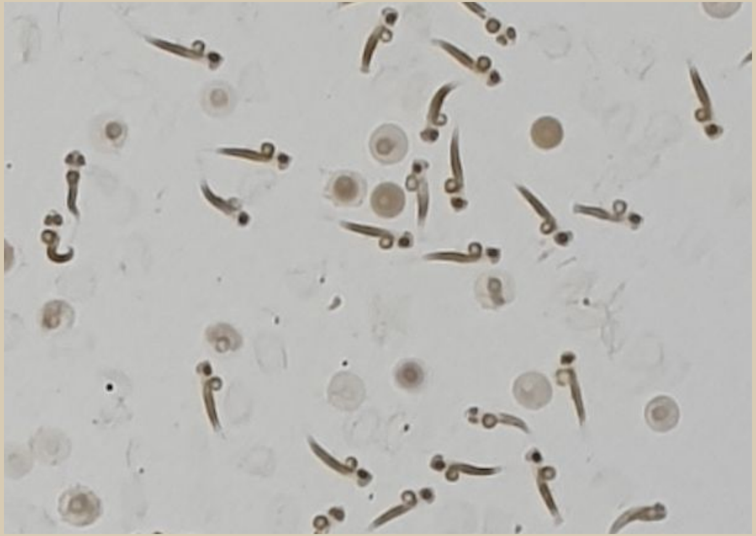
DSA4266 Group 3

Fish Larvae Counting

Colin Ng | Gary Lee | Colin Tan | Woon Hao Xuan

Introduction



Fish Larvae Counting

Monitor the stocking density of the fish larva and counts of fertilized and unfertilized fish eggs at regular intervals

Objective

Our goal is to train a **predictive model** that is able to **accurately classify** images of petri-dish containing three main classes: *Fertilised Eggs*, *Unfertilized Eggs* and *Fish Larvae*, and an *Unidentifiable* class to handle foreign objects as well.

Once trained, we are to implement an intuitive user interface with focus on accuracy and scalability.

Definition

Phase 1: Mid-Term Assessment

Phase 2: Final Assessment

Our Workflow

01 Data Pre-Processing

Data preparation

02 Modelling & Tuning

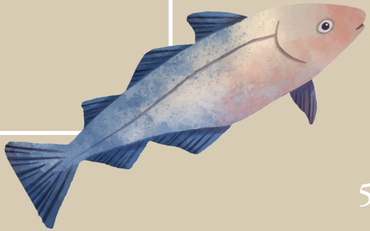
Experimenting to obtain optimal parameters

03 Testing

Pre-processing and predicting of test images

04 Implementation of Solution

Productionizing our solution



01 Data Pre-Processing

Data preparation

Labelling of Data

Fertilized Egg

Objects with partially formed head and curled up

Unfertilized Egg

Sphere like structure of at least a certain size

Fish Larva

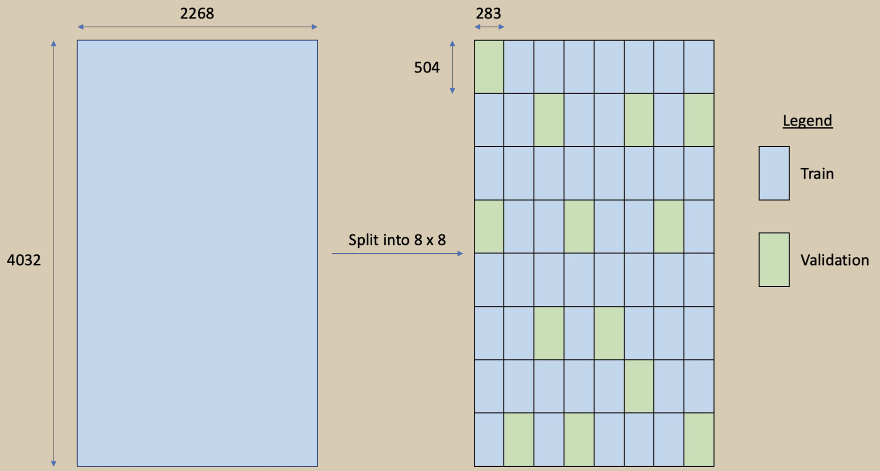
Obvious object that has a head and a long tail (can be curved)

