Oyster Seed Counting

MATH 4020 Fall 2025

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Figure 1: Oyster Farm

Background

Louisiana Sea Grant is an organization that aids in marine and coastal life conservation, protection, and research.

Figures 2 and 3: Oyster Farm (top image), Oysters (bottom image)

Our Project's Goals

- Count a total amount of oyster seeds (< 2 mm) from an image of a Petri dish.
- Compare the results of our YOLO v-10 (You Only Look Once) to the Stardist Models
- Putting the pre-trained model on a device that can be used by the end user (oyster farmers, researchers, etc.)

Figure 4: Oysters

Collection of Oyster Seeds

- Seeds are collected with a bottle and are then put through filters that separates them by size
- There are three size categories: 0-2 mm, 2-4 mm, and 4-6 mm
- We are focused on annotating 0-2 mm oyster seeds

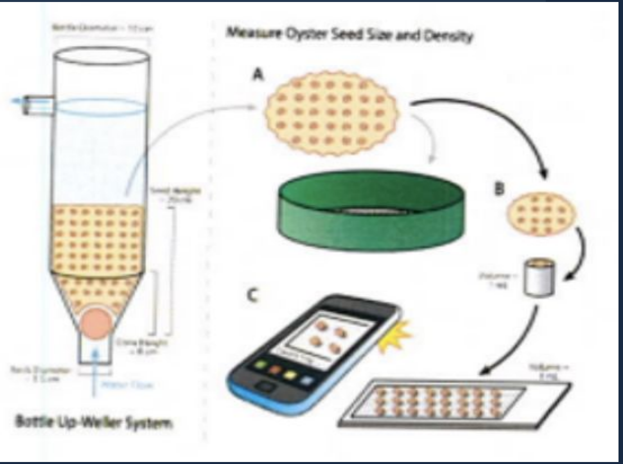

Figure 5: Bottle and Filtering Process

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VGG Image Annotator (VIA)

