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DEPARTMENT OF INFORMATION TECHNOLOGY

A REPORT

ON

”Detection, Classification and Semantic segmentation of apples”

SUBMITTED BY

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ACKNOWLEDGEMENT

It gives us great pleasure and satisfaction in presenting this project report on "Detection, Classification and Semantic segmentation of apples".

We would like to express our deep sense of gratitude towards **Prof. Pabitra Mitra** for providing us this great opportunity to work under his guidance and steering us at every step during this research internship.

We have furthermore to thank **Mr. Nadeem Yousuf** *for encouraging us to go ahead and for his continuous guidance.*

We would like to thank all those, who have directly or indirectly helped us for the completion of the work during this project.

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0.1 Introduction

It was a challenging problem that involves building upon methods for apple recognition (e.g. where are they), object localization (e.g. what are their extent), and object classification (e.g. rotten or fresh in our case). After doing some research, we found that in recent years, deep learning techniques are achieving state-of-the-art results for object detection, such as on standard benchmark datasets and in computer vision competitions. Notable is the "You Only Look Once," or YOLO, family of Convolutional Neural Networks that achieve near state-of-the-art results with a single end-to-end model that can perform object detection in real-time.

We would like to discuss about one specific task in Computer Vision called as Semantic Segmentation. Even though researchers have come up with numerous ways to solve this problem, we worked on a particular architecture namely UNET, which use a Fully Convolutional Network Model for the task.

In this project, we discovered how to develop a model for object detection, classification, counting and semantic segmentation on the given dataset.
https://arxiv.org/abs/1909.06441
After completing this project, we are familiar with the following:

- YOLO-based Convolutional Neural Network family of models for object detection and the most recent variation called YOLOv3.
- The best-of-breed open source library implementation of the YOLOv3 for the Keras deep learning library.
- How to use a pre-trained YOLOv3 to perform object localization, detection, classification(rotten / fresh) and counting on new images.
- The goal of semantic image segmentation is to label each pixel of an image with a corresponding class of what is being represented. Because we're predicting for every pixel in the image, this task is commonly referred to as dense prediction.

0.2 Problem Statement

To use computer vision to aid agricultural robotics.
1. Identification of fruits in a tree
2. Read and understand a fruit detection algorithm using semantic segmentation.
3. Devise an algorithm for counting fruits.
4. Implement the algorithm and run on above data set.
5. Devise an algorithm to identify fresh and rotten fruit..

0.3 Detection and classification of Apples

We used Artificial Intelligence through the use of computer vision and deep learning to automate apple detection, sorting and identification of rotten ones.

0.3.1 Step1 — Getting Training Data

We provided sufficient sample images (dataset) of the apples we need the model to detect and identify. We amended the YOLOV3 algorithm for detecting and counting apples as well as identify rotten apples in images. We used the following dataset:

https://github.com/OlafenwaMoses/AppleDetection/releases/download/v1/apple_detection_dataset.zip

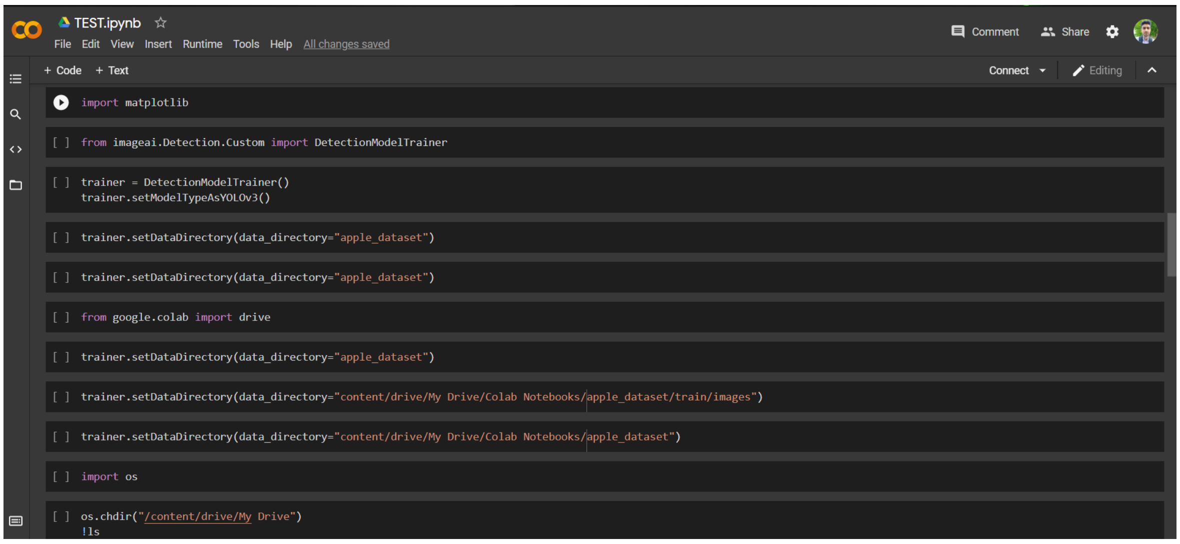
It is divided into:
1. 563 images for training the AI model
2. 150 images for testing the trained AI model

0.3.2 Step2 — Training our model

To generate our model, we trained a YOLOv3 model using ImageAI.
YOLO V3 is designed to be a multi-scaled detector, we also need features from multiple scales. Therefore, features from last three residual blocks are all used in the later detection. We are assuming the input is 416x416, so three scale vectors would be 52x52, 26x26, and 13x13.
Since the convolution outputs a square matrix of feature values (like 13x13, 26x26, and 52x52 in YOLO), we define this matrix as a "grid" and assign anchor boxes to each cell of the grid. In other words, anchor boxes anchor to the grid cells, and they share the same centroid.
With the final detection output, we can calculate the loss against the ground truth labels now. The loss function consists of four parts (or five, if you split noobj and obj): centroid (xy) loss, width and height (wh) loss, objectness (obj and noobj) loss and classification loss.