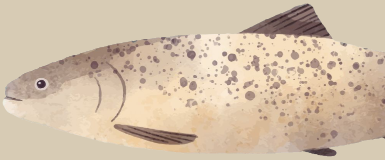
Unidentifiable

Objects that do not resemble any of the 3 classes, or foreign objects

Recap: Phase 1 Data Preparation

- Labelled images with references to slide provided (non-SFA images)
- Sliced each image 8x8 into 64 equal parts of size (504, 283) when view vertically
- Resulting in 640 slices (i.e. 640 = 64 * 10 images)
- Train-Validation Split (8:2) resulting in 507 training data and 133 validation data





Phase 2: Total Counts

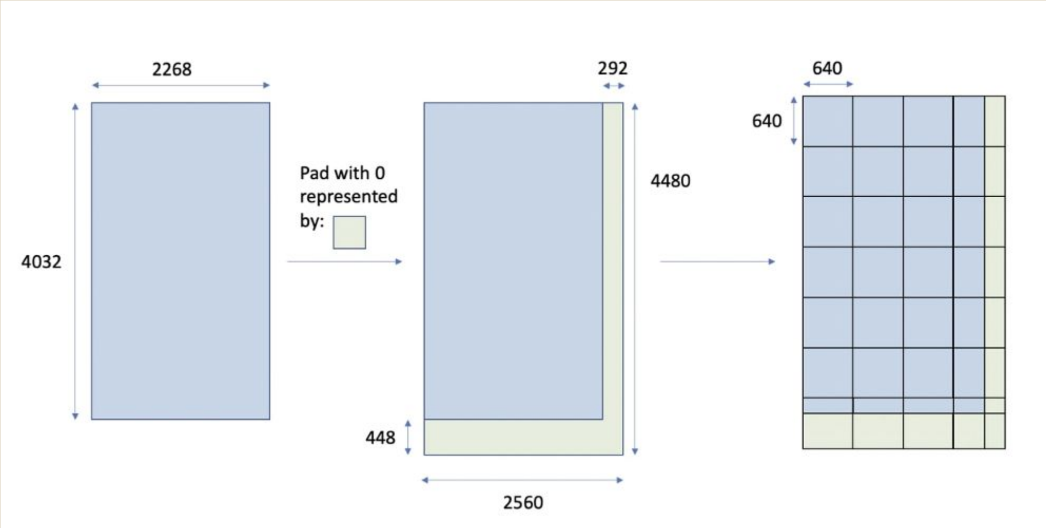
Label Type	Total Number of Labels
Fertilised Egg	376
Unfertilised Egg	244
Fish Larvae	956
Unidentifiable	129

Labelled using LabelImg: https://github.com/tzutalin/labelImg

Image Number	Fertilised Eggs	Unfertilised Eggs	Fish Larvae	Unidentifiable	Remark(s)
20210729_131410.jpg (1)	56	3	60	7	Low Unfert Eggs
20210729_132515.jpg (2)	1	64	41	10	Low Fert Eggs
20210729_132649.jpg (3)	5	137	174	11	Low Fert Eggs High Unfert Eggs High Larvae
20210729_134857.jpg (4)	21	3	66	6	Low Unfert Eggs
20210729_134912.jpg (5)	23	5	64	7	Low Unfert Eggs
20210903_095054.jpg (6)	42	10	117	34	High Fert Eggs High Unidentif
20210903_100603.jpg (7)	90	3	68	13	High Fert Eggs
20210903_100651.jpg (8)	43	15	124	13	High Larvae
20210903_100734.jpg (9)	76	3	81	18	High Fert Eggs Low Unfert Eggs High Larvae
20210903_100758.jpg (10)	19	1	161	10	High Larvae

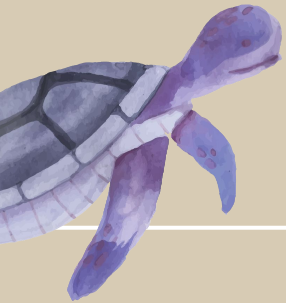
Phase 2: Slicing

- Right and bottom part of the image is padded with 0
- Slicing the incoming images results in squares of dimension (640, 640) regardless of input size
- In line with pre-trained weights which were trained on 640



Phase 2: Breakdown of Sliced Labels

Label Type	New Number of Sliced Labels	New Percentage of Total
Fertilised Egg	28	**7%**
Unfertilised Egg	17	**7%**
Fish Larvae	77	**8%**
Unidentifiable	8	**6%**



