U-Net on Graphene Images

This is a modification to a U-Net on the Oxford-IIIT Pet Dataset. Original code is located at https://colab.research.google.com/github/zaidalyafeai/Notebooks/blob/master/unet.ipynb

Mount Google Drive and define path to dataset. There are two paths: one to the dataset (dataset_dir) and another to the folder which you put `utils.py' in (project_dir).

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive",
```

```
import os
import sys

# directory of the project, folder which you put utils.py in
project_dir = os.path.abspath("/content/gdrive/Shared drives/Graphene_DL_2")
# path to the dataset, should contain 3 subfolders: train2019, val2019 and annotations
dataset_dir = os.path.abspath("/content/gdrive/Shared drives/Graphene_DL_2")

# model paths to save or load the models
model_path = "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/Five_layer_good_model.h5"
model_path1 = "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/Good_model7.h5"

few_layer_path = "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/Few_layer_test.h5"
RGB_model_path = "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/RGB_bilayer_with_attached_lr_00008_

SVM_model_path = "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/SVM_gaussian.sav"
SVM_model_path_l= "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/SVM_linear.sav"
SVM_model_path_p= "/content/gdrive/Shared drives/Graphene_DL_2/Unet_h5_files/SVM_poly_3.sav"
sys.path.append(project_dir)  # To find local version of the library: utils
import utils
```

Import the libraries for use

```

from tensorflow.keras.utils import get_custom_objects
from tensorflow.keras.models import load_model


import numpy as np
import matplotlib.pyplot as plt
import tensorflow.keras as keras
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Input, Conv2DTranspose, Concatenate
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras import backend as K
import tensorflow as tf
import cv2
from imgaug import augmenters as iaa

# from random import shuffle
```

Define hyper-parameters

```
epochs = 0 # no. of training epochs
batch_size = 32
default_learning_rate = 0.001

# define U-Net input image size
default_input_size = (256,256,3)

# define weight of positive errors
pos_weight = 200

# start training your model. Set to 0 if you want to train from scratch
initial_epoch =0
```

```
threshold = 0.5
```

Define augmenter:

```
# define augmenter
# first crop images at a random position
# then randomly apply 0 to 4 of the methods: horizontally flip, vertically flip, rotate and shift
seq_train = iaa.Sequential([
            iaa.SomeOf((0, 4),[
                iaa.Fliplr(), # horizontally flip
                iaa.Flipud(), # vertically flip
                iaa.Affine(rotate=(0,359)), # rotate
                iaa.Affine(translate_percent={"x": (-0.1, 0.1),"y": (-0.1, 0.1)}), # shift
                # More as you want ...
    ])
])

```

Generator function

Functions contains "yield" keyword are called generator functions. Unlike "return", "yield" doesn't destroy the state of function. Intuitively, generator functions are similar to a for loop that can only be iterated over once. To learn more, read this: https://pythontips.com/2013/09/29/the-python-yield-keyword-explained/

```
def image_generator(dataset,seq=None, batch_size = 32, image_size = (1024,1024)):

  while True:

    #extract a random batch
    batch = np.random.choice(dataset.image_ids, size = batch_size)

    #variables for collecting batches of inputs and outputs
    batch_x = []
    batch_y = []
```

```
    if seq: # apply augmentation
      # make stochastic augmenter deterministic (similar to drawing random samples from a distribution)
        seq_det = seq.to_deterministic()

    for f in batch:

        #preprocess the raw images
        raw = dataset.load_image(f)

        raw = np.clip(cv2.resize(raw, dsize=image_size,interpolation=cv2.INTER_CUBIC),0, 255)

        #get the mask
        #mask = np.clip(np.sum(dataset.load_mask(f)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
        ##gt_mask = dataset.load_mask(f)
        mask = np.clip(np.sum(dataset.load_mask(f)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
        ##mask = np.clip(np.sum(gt_mask[0][:,:,[i for i in range(len(gt_mask[1])) if gt_mask[1][i] ==1]], axis
        mask = cv2.resize(mask.astype(np.float32), dsize=image_size, interpolation=cv2.INTER_CUBIC)