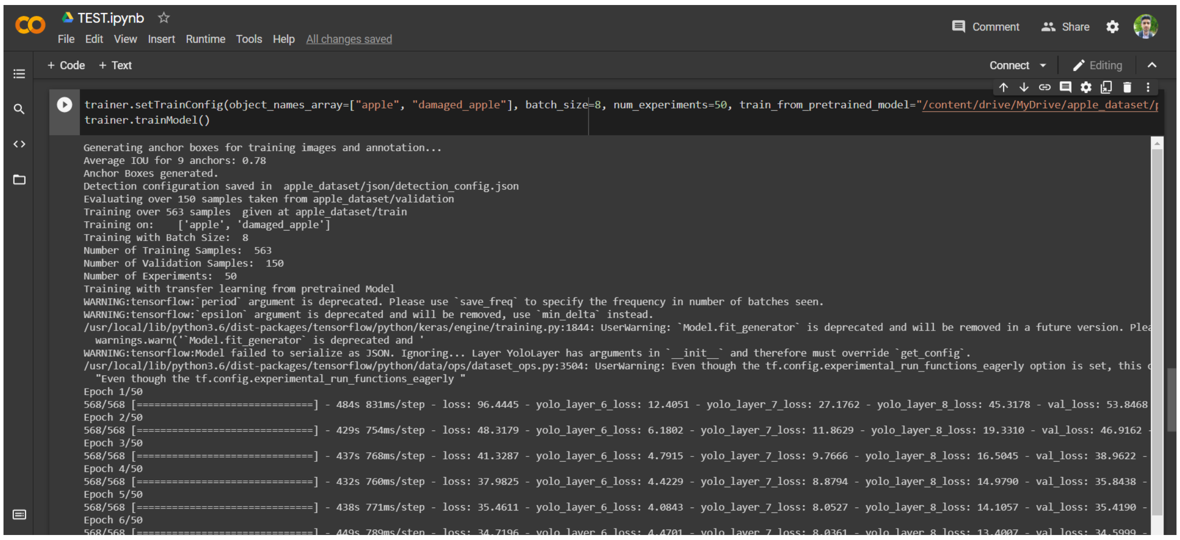
```
Loss = Lambda_Coord * Sum(Mean_Square_Error((tx, ty),
(tx', ty') * obj_mask)
 + Lambda_Coord * Sum(Mean_Square_Error((tw, th), (tw',
th') * obj_mask)
 + Sum(Binary_Cross_Entropy(obj, obj') * obj_mask) +
Lambda_Noobj * Sum(Binary_Cross_Entropy(obj, obj') * (1
-obj_mask) * ignore_mask)
 + Sum(Binary_Cross_Entropy(class, class'))
```

The below lines of code is to initiate the training on our apple dataset. Now we import the "DetectionModelTrainer" class from ImageAI. After that we created an instance of the class and set our model type to YOLOv3 ,we set the path to our apple dataset and finally we specified the parameters.



```
import matplotlib

from imageai.Detection.Custom import DetectionModelTrainer

trainer = DetectionModelTrainer()
trainer.setModelTypeAsYOLOv3()

trainer.setDataDirectory(data_directory="apple_dataset")

trainer.setDataDirectory(data_directory="apple_dataset")

from google.colab import drive

trainer.setDataDirectory(data_directory="apple_dataset")

trainer.setDataDirectory(data_directory="content/drive/My Drive/Colab Notebooks/apple_dataset/train/images")

trainer.setDataDirectory(data_directory="content/drive/My Drive/Colab Notebooks/apple_dataset")

import os

os.chdir("/content/drive/My Drive")
!ls
```

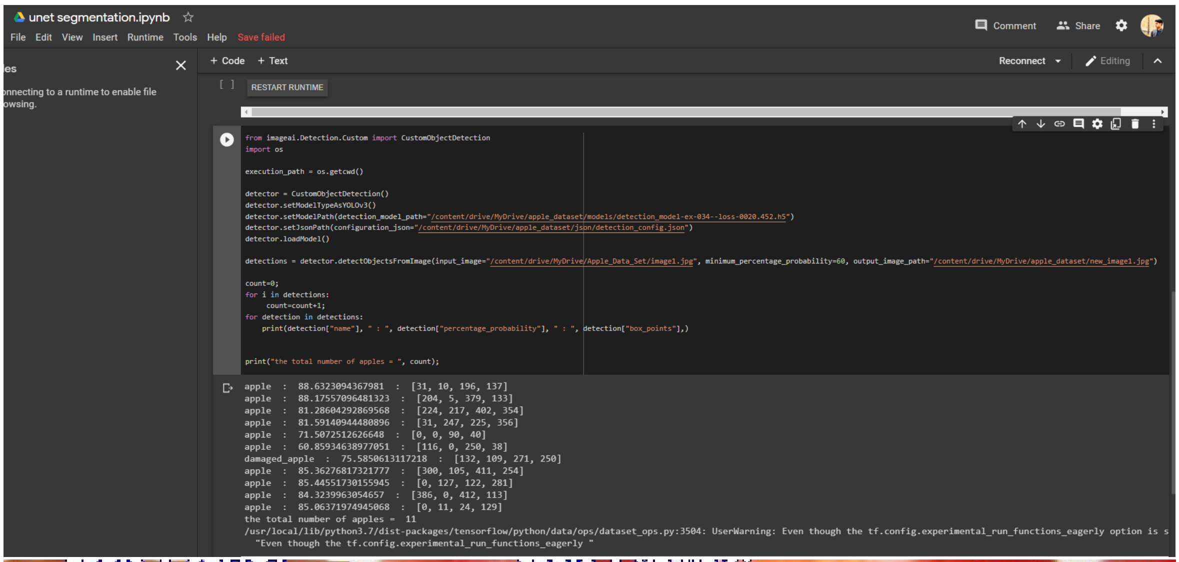
ImageAI will create apple dataset/models folder which is where all generated models will be saved.



```
trainer.setTrainConfig(object_names_array=["apple", "damaged_apple"], batch_size=8, num_experiments=50, train_from_pretrained_model="/content/drive/MyDrive/apple_dataset/p
trainer.trainModel()
```