Label Type	Old Number of Sliced Labels (from Old Slices)	Old Percentage of Total (from Old Slices)
Fertilised Egg	93	13%
Unfertilised Egg	27	10%
Fish Larvae	106	16%
Unidentifiable	18	10%

Phase 2: Total Counts Post-Slicing

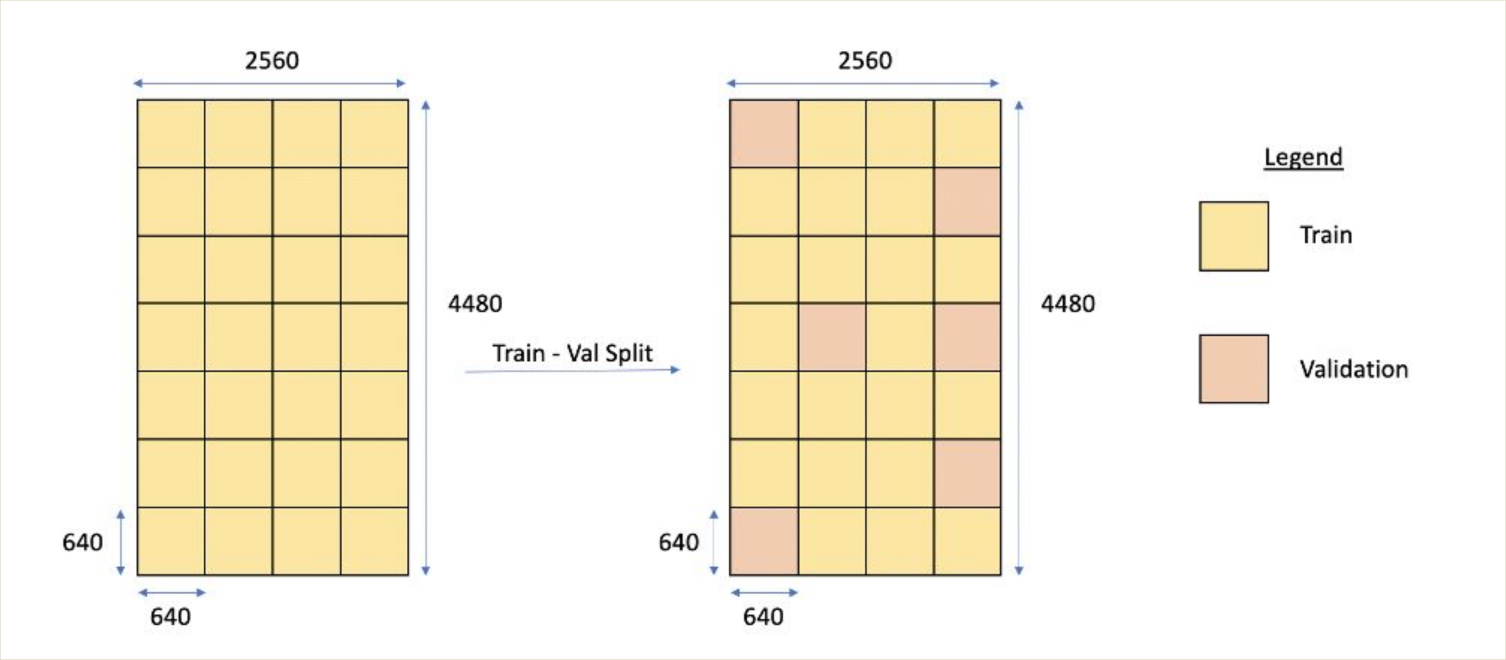
Label Type	New Overall Number of Labels
Fertilised Egg	348
Unfertilised Egg	227
Fish Larvae	**879**
Unidentifiable	121

Phase 2: Data Augmentation on Training Set

- Validation set is untouched
- Mainly increase the counts of Fertilised Eggs [Unfertilised Eggs have distinct features]
- New training set has 296 slices (original had 224 slices)
- Ratio of major three classes is approximately 3:1:3

Label Type	Final Overall Number of Labels
Fertilised Egg	**952**
Unfertilised Egg	**360**
Fish Larvae	**953**
Unidentifiable	137

Phase 2: Training-Validation Split (8:2)



Phase 2: Training-Validation Split Counts

Total: 10 images × 28 Slices each = 280 Slices

Training Set: 224 Slices

Label Type	Number of Labels
Fertilised Egg	286
Unfertilised Egg	186
Fish Larvae	695
Unidentifiable	95

