

- **GitHub** : [https://github.com/dodo0517cc/VRDL\\_HW2](https://github.com/dodo0517cc/VRDL_HW2)

- **Reference** :

Scaled-YOLOv4—<https://github.com/WongKinYiu/ScaledYOLOv4>

Mish-Cuda—<https://github.com/thomasbrandon/mish-cuda>

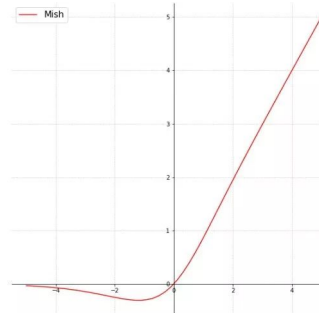


Figure 1. Mish Activation Function

We can see that positive values can reach any height to avoid saturation due to capping. The theoretically slight allowance for negative values allows for better gradient flow instead of hard zero boundaries like in ReLU. A smooth activation function allows better information to penetrate the neural network, resulting in better accuracy and generalization.

- **Brief introduction** :

First, we have to read the mat file and check the details of all the boxes and turn it to yolo format. Generate the files that yolo need. Then, put all the images, boxes and labels to ScaledYOLOv4 model. The most important thing is to tune the parameters. Finally train the images and test it with the best weight.

- **Methodology** :

- ✓ **Data pre-process** :

Read the .mat file : change it to boxes.csv, list the detail of boxes of each box.

Augmentation :

hsv\_h ( HSV-Hue augmentation ) : 0.015

hsv\_s ( HSV-Saturation augmentation ) : 0.7

hsv\_v ( HSV-Value augmentation ) : 0.4

degrees ( image rotation ) : 20.0

scale ( image scale ) : 0.5

shear ( image shear ) : 10.0

perspective ( image perspective ) : 0.0008      range 0-0.001

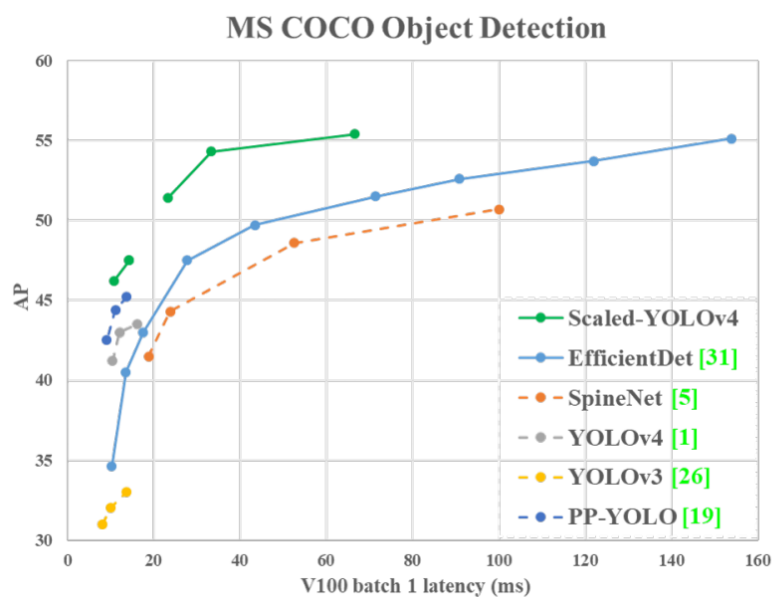
mosaic: 1.0 ( probability )

✓ **Model architecture :**

Scaled YOLOv4 — <https://github.com/WongKinYiu/ScaledYOLOv4>

Scaled-YOLOv4 was proposed on November 16, 2020 to improve YOLOv4.

- ◆ Designed a powerful model scaling method for small models, which systematically balances the computational cost and storage bandwidth of shallow CNN
- ◆ Design a simple and effective scaling strategy for large-scale target detectors
- ◆ Analyze the relationship between the scaling factors of each model, and scale the model based on the optimal group division
- ◆ Experiments confirmed that the FPN structure is essentially a one-off structure;
- ◆ Use the above methods to develop yolov4-tiny and yolo4v4-large



✓ **Hyperparameters :**

lr0: 0.01    # initial learning rate (SGD=1E-2, Adam=1E-3)

lrf: 0.2    # final OneCycleLR learning rate (lr0 \* lrf)

momentum: 0.937    # SGD momentum/Adam beta1

weight\_decay: 0.0005    # optimizer weight decay 5e-4

warmup\_epochs: 3.0    # warmup epochs (fractions ok)

warmup\_momentum: 0.8    # warmup initial momentum

warmup\_bias\_lr: 0.1 # warmup initial bias lr  
box: 0.05 # box loss gain  
cls: 0.3 # cls loss gain  
cls\_pw: 1.0 # cls BCELoss positive\_weight  
obj: 0.9 # obj loss gain (scale with pixels)  
obj\_pw: 0.9 # obj BCELoss positive\_weight  
iou\_t: 0.20 # IoU training threshold  
anchor\_t: 4.0 # anchor-multiple threshold

- **Summary**

File in coco/annotations in mydrive:  
instances\_val2017.json

File in yolov4 in mydrive :

png\_to\_jpg.py  
generate\_txt.py  
generate\_train.py  
generate\_test.py  
test.txt  
boxes.csv  
obj.zip  
obj\_test.zip  
train\_txt.zip  
obj.names  
weights—best.pt

Training:

Step1: Use GPU. Set up the environment.