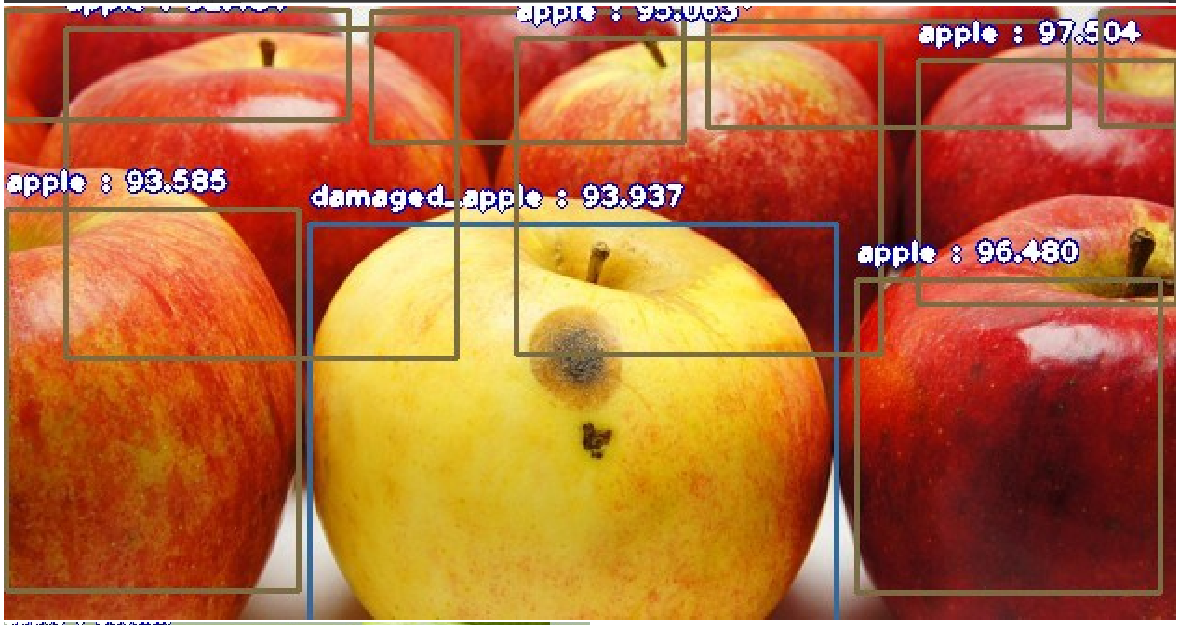
```
Generating anchor boxes for training images and annotation...
Average IOU for 9 anchors: 0.78
Anchor Boxes generated.
Detection configuration saved in  apple_dataset/json/detection_config.json
Evaluating over 150 samples taken from apple_dataset/validation
Training over 563 samples  given at apple_dataset/train
Training on:    ['apple', 'damaged_apple']
Training with Batch Size:  8
Number of Training Samples:  563
Number of Validation Samples:  150
Number of Experiments:  50
Training with transfer learning from pretrained Model
WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to specify the frequency in number of batches seen.
WARNING:tensorflow:`epsilon` argument is deprecated and will be removed, use `min_delta` instead.
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Plea
  warnings.warn('`Model.fit_generator` is deprecated and '
WARNING:tensorflow:Model failed to serialize as JSON. Ignoring... Layer YoloLayer has arguments in `__init__` and therefore must override `get_config`.
/usr/local/lib/python3.6/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504: UserWarning: Even though the tf.config.experimental_run_functions_eagerly option is set, this c
  "Even though the tf.config.experimental_run_functions_eagerly "
Epoch 1/50
568/568 [==============================] - 484s 831ms/step - loss: 96.4445 - yolo_layer_6_loss: 12.4051 - yolo_layer_7_loss: 27.1762 - yolo_layer_8_loss: 45.3178 - val_loss: 53.8468
Epoch 2/50
568/568 [==============================] - 429s 754ms/step - loss: 48.3179 - yolo_layer_6_loss: 6.1802 - yolo_layer_7_loss: 11.8629 - yolo_layer_8_loss: 19.3310 - val_loss: 46.9162 -
Epoch 3/50
568/568 [==============================] - 437s 768ms/step - loss: 41.3287 - yolo_layer_6_loss: 4.7915 - yolo_layer_7_loss: 9.7666 - yolo_layer_8_loss: 16.5045 - val_loss: 38.9622 -
Epoch 4/50
568/568 [==============================] - 432s 760ms/step - loss: 37.9825 - yolo_layer_6_loss: 4.4229 - yolo_layer_7_loss: 8.8794 - yolo_layer_8_loss: 14.9790 - val_loss: 35.8438 -
Epoch 5/50
568/568 [==============================] - 438s 771ms/step - loss: 35.4611 - yolo_layer_6_loss: 4.0843 - yolo_layer_7_loss: 8.0527 - yolo_layer_8_loss: 14.1057 - val_loss: 35.4190 -
Epoch 6/50
568/568 [==============================] - 449s 789ms/step - loss: 34.7196 - yolo_layer_6_loss: 4.4701 - yolo_layer_7_loss: 8.0361 - yolo_layer_8_loss: 13.4007 - val_loss: 34.5999 -
```

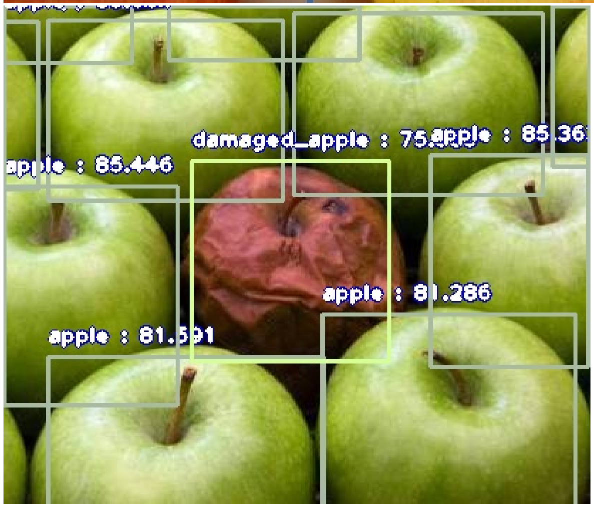
0.3.3 Step 3 — Predicting using our trained Model