Validation Set: 56 Slices

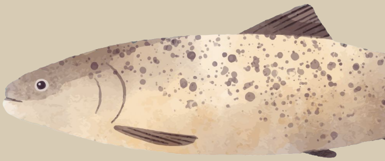
Label Type	Number of Labels
Fertilised Egg	62
Unfertilised Egg	41
Fish Larvae	184
Unidentifiable	26

02 Modelling & Tuning

Experimenting to obtain optimal parameters

Recap: Phase 1 Modelling & Tuning

- Made use of YOLOv3 model
- Baseline model: Batch size 8, epochs 50 and SGD
- Run evolution of 100 iterations
- Tune parsable parameters of the best model from evolution
- Attempted ensemble (but no improvements)
- Final model: mAP@0.5 of 0.872 for 3 main classes



110.Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
all	133	341	0.665	0.76	0.729	0.341
Fertilised Egg	133	115	0.69	0.922	0.821	0.332
Unfertilised Egg	133	60	0.775	0.917	0.871	0.464
Fish Larvae	133	136	0.813	0.934	0.924	0.431
Unidentifiable	133	30	0.38	0.267	0.301	0.139

Phase 2: Baseline Model

- Made use of YOLOv5s weights
- Using batch size of 8 and 50 epochs
- Default hyp.scratch file
- Auto-Anchor enabled
- Default SGD

```
     Epoch   gpu_mem       box       obj       cls     total    labels  img_size
     49/49     7.67G   0.04068  0.008723   0.01044   0.05985         7       704: 100% 64/64 [02:17<00:00,  2.15s/it]
               Class     Images     Labels          P          R     mAP@.5 mAP@.5:.95: 100% 9/9 [00:07<00:00,  1.19it/s]
                 all        133        341      0.516      0.782       0.68      0.262
      Fertilised Egg        133        115      0.515      0.896      0.782      0.285
    Unfertilised Egg        133         60       0.61      0.917      0.875      0.348
         Fish Larvae        133        136      0.626      0.949      0.847      0.358
      Unidentifiable        133         30      0.314      0.367      0.215     0.0574
50 epochs completed in 2.067 hours.
```

Phase 2: Evolution

Weights	Image Size	Batch Size	Epochs	Optimizer	mAP
YOLOv5s	640	30	150	SGD	0.71606
YOLOv5m	640	30	150	SGD	0.71772
YOLOv5l	640	30	150	SGD	0.74272
YOLOv5x	640	30	150	SGD	0.7116
YOLOv5s	640	30	150	Adam	0.7406
YOLOv5m	640	30	150	Adam	0.7410
YOLOv5l	640	30	150	Adam	0.7424
YOLOv5x	640	30	150	Adam	0.7347

Phase 2: Leading Model from Evolution

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95
all	56	313	0.727	0.727	0.743	0.395
Fertilised Egg	56	62	0.723	0.774	0.839	0.432
Unfertilised Egg	56	41	0.948	0.893	0.962	0.57
Fish Larvae	56	184	0.849	0.973	0.908	0.474
Unidentifiable	56	26	0.389	0.269	0.264	0.103

- The best model from our evolution had a overall mAP of 0.743
- 3-class mAP of 0.903

Phase 2: Ensemble

- Similar to our Phase I experiment, we used BAGGING approach to ensemble our models
- Trained 10 separate YOLOv5l models with different bootstrap samples and hyperparameters
- Experimented with different aggregation techniques, namely:

  - Max aggregation
  - Mean aggregation
  - NMS aggregation

Phase 2: Ensemble

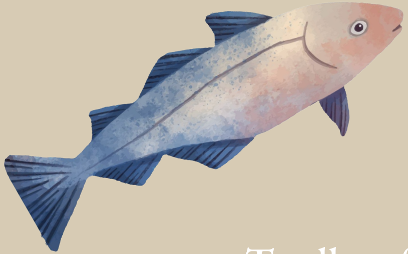
Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
all	56	313	0.732	0.728	0.754	0.366
Fertilised Egg	56	62	0.672	0.79	0.871	0.425
Unfertilised Egg	56	41	0.901	0.878	0.923	0.45
Fish Larvae	56	184	0.821	0.935	0.933	0.451
Unidentifiable	56	26	0.533	0.308	0.29	0.137

- Out of the 3 aggregation techniques, our ensemble model performed the best with mean aggregation
- Achieved the best overall mAP of 0.754 and 3-class mAP of 0.909

Phase 2: Final Model

While our ensemble model performed the best:

- Time and hardware constraint was an issue
- Decided to stick to single-model solutions for this assignment
- Nonetheless, we have shown that ensembling is an effective method to increase model performance.