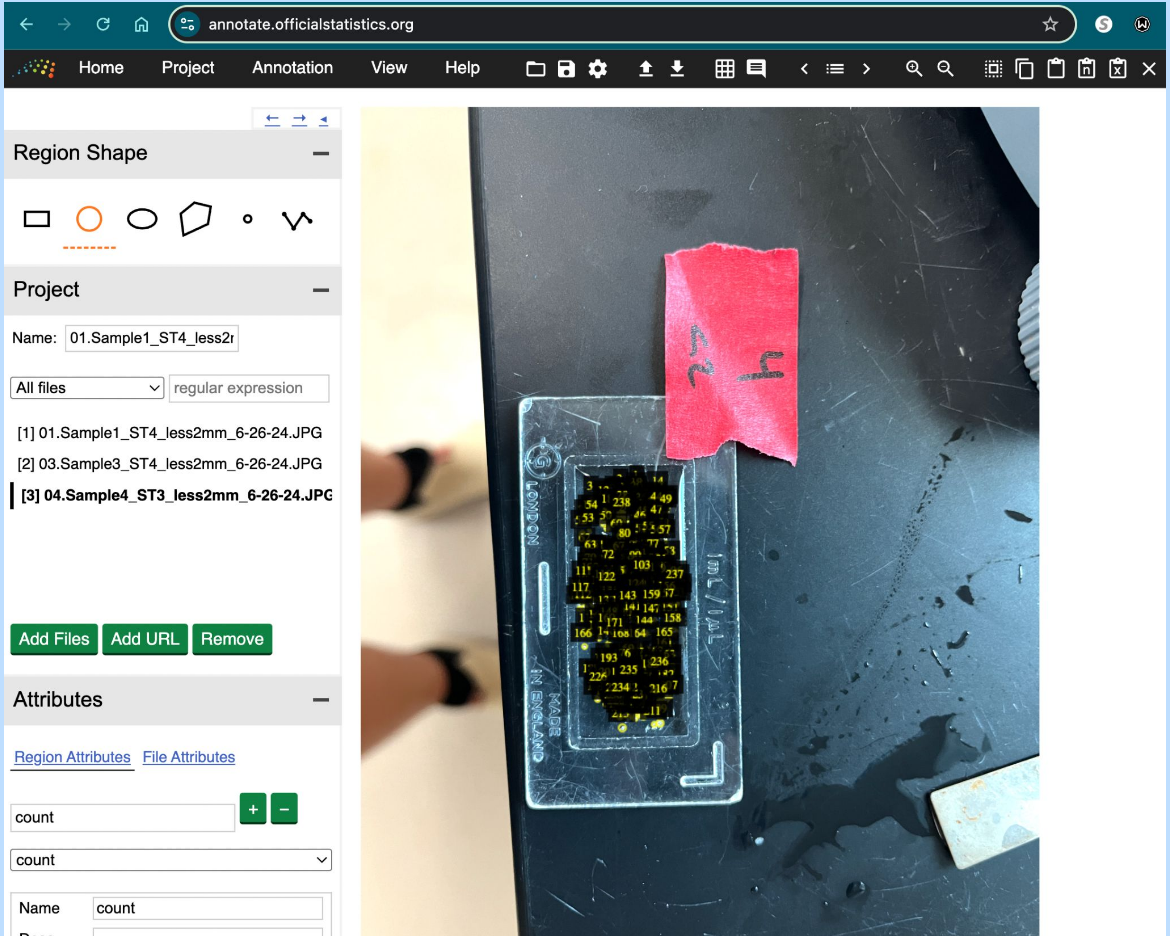

Figure 6: VIA Interface

Before and After Images of Annotations

Figures 7 and 8: original oyster image (left) and annotated image (right)

Challenges with Annotations

- Seeds are usually not circular
- Hard to differentiate between seeds and debris
- Time-consuming

Figure 9: Image of non-circular, bunched-together oyster seeds

CSV File Example

K8

	A	B	C	D	E	F	G
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Figure 10: CSV File Example

StarDist Architecture

- U-net:
  - Convolutional Neural Network

- Post-Processing
  - Intersection over Union (IOU) Metrics
  - Non-maximum suppression

- Use of star-convex polygons

- Object Probabilities: how likely a pixel is part of an object (pixels near seed's center are favored)

- Predicts distance to object's boundaries along 32 radial distances

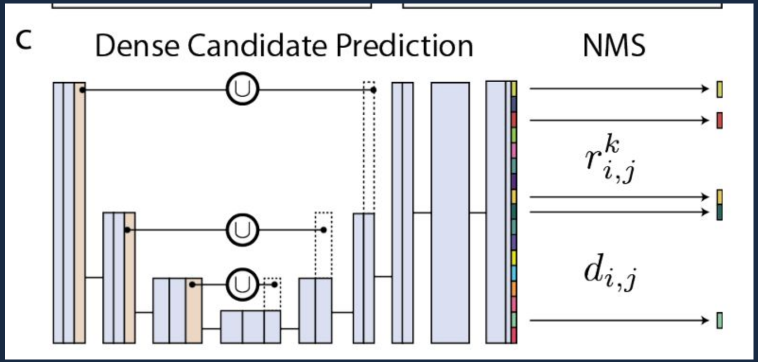


Figure 11: U-Net

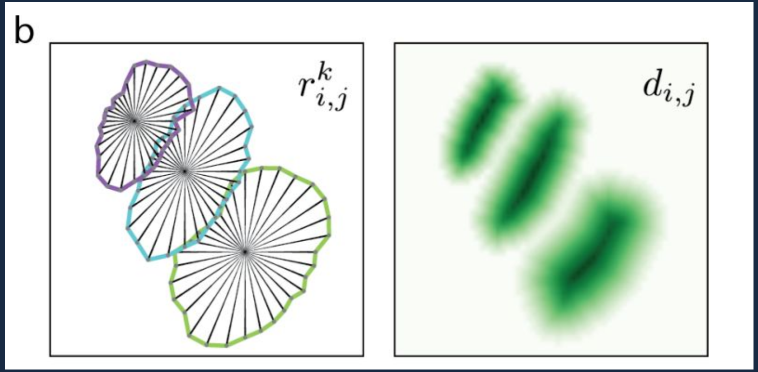


Figure 12: Star-convex distances and object probabilities

VLM Approch

- Deprecated this approach for reasons:
  - Poor performance without tilling
  - High Inference cost
  - Edge-Hardware constraints