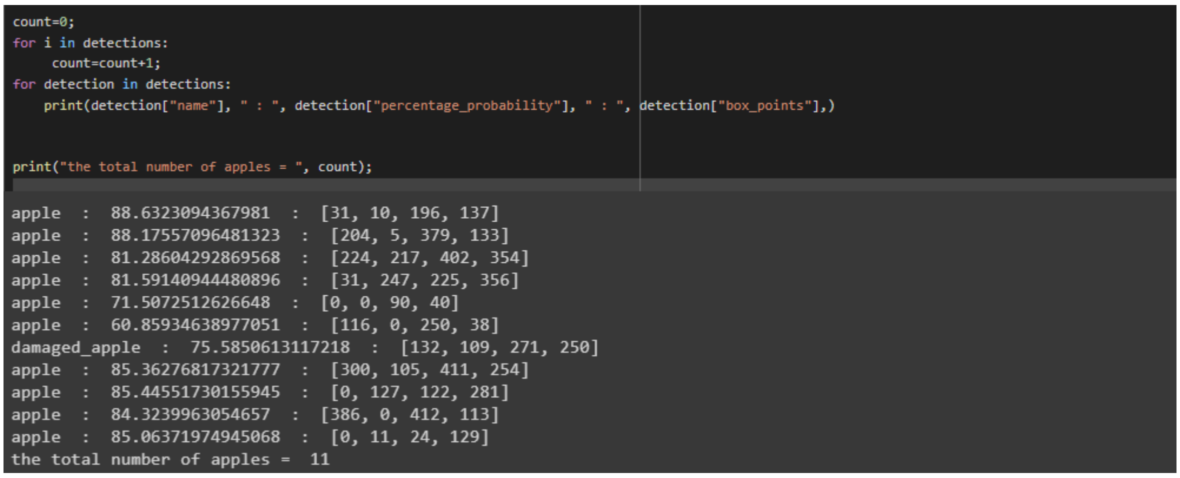
```python
from imageai.Detection.Custom import CustomObjectDetection
import os

execution_path = os.getcwd()

detector = CustomObjectDetection()
detector.setModelTypeAsYOLOv3()
detector.setModelPath(detection_model_path="/content/drive/MyDrive/apple_dataset/models/detection_model-ex-034--loss-0020.452.h5")
detector.setJsonPath(configuration_json="/content/drive/MyDrive/apple_dataset/json/detection_config.json")
detector.loadModel()

detections = detector.detectObjectsFromImage(input_image="/content/drive/MyDrive/Apple_Data_Set/image1.jpg", minimum_percentage_probability=60, output_image_path="/content/drive/MyDrive/apple_dataset/new_image1.jpg")

count=0;
for i in detections:
     count=count+1;
for detection in detections:
    print(detection["name"], " : ", detection["percentage_probability"], " : ", detection["box_points"],)


print("the total number of apples = ", count);
```

```
apple  :  88.6323094367981  :  [31, 10, 196, 137]
apple  :  88.17557096481323  :  [204, 5, 379, 133]
apple  :  81.28604292869568  :  [224, 217, 402, 354]
apple  :  81.59140944480896  :  [31, 247, 225, 356]
apple  :  71.5072512626648  :  [0, 0, 90, 40]
apple  :  60.85934638977051  :  [116, 0, 250, 38]
damaged_apple  :  75.5850613117218  :  [132, 109, 271, 250]
apple  :  85.36276817321777  :  [300, 105, 411, 254]
apple  :  85.44551730155945  :  [0, 127, 122, 281]
apple  :  84.3239963054657  :  [386, 0, 412, 113]
apple  :  85.06371974945068  :  [0, 11, 24, 129]
the total number of apples =  11
/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504: UserWarning: Even though the tf.config.experimental_run_functions_eagerly option is s
  "Even though the tf.config.experimental_run_functions_eagerly "
```





As we can see, the trained apple detection model is able to detect all the apples in the image as well as identify the apple with a defect (apple with a spot). You can use this trained model to count apples



```
count=0;
for i in detections:
     count=count+1;
for detection in detections:
    print(detection["name"], " : ", detection["percentage_probability"], " : ", detection["box_points"],)


print("the total number of apples = ", count);
```

```
apple  :  88.6323094367981  :  [31, 10, 196, 137]
apple  :  88.17557096481323  :  [204, 5, 379, 133]
apple  :  81.28604292869568  :  [224, 217, 402, 354]
apple  :  81.59140944480896  :  [31, 247, 225, 356]
apple  :  71.5072512626648  :  [0, 0, 90, 40]
apple  :  60.85934638977051  :  [116, 0, 250, 38]
damaged_apple  :  75.5850613117218  :  [132, 109, 271, 250]
apple  :  85.36276817321777  :  [300, 105, 411, 254]
apple  :  85.44551730155945  :  [0, 127, 122, 281]
apple  :  84.3239963054657  :  [386, 0, 412, 113]
apple  :  85.06371974945068  :  [0, 11, 24, 129]
the total number of apples =  11
```

The complete code along with other predicted images can be accessed here:

https://github.com/Tajamul21/Detection-Classification-and-Semantic_Segmentation-of-apples

