pixels = 52 (After applying Homography)

Pixel Distance = 0.1016/52 = 0.0019538 m

- Y1 = 445 pixel (**Image at t = 0 sec**)
- Y2 = 611 pixel (Image at t = 1 sec)

Water Flow = (Y2 - Y1) * Pixel Distance = 0.32 m/s





Water Flow Calculation For Defence Road

Checker dimension = 4 inches = 0.1016 m

Checker Pixels = 27 (After applying Homography)

Pixel Distance = 0.1016/27 = 0.0037629 m

- Y1 = 266 pixel (**Image at t = 0 sec**)
- Y2 = 447 pixel (**Image at t = 1 sec**)

Water Flow = (Y2 - Y1) * Pixel Distance = 0.67 m/s





Liaquatabad (Cantonment Drain) 10.96m



Defence Road (Hudiara Drain) 30.18m



Water Flow: 0.67 m/s

Water Flow: 0.32 m/s

Summary

Achieved

- Dataset for fine-grained trash detection and classification (TCD)
- Improvement in localisation, detection and classification
- Dataset for trash class distribution (TFD)
- Trash class distribution analysis
- Water flow measurement

Future Work

- Solve data imbalance
- Validity of water flow measurement through flow meters

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Thank You!