Phase 2: Final Model

- To allow for greatly flexibility, we deployed two YOLOv5 models a user can choose to run inference on:
- Accurate: YOLOv5 (large) with a 3-class mAP of 0.903 and inference time of 37 seconds
- Speed: YOLOv5 (small) with a 3-class mAP of 0.839 and inference time of 10 seconds
- This flexibility allows user to choose between having

  - Better accuracy, or

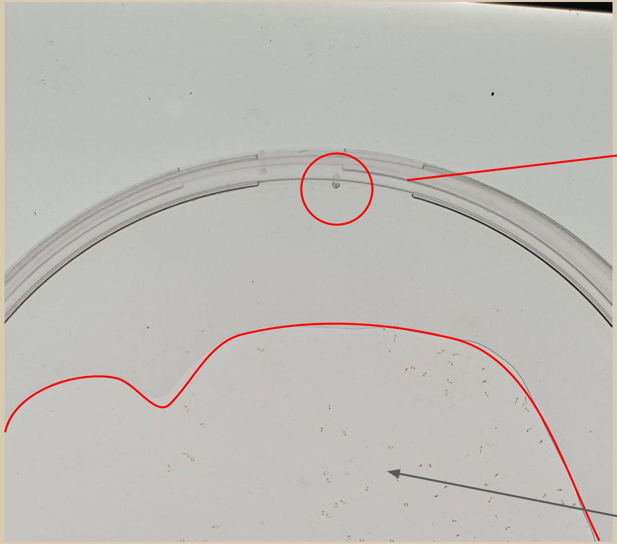
  - Faster prediction

03	Testing

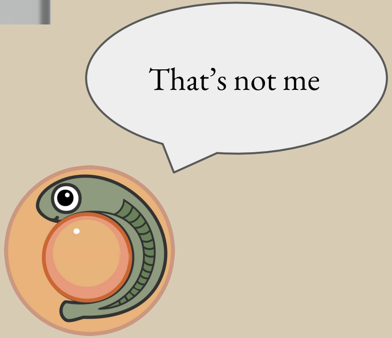
Pre-processing and predicting of test images

Masking of Test Images

Want to ensure that predictions are only made in the area of interest (and not outside the blob/around the edge of the petri-dish)



Area of interest (water blob)



Recap: Phase 1 Masking

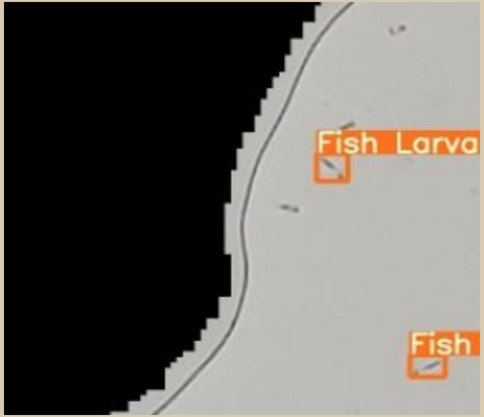
- Edges of masking are uneven and do not lie along the lie of the area of interest nicely

Before Masking

Area outside water blob

Area of interest (water blob)