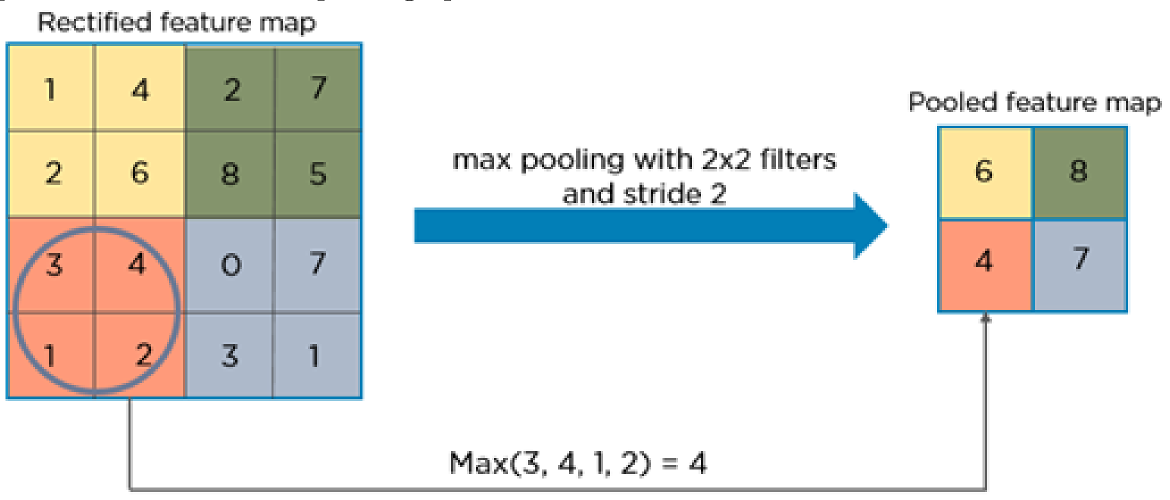
0.4 Semantic Segmentation

The goal of semantic image segmentation is to label each pixel of an image with a corresponding class of what is being represented. Because we're predicting for every pixel in the image, this task is commonly referred to as dense prediction.
Unlike the previous tasks, the expected output in semantic segmentation are not just labels and bounding box parameters. The output itself is a high resolution image (typically of the same size as input image) in which each pixel is classified to a particular class. Thus it is a pixel level image classification.
The different operations that are typically used in a Convolutional Network. Please make a note of the terminologies used.
i. Convolution operation
There are two inputs to a convolutional operation i) A 3D volume (input image) of size (nin x nin x channels)
ii) A set of 'k' filters (also called as kernels or feature extractors) each one of size (f x f x channels), where f is typically 3 or 5.
The output of a convolutional operation is also a 3D volume (also called as output image or feature map) of size (nout x nout x k).
The relationship between nin and nout is as follows:

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1$$

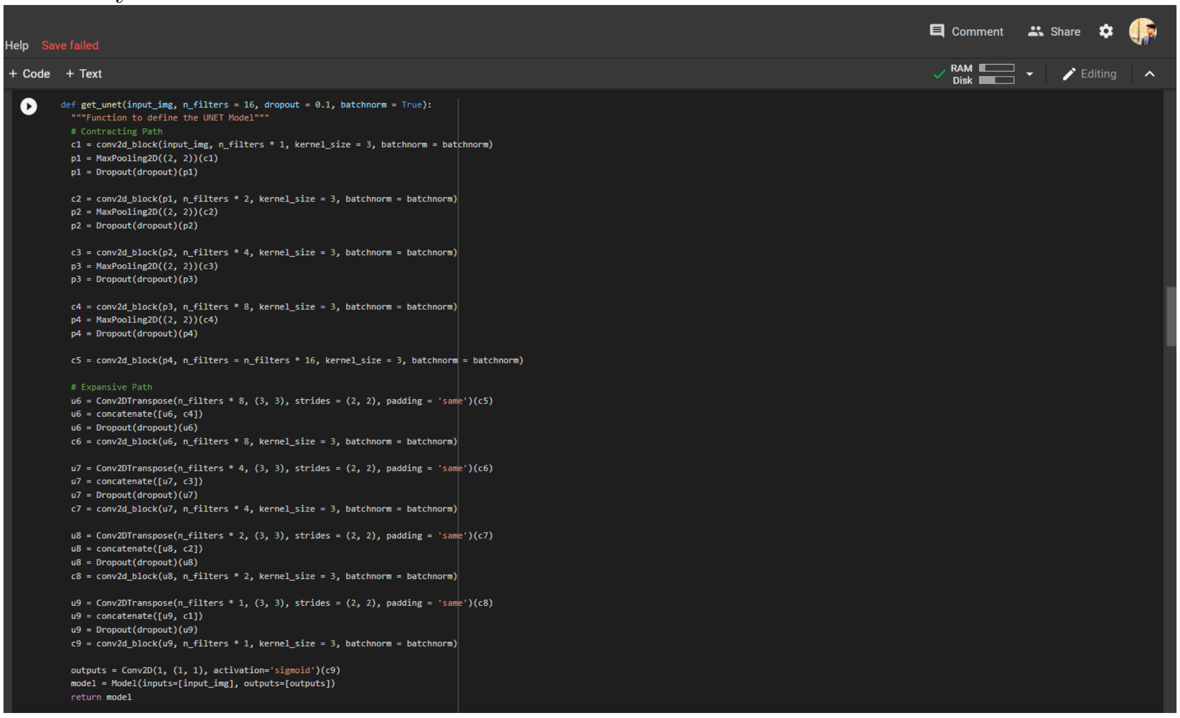
n_{in}:	number of input features
n_{out}:	number of output features
k:	convolution kernel size
p:	convolution padding size
s:	convolution stride size

The function of pooling is to reduce the size of the feature map so that we have fewer parameters in the network.the size of the filter and strides are two important hyper-parameters in the max pooling operation.