        # pre-process the mask
        mask[mask != 0 ] = 1
        batch_x.append(raw)
        batch_y.append(mask)

    # pre-process a batch of images and masks
    batch_x = np.array(batch_x)/255. # normalize raw images
    batch_y = np.expand_dims(np.array(batch_y),3)# add color channel to the black-and-white masks

    if seq:
        # augment images and masks
        batch_x = np.array(seq_det.augment_images(batch_x))
        batch_y = np.array(seq_det.augment_images(batch_y))

    yield (batch_x, batch_y)
```

```
# build a CocoDataset object for training images
dataset_train = utils.CocoDataset()
dataset_train.load_coco(dataset_dir, "train")
dataset_train.prepare()
```

```
dataset_train.prepare()

# build a CocoDataset object for validation images
dataset_val = utils.CocoDataset()
dataset_val.load_coco(dataset_dir, "val")
dataset_val.prepare()

# build generators for training and testing
train_generator = image_generator(dataset_train,seq=seq_train, batch_size = batch_size,image_size=default_input_

test_generator  = image_generator(dataset_val,seq=None, batch_size = 57,image_size=default_input_size[:2])
```

```
loading annotations into memory...
Done (t=0.01s)
creating index...
index created!
loading annotations into memory...
Done (t=0.00s)
creating index...
index created!
```

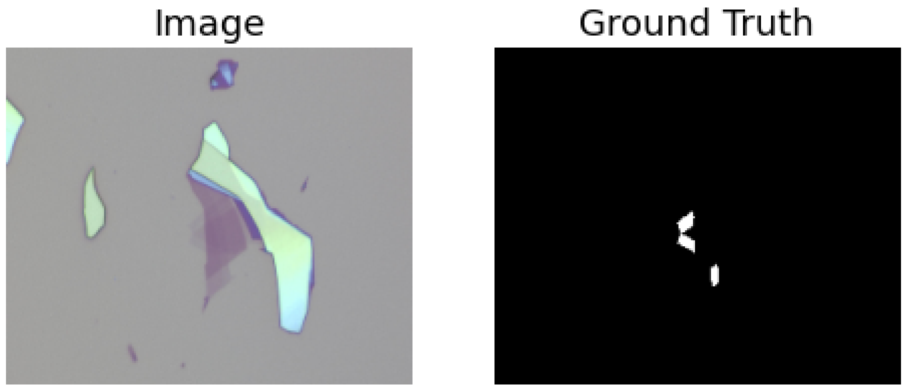
Test the generators by plotting the images

```
x, y= next(test_generator) # x is the raw images, y is the ground truth masks

img = x[0]
msk = y[0].squeeze()
msk = np.stack((msk,)*3, axis = -1)

fig, ax = plt.subplots(1,2,figsize = (8,16))
[axi.set_axis_off() for axi in ax]
ax[0].imshow(img)
ax[0].set_title('Image',fontsize=18)
ax[1].imshow(msk)
ax[1].set_title('Ground Truth',fontsize=18)
```

```
Text(0.5, 1.0, 'Ground Truth')
```



IoU metric

The intersection over union (IoU) metric is a simple metric used to evaluate the performance of a segmentation algorithm. Given two masks y_{true}, y_{pred} we evaluate

$$IoU = \frac{y_{true} \cap y_{pred}}{y_{true} \cup y_{pred}}$$

```
def mean_iou(y_true, y_pred):
    yt0 = y_true[:,:,:,0]
    yp0 = K.cast(y_pred[:,:,:,0] > 0.5, 'float32')
    inter = tf.math.count_nonzero(tf.math.logical_and(tf.equal(yt0, 1), tf.equal(yp0, 1)))
    union = tf.math.count_nonzero(tf.add(yt0, yp0))
    iou = tf.where(tf.equal(union, 0), 1., tf.cast(inter/union, 'float32'))
    return iou
```

Weighted binary crossentropy loss

Assume we have N samples in total, y_{true} is a ground truth segmentation mask, y_{pred} is the CNN-predicted segmentation mask, the binary crossentropy is defined as:

$$L_{binary\_ce} = -\frac{1}{N}\sum_{1}^{N} y_{true} * log(y_{pred}) + (1 - y_{true}) * log(1 - y_{pred})$$

And weighted binary crossentropy is defined as:

$$L_{w\_binary\_ce} = -\frac{1}{N}\sum_{1}^{N} w * y_{true} * log(y_{pred}) + (1 - y_{true}) * log(1 - y_{pred})$$

```
def create_weighted_binary_crossentropy(pos_weight):

    def weighted_binary_crossentropy(y_true, y_pred):