Figure 13: Raw non-fine tuned moondream prediction on oyster seeds

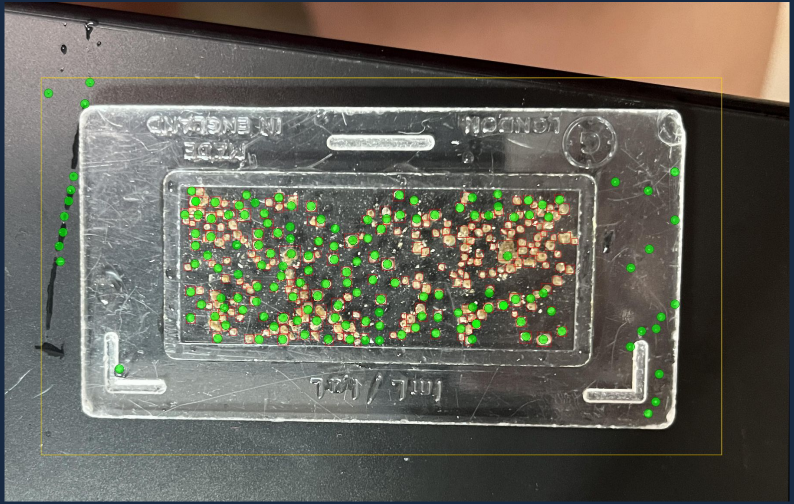


Figure 14: Fine tuned moondream prediction on oyster seeds with tilling and pre cropping

YOLO v-10 architecture

- Small, efficient real-time object detector
- NMS (Non-Maximum Suppression)-free architecture eliminates post-processing overhead
- Out of the box only knows a few objects (person, stop sign, ect.)