0.4.1 U-Net

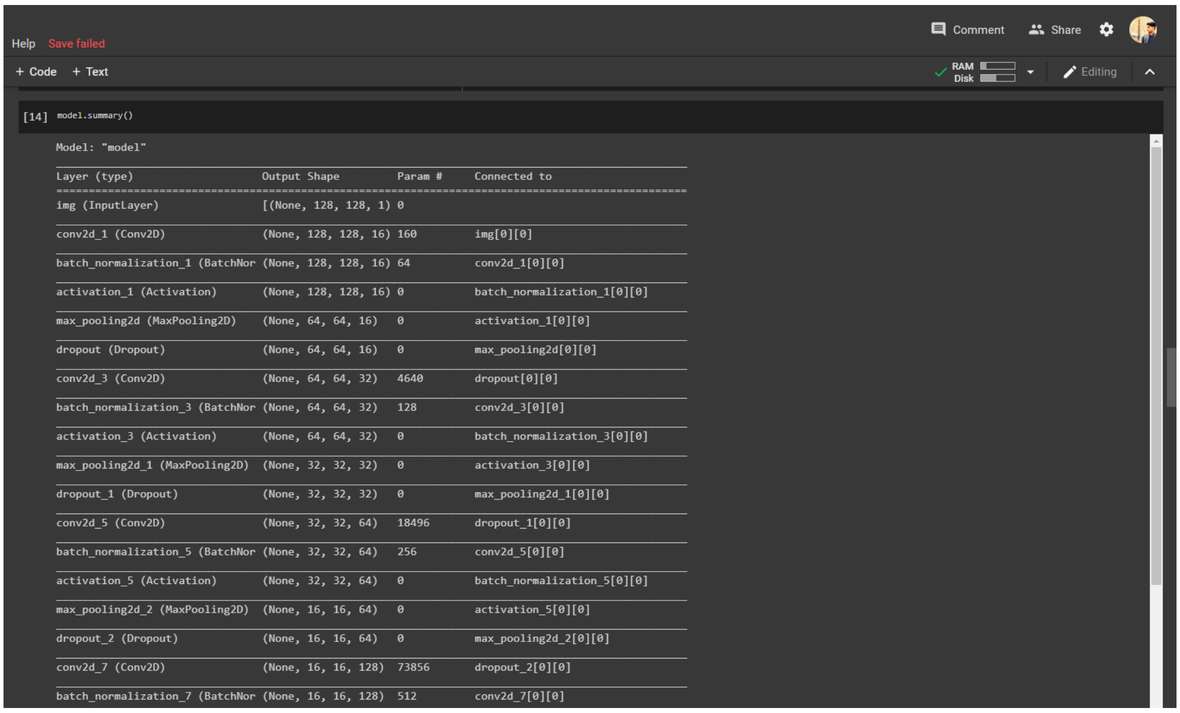
U-Net is an architecture for semantic segmentation. It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers.



```
def get_unet(input_img, n_filters = 16, dropout = 0.1, batchnorm = True):
  """Function to define the UNET Model"""
  # Contracting Path
  c1 = conv2d_block(input_img, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)
  p1 = MaxPooling2D((2, 2))(c1)
  p1 = Dropout(dropout)(p1)

  c2 = conv2d_block(p1, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)
  p2 = MaxPooling2D((2, 2))(c2)
  p2 = Dropout(dropout)(p2)

  c3 = conv2d_block(p2, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)
  p3 = MaxPooling2D((2, 2))(c3)
  p3 = Dropout(dropout)(p3)

  c4 = conv2d_block(p3, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)
  p4 = MaxPooling2D((2, 2))(c4)
  p4 = Dropout(dropout)(p4)

  c5 = conv2d_block(p4, n_filters = n_filters * 16, kernel_size = 3, batchnorm = batchnorm)

  # Expansive Path
  u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides = (2, 2), padding = 'same')(c5)
  u6 = concatenate([u6, c4])
  u6 = Dropout(dropout)(u6)
  c6 = conv2d_block(u6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)

  u7 = Conv2DTranspose(n_filters * 4, (3, 3), strides = (2, 2), padding = 'same')(c6)
  u7 = concatenate([u7, c3])
  u7 = Dropout(dropout)(u7)
  c7 = conv2d_block(u7, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)

  u8 = Conv2DTranspose(n_filters * 2, (3, 3), strides = (2, 2), padding = 'same')(c7)
  u8 = concatenate([u8, c2])
  u8 = Dropout(dropout)(u8)
  c8 = conv2d_block(u8, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)

  u9 = Conv2DTranspose(n_filters * 1, (3, 3), strides = (2, 2), padding = 'same')(c8)
  u9 = concatenate([u9, c1])
  u9 = Dropout(dropout)(u9)
  c9 = conv2d_block(u9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)

  outputs = Conv2D(1, (1, 1), activation='sigmoid')(c9)
  model = Model(inputs=[input_img], outputs=[outputs])
  return model
```

0.4.2 Training

Model is compiled with Adam optimizer and we use binary cross entropy loss function since there are only two classes (apple and no apple). We use Keras callbacks to implement:
Learning rate decay if the validation loss does not improve for 5 continues epochs.
Early stopping if the validation loss does not improve for 10 continues epochs.
Save the weights only if there is improvement in validation loss.
We use a batch size of 32.

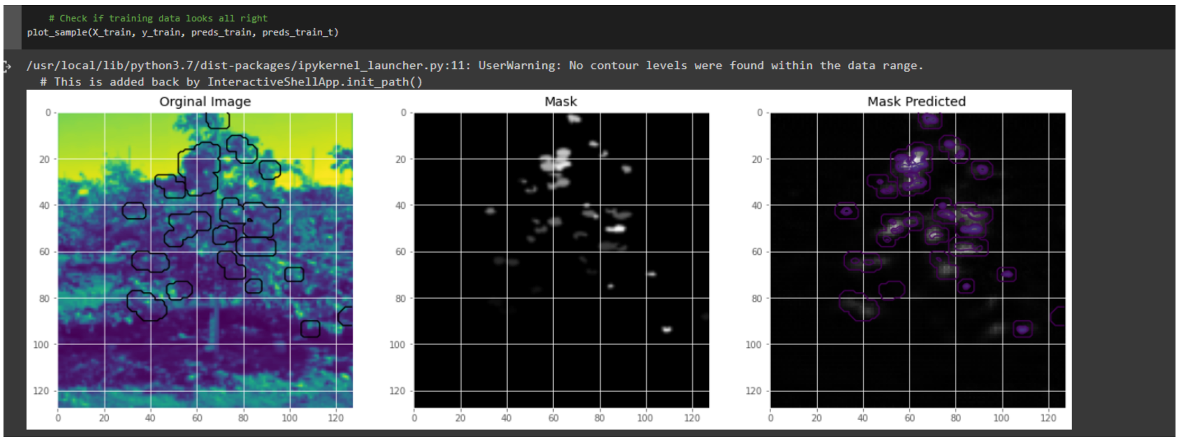


```
[14] model.summary()

Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
img (InputLayer)                [(None, 128, 128, 1) 0
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 128, 128, 16) 160         img[0][0]
__________________________________________________________________________________________________
batch_normalization_1 (BatchNor (None, 128, 128, 16) 64          conv2d_1[0][0]
__________________________________________________________________________________________________
activation_1 (Activation)       (None, 128, 128, 16) 0           batch_normalization_1[0][0]
__________________________________________________________________________________________________
max_pooling2d (MaxPooling2D)    (None, 64, 64, 16)   0           activation_1[0][0]
__________________________________________________________________________________________________
dropout (Dropout)               (None, 64, 64, 16)   0           max_pooling2d[0][0]
__________________________________________________________________________________________________
conv2d_3 (Conv2D)               (None, 64, 64, 32)   4640        dropout[0][0]
__________________________________________________________________________________________________
batch_normalization_3 (BatchNor (None, 64, 64, 32)   128         conv2d_3[0][0]
__________________________________________________________________________________________________
activation_3 (Activation)       (None, 64, 64, 32)   0           batch_normalization_3[0][0]
__________________________________________________________________________________________________
max_pooling2d_1 (MaxPooling2D)  (None, 32, 32, 32)   0           activation_3[0][0]
__________________________________________________________________________________________________
dropout_1 (Dropout)             (None, 32, 32, 32)   0           max_pooling2d_1[0][0]
__________________________________________________________________________________________________
conv2d_5 (Conv2D)               (None, 32, 32, 64)   18496       dropout_1[0][0]
__________________________________________________________________________________________________
batch_normalization_5 (BatchNor (None, 32, 32, 64)   256         conv2d_5[0][0]
__________________________________________________________________________________________________
activation_5 (Activation)       (None, 32, 32, 64)   0           batch_normalization_5[0][0]
__________________________________________________________________________________________________
max_pooling2d_2 (MaxPooling2D)  (None, 16, 16, 64)   0           activation_5[0][0]
__________________________________________________________________________________________________
dropout_2 (Dropout)             (None, 16, 16, 64)   0           max_pooling2d_2[0][0]
__________________________________________________________________________________________________
conv2d_7 (Conv2D)               (None, 16, 16, 128)  73856       dropout_2[0][0]
__________________________________________________________________________________________________
batch_normalization_7 (BatchNor (None, 16, 16, 128)  512         conv2d_7[0][0]
```