        # Original binary crossentropy (see losses.py):
        # K.mean(K.binary_crossentropy(y_true, y_pred), axis=-1)

        # Calculate the binary crossentropy
        b_ce = K.binary_crossentropy(y_true, y_pred)

        # Apply the weights
        weight_vector = y_true * pos_weight + (1. - y_true)
        weighted_b_ce = weight_vector * b_ce

        # Return the mean error
        return K.mean(weighted_b_ce)

    return weighted_binary_crossentropy
```

Define the UNet model function

```
def unet_attached(sz = default_input_size):
  x = Input(sz)
  inputs = x

  #down sampling
  Num_of_filters = 8
  layers = []
```

```
layers = []

for i in range(6):
  x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
  x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
  layers.append(x)
  x = MaxPooling2D() (x)
  Num_of_filters = Num_of_filters * 2


ff2 = 64

#bottleneck
j = len(layers) - 1
x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
x = Conv2DTranspose(ff2, 2, strides=(2, 2), padding='same') (x)
x = Concatenate(axis=3)([x, layers[j]])
j = j -1

#upsampling
for i in range(5):
  ff2 = ff2//2
  Num_of_filters = Num_of_filters // 2
  x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
  x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
  x = Conv2DTranspose(ff2, 2, strides=(2, 2), padding='same') (x)
  x = Concatenate(axis=3)([x, layers[j]])
  j = j -1


#classification
x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)
x = Conv2D(Num_of_filters, 3, activation='relu', padding='same') (x)


#########################################################
###### Attached layers to the original UNet model ######
#########################################################
x = Conv2D(256, 5,activation='linear', padding='same')(x)
```

```
  x = Conv2D(256, 5,activation='linear', padding='same')(x)
  x=tf.keras.layers.LeakyReLU(alpha=0.1)(x)
  x = Conv2D(128, 5,activation='linear', padding='same')(x)
  x=tf.keras.layers.LeakyReLU(alpha=0.1)(x)
  x = Conv2D(64, 5,activation='linear', padding='same')(x)
  x=tf.keras.layers.LeakyReLU(alpha=0.1)(x)
  x = Conv2D(32, 5,activation='linear', padding='same')(x)
  x=tf.keras.layers.LeakyReLU(alpha=0.1)(x)
  x = Conv2D(16, 5,activation='linear', padding='same')(x)
  x=tf.keras.layers.LeakyReLU(alpha=0.1)(x)
  ########################################################
  ########################################################

  outputs = Conv2D(1, 1, activation='sigmoid') (x)

  #model creation
  model = Model(inputs=[inputs], outputs=[outputs])

  # Optimizer for the model
  opt = keras.optimizers.Adam(learning_rate = default_learning_rate) # use Adam as optimizer

  # Compile the model
  model.compile(optimizer = opt, loss = create_weighted_binary_crossentropy(pos_weight), metrics = [mean_iou])

  return model

```

Define custom callbacks

```
def build_callbacks():
  checkpointer = ModelCheckpoint(filepath=model_path, verbose=0, save_best_only=True, save_weights_only=False)
  callbacks = [checkpointer, PlotLearning()]
  return callbacks

# inheritance for training process plot
class PlotLearning(keras.callbacks.Callback):

```

```
    def on_train_begin(self, logs={}):
        self.i = 0
        self.x = []
        self.losses = []
        self.val_losses = []
        self.acc = []
        self.val_acc = []
        self.logs = []
    def on_epoch_end(self, epoch, logs={}):
        self.logs.append(logs)
        self.x.append(epoch)
        self.losses.append(logs.get('loss'))
        self.val_losses.append(logs.get('val_loss'))
        self.acc.append(logs.get('mean_iou'))
        self.val_acc.append(logs.get('val_mean_iou'))

        print('epoch =',epoch,'loss=',logs.get('loss'),'val_loss=',logs.get('val_loss'),'mean_iou=',logs.get('m

        #choose a test image and preprocess
        raw = cv2.resize(dataset_val.load_image(0),
                         dsize=default_input_size[:2],
                         interpolation=cv2.INTER_CUBIC)/255.
        # get ground truth mask
        mask = np.clip(np.sum(dataset_val.load_mask(0)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
        mask = cv2.resize(mask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)