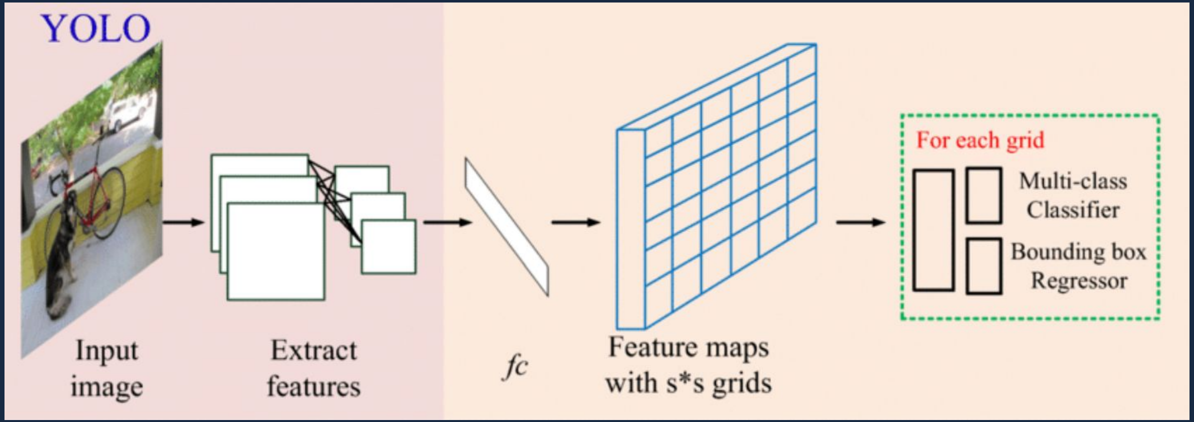


Figure 15: YOLOv10 Model Workflow

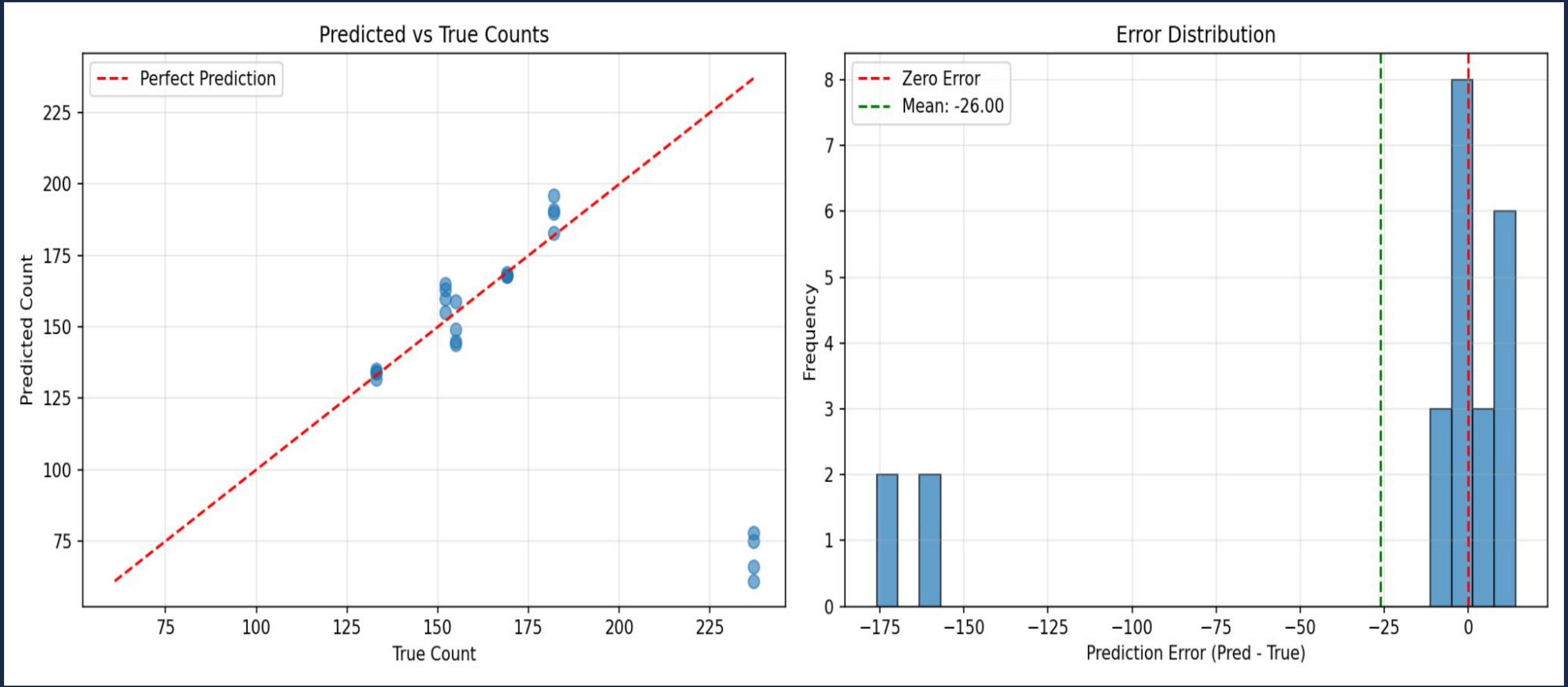
YOLO v-10 Results

- MAE (Mean Absolute Error): 32.25 seeds
- RMSE (Root-mean-square deviation): 68.54 seeds
- MAPE (Mean Absolute Percentage Error): 14.50%
- R^2 Score: -3.3084
- Bias: -26.00 (positive = overcounting)

Figure 16: Fine tuned YOLOv10s output (best performance)