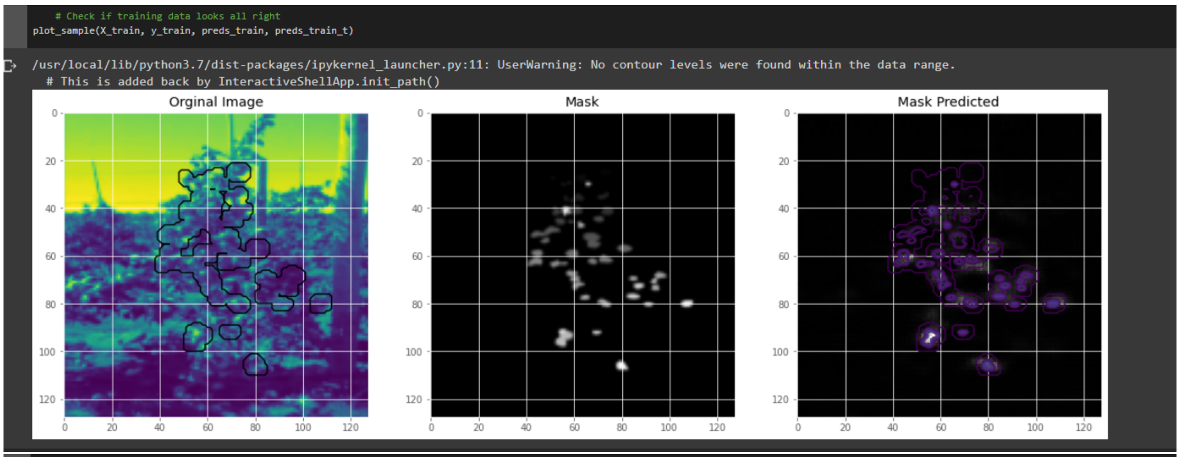
0.4.3 Inference

For each pixel we get a value between 0 to 1.
0 represents no apple and 1 represents apple.
We take 0.5 as the threshold to decide whether to classify a pixel as 0 or 1.