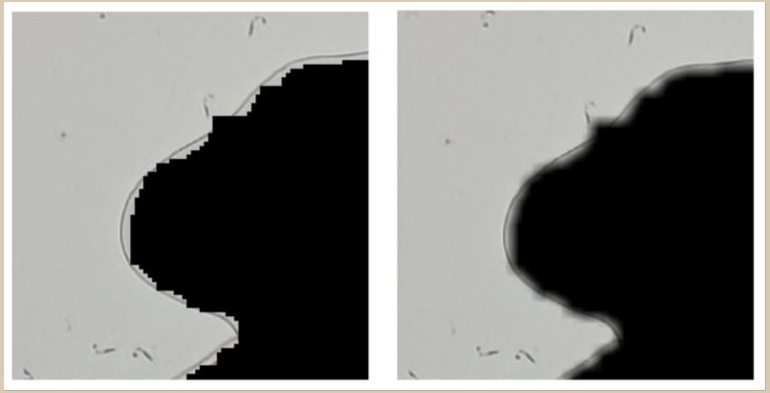
After Masking



Phase 2: Masking

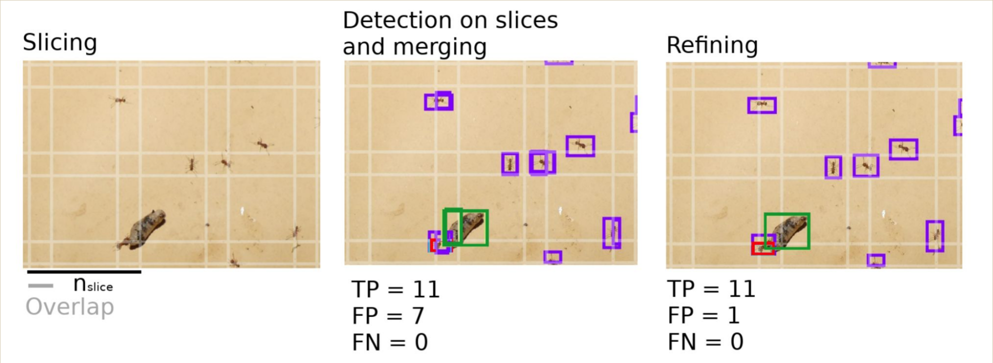
- Added some degree of blurring to the mask
- Obtained mask which is smoother and better aligned with the area of interest

Phase 1 **Phase 2**



Recap: Phase 1 Testing

- Using image from post-masking, we slice the masked image into 64 parts
- Slice with overlap to account for objects that are lost during slicing
- Run inference on individual slices: get normalized BB coordinates
- Rescale BB coordinates and redraw onto original size image



Phase 2: Testing

- Testing directly on full image (no longer slicing test images)
- Higher emphasis on Non-Max Suppression Parameters
- Tuned Confidence Threshold to 0.45, IOU Threshold to 0.15

Percentile	Minimum	25th Percentile	Mean	75th Percentile	Maximum
Confidence Scores at conf_t = 0.45	0.455	**0.789**	0.814	0.860	0.952

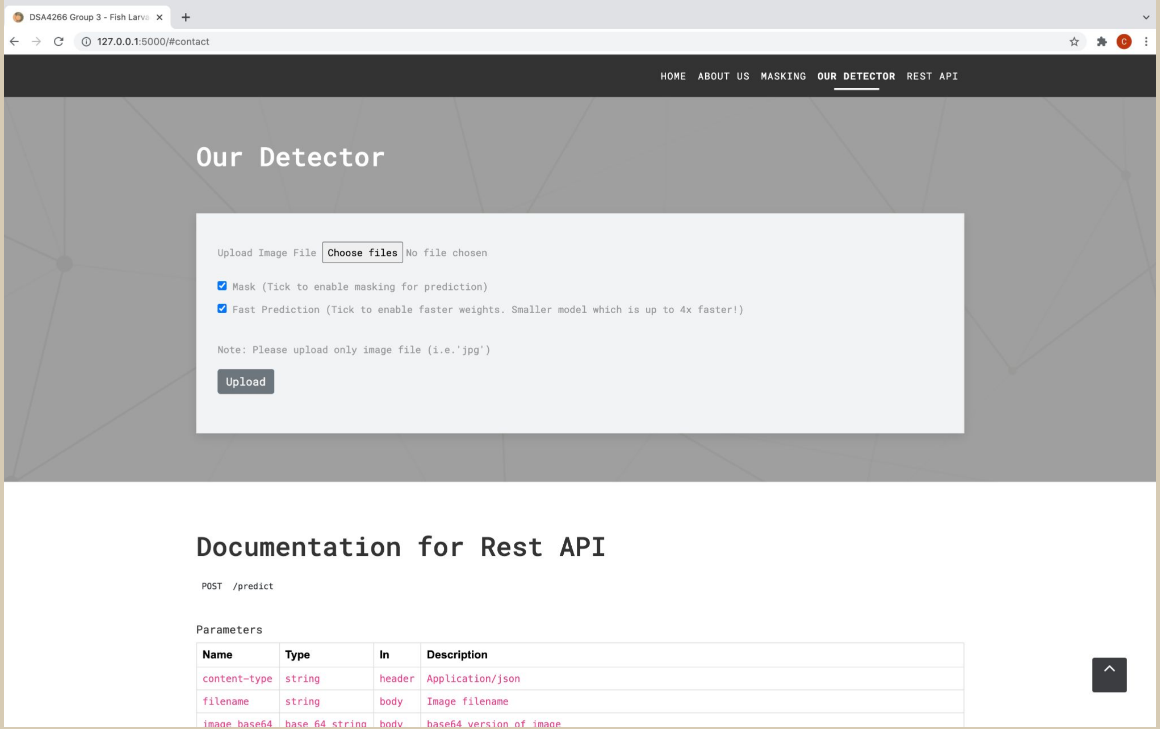
- Saves up on predicting time and computational space: no rescaling needed