Step2: Git clone the project : <https://github.com/WongKinYiu/ScaledYOLOv4>

Step3: Install torch==1.6.0+cu101, torchvision==0.7.0+cu101

Step4: Git clone <https://github.com/thomasbrandon/mish-cuda>, then install.

Step5: Update YAML

Step6 ( Done by png\_to\_jpg.py ) : Turn the images from png file to jpg file and upload the zip file ( obj.zip, obj\_test.zip ) of the images. Unzip it to the data folder that is in ScaledYOLOv4-yolov4-csp file.

Step7 ( Done by generate\_txt.py): Change labels to yolo format and save it to .txt file. The yolo format is standardized to 0~1 class, x\_center, y\_center, width, height. Upload the zip file ( train\_txt.zip ) of all of the

txt files. Unzip it to the data folder that is in ScaledYOLOv4-yolov4-csp file.

Step8: Copy `gerenate_train.py` to ScaledYOLOv4-yolov4-csp file. Then, run it. It will generate two files, `train.txt` and `valid.txt`, respectively.

Step9: Create a `digits.yaml` in the data folder, which stores the training set, validation set and test set paths, the number of categories and the category names

Step10: Modify `cfg` file. Copy a original `cfg` file and change the image width and height to 576, filters to  $45(\text{filters}=(\text{classes} + 5)*3)$ , and classes to 10.

Step11: Train

Inference :

Step1: Use GPU. Set up the environment.

`!sudo apt update`

`!sudo apt install libgl1-mesa-glx -y`

Step2: Git clone the project : <https://github.com/WongKinYiu/ScaledYOLOv4>

Step3: Install `torch==1.6.0+cu101`, `torchvision==0.7.0+cu101`

Step4: Git clone <https://github.com/thomasbrandon/mish-cuda>, then install.

Step5: Update YAML

Step6: Create a `digits.yaml` in the data folder, which stores the training set, validation set and test set paths, the number of categories and the category names

Step7: Modify `cfg` file. Copy a original `cfg` file and change the image width and height to 576, filters to  $45(\text{filters}=(\text{classes} + 5)*3)$ , and classes to 10.

Step8: Upload the zip file ( `obj_test.zip` ) of all of the test images. Unzip it to the data folder that is in ScaledYOLOv4-yolov4-csp file. Copy `gerenate_test.py` to ScaledYOLOv4-yolov4-csp file. Then, run it. It will generate `test.txt`.

Step9: Copy `weights(best.pt)` to ScaledYOLOv4-yolov4-csp file and `obj.names` to the data folder that is in ScaledYOLOv4-yolov4-csp file

Step10: Test

Colab link :

<https://colab.research.google.com/drive/1ZydfPIARDwjBYsIWqYspbx88jJlczGL?usp=sharing>

```
data_listdir = os.listdir("./data/test_jpg")
# Test your inference time
TEST_IMAGE_NUMBER = 100 # This number is fixed.
test_img_list = []

# Read image (Be careful with the image order)
data_listdir.sort(key = lambda x: int(x[:-4]))

with open("./data/test.txt", "w") as outfile:
    for img_name in data_listdir[:TEST_IMAGE_NUMBER]:
        img_path = os.path.join("/content/gdrive/MyDrive/ScaledYOLOv4-yolov4-csp/data/test_jpg", img_name)
        test_img_list.append(img_path)

float: start_time _path)
1637740581.7288082
start_time = time.time()
# for img in tqdm(test_img_list):
# your model prediction
!python test.py --img 576 --conf 0.001 --batch 8 --device 0 --data data/digits.yaml --names data/obj.names --cfg models/yolov4-csp_416.cfg --weights best.pt --task test
end_time = time.time()
print("\nInference time per image: ", (end_time - start_time) / len(test_img_list))

Namespace(augment=False, batch_size=8, cfg='models/yolov4-csp_416.cfg', conf_thres=0.001, data='data/digits.yaml', device='0', exist_ok=False, img_size=576, iou_thres=0.65, name
Using torch 1.6.0+cu101 CUDA:0 (Tesla K80, 11441MB)

Model Summary: 516 layers, 52544487 parameters, 52544487 gradients
Scanning images: 100% 100/100 [00:00<00:00, 516.17it/s]
Scanning labels /content/gdrive/MyDrive/ScaledYOLOv4-yolov4-csp/data/test.txt.cache3 (0 found, 0 missing, 100 empty, 0 duplicate, for 100 images): 100it [00:00, 419858.25it/s]
WARNING: No labels found in /content/gdrive/MyDrive/ScaledYOLOv4-yolov4-csp/data/test.txt/. See https://github.com/ultralytics/yolov5/wiki/Train-Custom-Data
Class      Images  Targets    P      R   mAP@.5  mAP@.5:.95: 100% 13/13 [00:06<00:00, 2.13it/s]
all         100         0         0         0   0.0000    0.0000
Speed: 44.1/2.0/46.0 ms inference/NMS/total per 576x576 image at batch-size 8
Results saved to runs/test/exp7

Inference time per image: 0.13941767454147339
```