YOLO v-10 Results

- Often under counting on dense or far images



YOLO v-10 Results

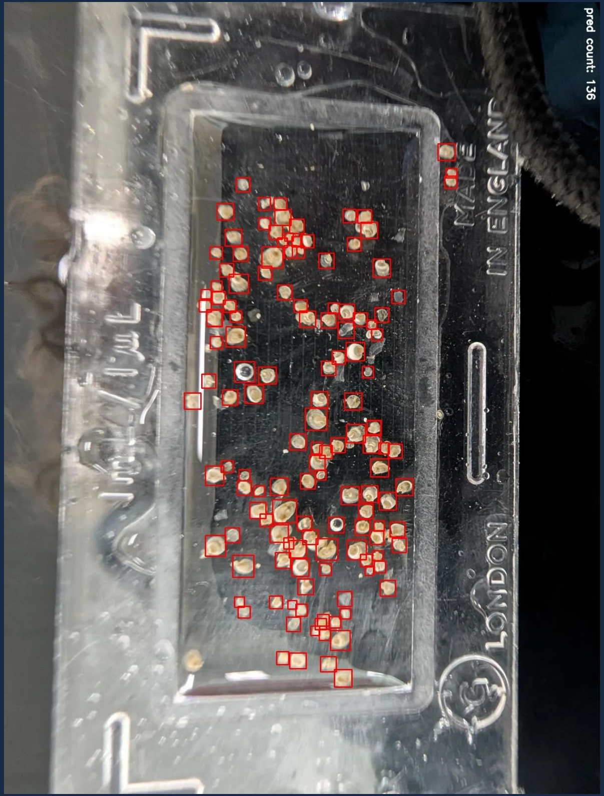


Figure 17: Fine tuned YOLOv10s output (best performance)

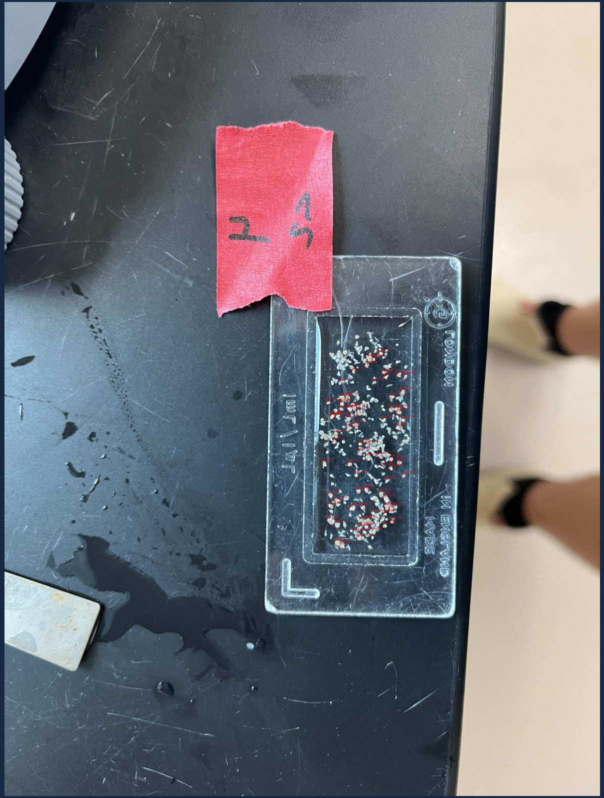


Figure 18: Fine tuned YOLOv10s output (worst performance)