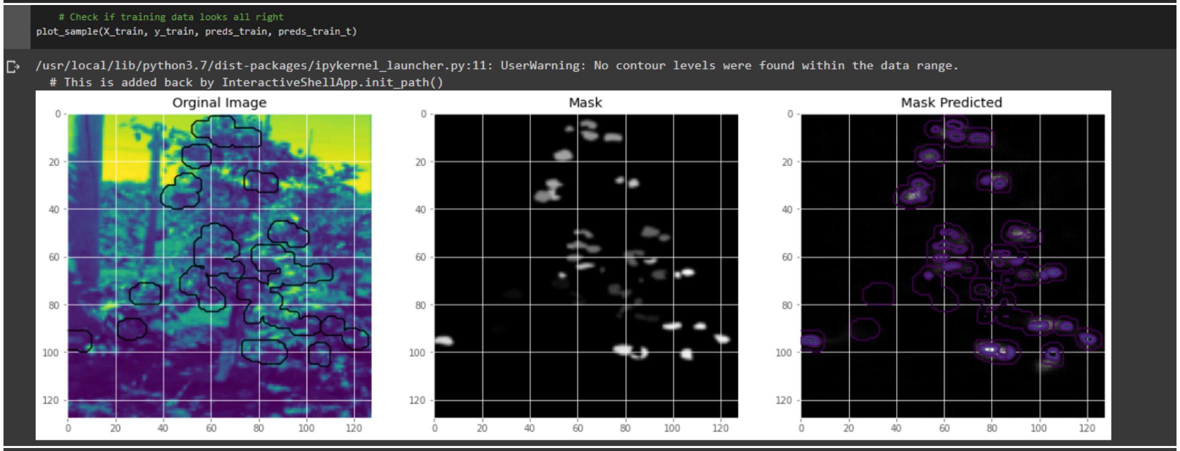
0.4.4 Our Results on training set



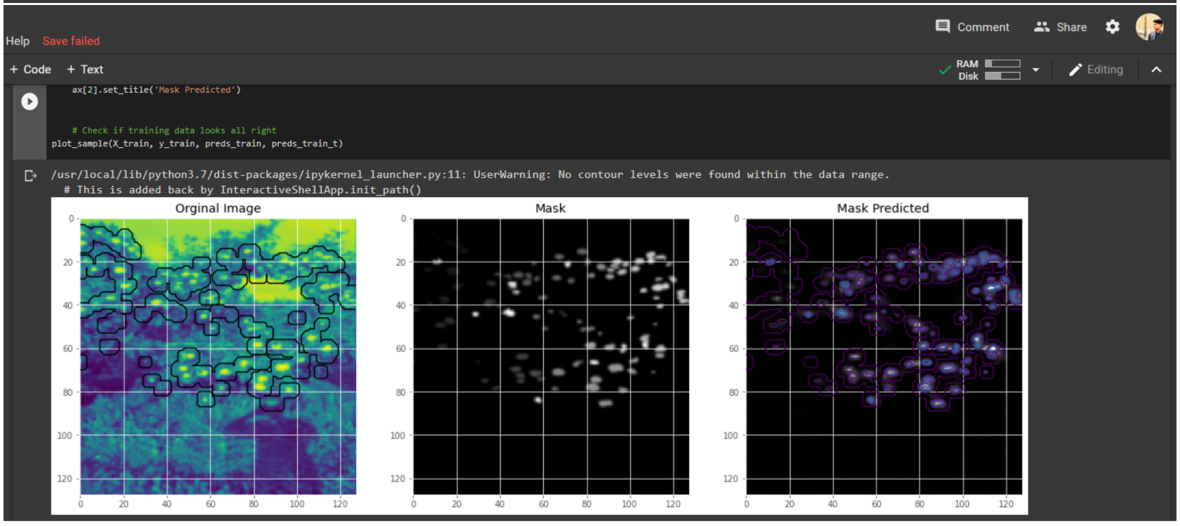
```
    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```



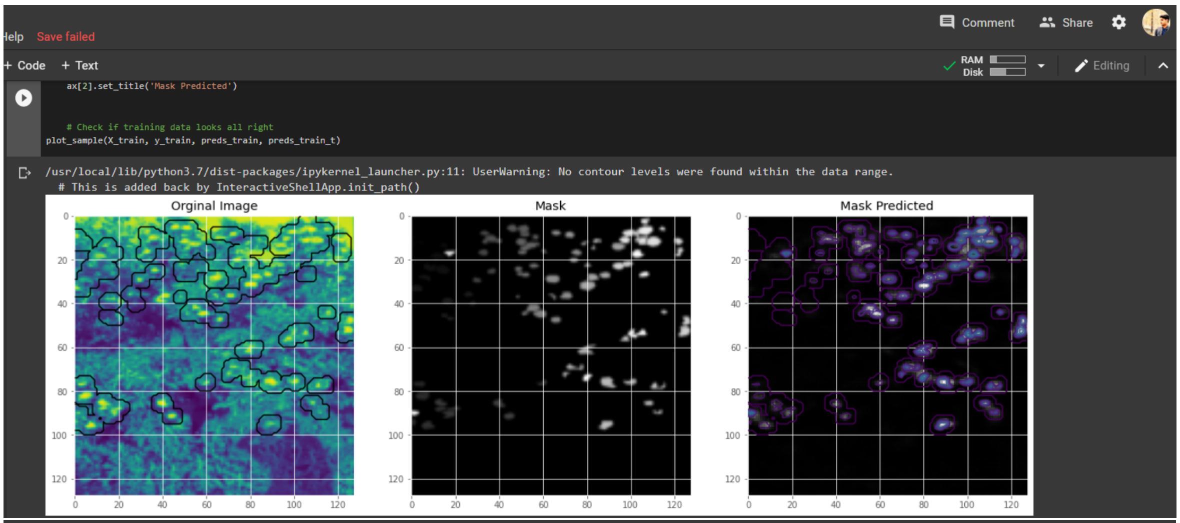
```
    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```



```
    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```

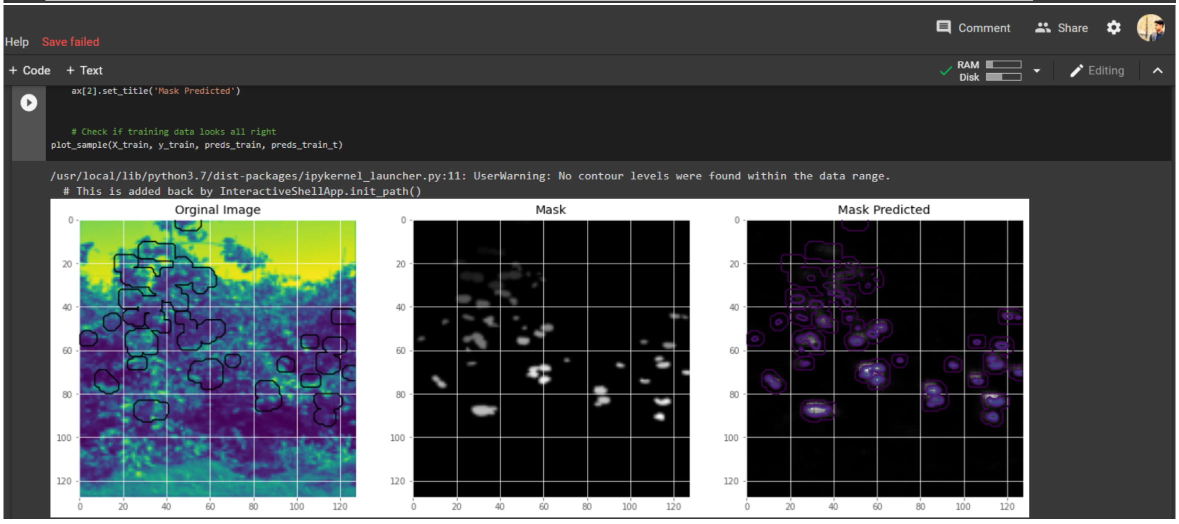


```
    ax[2].set_title('Mask Predicted')


    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```



```
    ax[2].set_title('Mask Predicted')


    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```



```
    ax[2].set_title('Mask Predicted')


    # Check if training data looks all right
plot_sample(X_train, y_train, preds_train, preds_train_t)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:11: UserWarning: No contour levels were found within the data range.
  # This is added back by InteractiveShellApp.init_path()
```

The complete code along with other predicted(segmented) images can be accessed here:

https://github.com/Tajamul21/Detection-Classification-and-Semantic_Segmentation-of-apples