04

Implementation of Solution

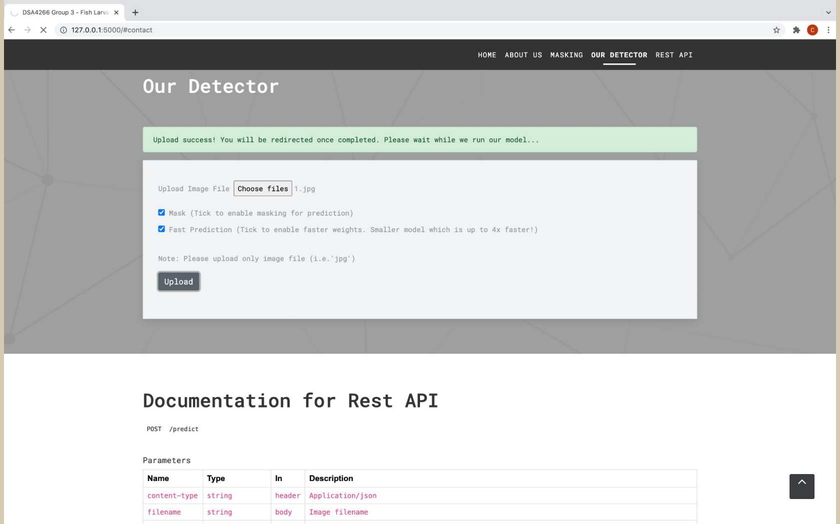
Productionizing our solution

UI: Intuitive & Easy to Use

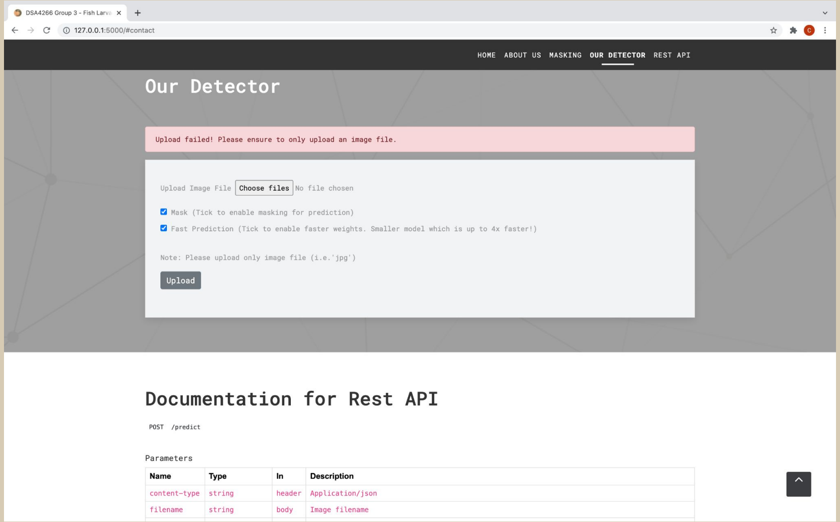


UI: Handles Right & Wrong Inputs

Right Input

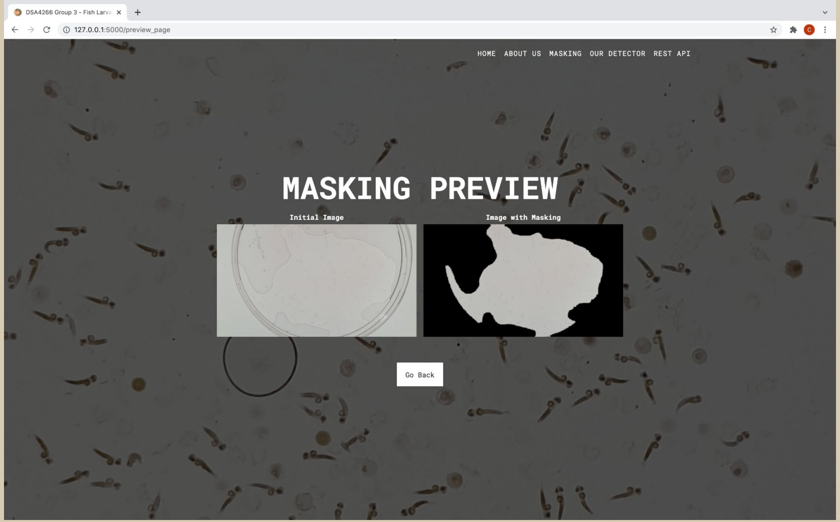


Wrong Input

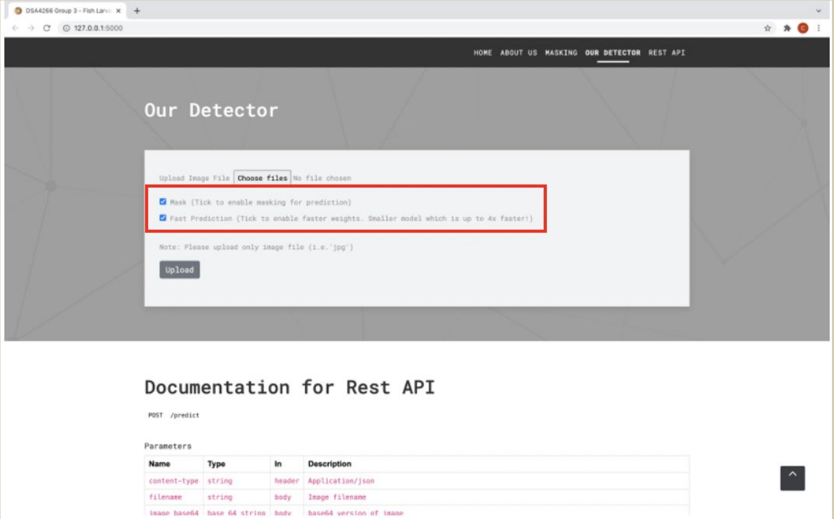


UI: Additional Features

Masking Preview



Option to Mask/Use Faster Weights



UI: Additional Outputs

- JSON file(s) (required)
- Annotated Image(s)
- Counts of classes in each image

Name	Date Modified	Size	Kind
2.jpg	Today at 9:39 PM	1.2 MB	JPEG image
2.json	Today at 9:39 PM	1.6 MB	Plain Text
3.jpg	Today at 9:39 PM	1.4 MB	JPEG image
3.json	Today at 9:39 PM	1.7 MB	Plain Text
counts.csv	Today at 9:39 PM	102 bytes	CSV Document

UI: Rest API

DSA4266 Group 3 - Fish Larva

127.0.0.1:5000/#contact

HOME ABOUT US MASKING OUR DETECTOR REST API

Fast Prediction (Tick to enable faster weights. Smaller model which is up to 4x faster!)

Note: Please upload only image file (i.e.'jpg')

Upload

Documentation for Rest API

POST /predict

Parameters

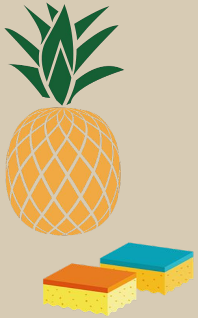
Name	Type	In	Description
content-type	string	header	Application/json
filename	string	body	Image filename
image_base64	base 64 string	body	base64 version of image
mask	boolean	body	(Optional, Default = True) Apply masking before prediction
fast	boolean	body	(Optional, Default = True) Enable fast prediction (smaller model for 4x faster prediction)

Future Work: Scalability

- <u>Auto-balance of new dataset to remove class imbalance</u>

  - Fish data expected to be highly skewed

  - Our data augmentation solution can be automated to balance new incoming fish data based on different seasons



Label Type	Original Overall Number of Labels
Fertilised Egg	348
Unfertilised Egg	227
Fish Larvae	879
Unidentifiable	121

Label Type	New Overall Number of Labels
Fertilised Egg	952
Unfertilised Egg	360
Fish Larvae	953
Unidentifiable	137

Future Work: Scalability

- Speed accuracy tradeoff

  - Whilst our ensemble model performed the best with a 3-class mAP of 0.909, time and hardware constraint was a limiting factor

  - With access to better hardware (eg. GPUs) in the future, ensemble models is viable for future offline predictions

- Transfer learning for efficient future training

  - Upstream feature extraction layers are frozen while downstream layers are allowed to learn the variation in new datasets

  - No need to train full model; reducing training times

Thank you