YOLO v-10 Results

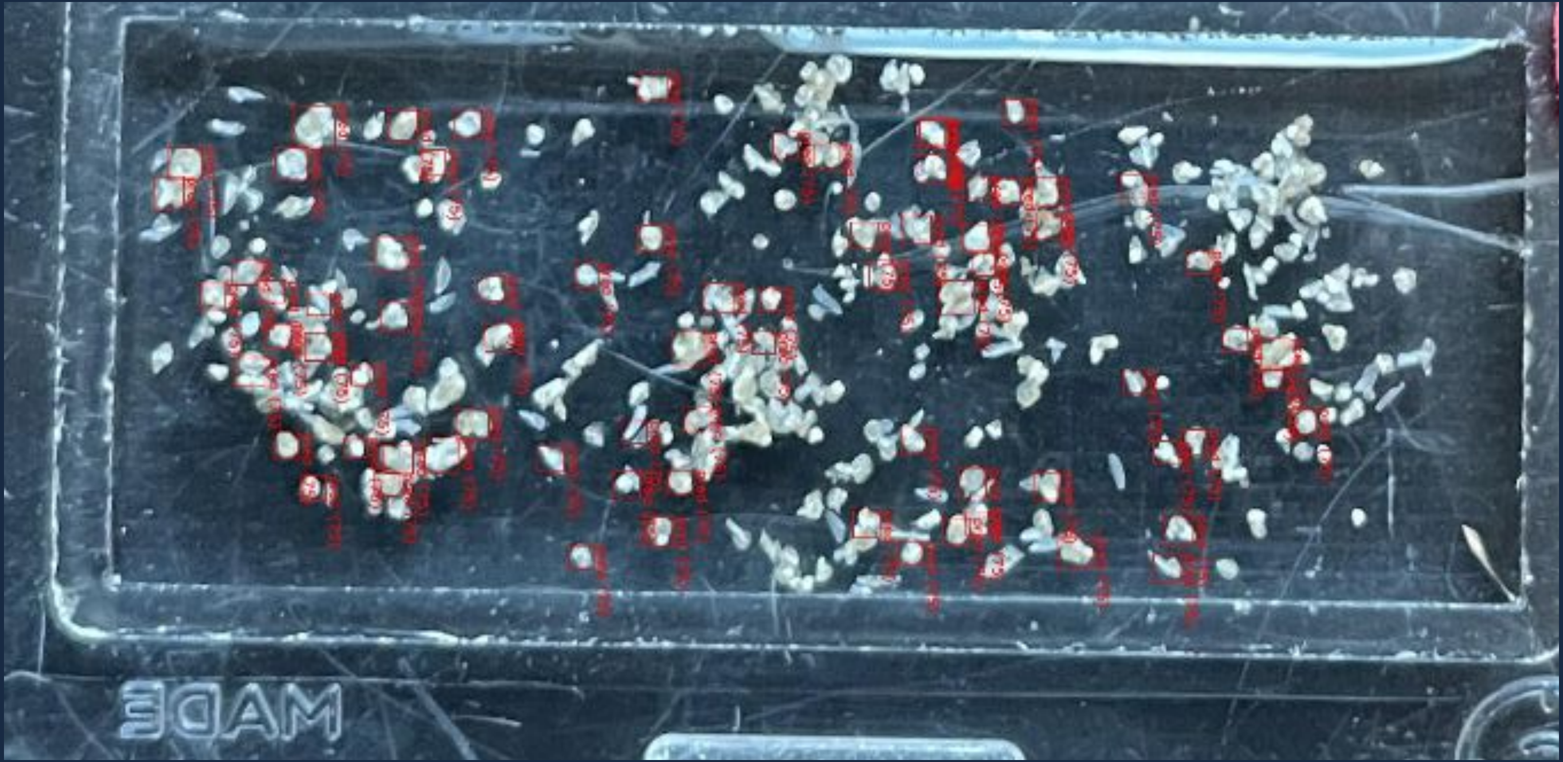


Figure 19: Fine tuned YOLOv10s output (worst case zoomed in)

Stardist vs YOLO Results

Table 1. Comparison of StarDist and YOLOv10s predictions on test images

Image	Actual Count	StarDist Pred.	YOLOv10s Pred.	StarDist Error	YOLOv10s Error
Sample19-16-25	118	62	117	-56	-1
Sample2_9-16-25	128	99	136	-29	+8
Sample3_9-16-25	161	128	184	-33	+23
Sample4_9-16-25	138	116	151	-22	+13
Sample5_9-16-25	186	153	214	-33	+28
Sample1_5-13-24	254	112	70	-142	-184
Sample2_5-13-24	275	252	179	-23	-96
Sample3_5-13-24	221	201	145	-20	-76
Sample4_5-13-24	249	235	187	-14	-62
MAE				41.3	54.6
Accuracy				77.4%	76.4%

Future Work

- Putting the YOLO model on the Raspberry Pi
- Improving performance

Acknowledgements

We would like to thank the LSU Department of Mathematics, the Louisiana Sea Grant, Dr. Peter Wolenski, Dr. Nadejda Drenska, Gowri Priya Sunkara, Maganizo Kapita, and the previous oyster teams.

Works Referenced

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