        # pre-process the mask
        mask[mask != 0 ] = 1
        # mask = np.tile(mask[:,:,np.newaxis], (1,1,3))

        #predict the mask
        pred = model.predict(np.expand_dims(raw, 0))

        # predicted mask post-processing
        pred  = pred.squeeze()

        pred_mask = np.array(pred)
        pred_mask = exponen(pred_mask)

```

```
        fig, ax = plt.subplots(1,4,figsize=(10,40))
        [axi.set_axis_off() for axi in ax.ravel()]
        ax[0].imshow(raw)
        ax[0].set_title('Image',fontsize=14)
        ax[1].imshow(mask,cmap='gray')
        ax[1].set_title('Ground Truth',fontsize=14)
        ax[2].imshow(pred,cmap='gray')
        ax[2].set_title('Prediction',fontsize=14)
        ax[3].imshow(pred_mask,cmap='gray')
        ax[3].set_title('Post-processed prediction',fontsize=14)

        plt.show()
```

Build the model and train

```
train_steps = dataset_train.num_images //batch_size
test_steps = dataset_val.num_images //batch_size

# code checking if ckpt exists
if os.path.isfile(model_path):
    get_custom_objects().update({"weighted_binary_crossentropy":create_weighted_binary_crossentropy(pos_weight)
                                 "mean_iou":mean_iou})
    model_attached = load_model(model_path)
else:
    initial_epoch = 0
    model_attached = unet_attached()

# print model summary
model_attached.summary()

# history object
history = model_attached.fit(train_generator,
          epochs = epochs,
          initial_epoch = initial_epoch,
          steps_per_epoch = train_steps,
          validation_data = test_generator,
```

```
        validation_data = test_generator,
        validation_steps = test_steps,
        callbacks = build_callbacks(),
        verbose = 0)

```

```
Model: "functional_5"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 256, 256, 3) 0
__________________________________________________________________________________________________
conv2d_64 (Conv2D)              (None, 256, 256, 8)  224         input_3[0][0]
__________________________________________________________________________________________________
conv2d_65 (Conv2D)              (None, 256, 256, 8)  584         conv2d_64[0][0]
__________________________________________________________________________________________________
max_pooling2d_12 (MaxPooling2D) (None, 128, 128, 8)  0           conv2d_65[0][0]
__________________________________________________________________________________________________
conv2d_66 (Conv2D)              (None, 128, 128, 16) 1168        max_pooling2d_12[0][0]
__________________________________________________________________________________________________
conv2d_67 (Conv2D)              (None, 128, 128, 16) 2320        conv2d_66[0][0]
__________________________________________________________________________________________________
max_pooling2d_13 (MaxPooling2D) (None, 64, 64, 16)   0           conv2d_67[0][0]
__________________________________________________________________________________________________
conv2d_68 (Conv2D)              (None, 64, 64, 32)   4640        max_pooling2d_13[0][0]
__________________________________________________________________________________________________
conv2d_69 (Conv2D)              (None, 64, 64, 32)   9248        conv2d_68[0][0]
__________________________________________________________________________________________________
max_pooling2d_14 (MaxPooling2D) (None, 32, 32, 32)   0           conv2d_69[0][0]
__________________________________________________________________________________________________
conv2d_70 (Conv2D)              (None, 32, 32, 64)   18496       max_pooling2d_14[0][0]
__________________________________________________________________________________________________
conv2d_71 (Conv2D)              (None, 32, 32, 64)   36928       conv2d_70[0][0]
__________________________________________________________________________________________________
max_pooling2d_15 (MaxPooling2D) (None, 16, 16, 64)   0           conv2d_71[0][0]
__________________________________________________________________________________________________
conv2d_72 (Conv2D)              (None, 16, 16, 128)  73856       max_pooling2d_15[0][0]
__________________________________________________________________________________________________
conv2d_73 (Conv2D)              (None, 16, 16, 128)  147584      conv2d_72[0][0]
__________________________________________________________________________________________________
max_pooling2d_16 (MaxPooling2D) (None, 8, 8, 128)    0           conv2d_73[0][0]
__________________________________________________________________________________________________
conv2d_74 (Conv2D)              (None, 8, 8, 256)    295168      max_pooling2d_16[0][0]
```

conv2d_75 (Conv2D)	(None, 8, 8, 256)	590080	conv2d_74[0][0]
max_pooling2d_17 (MaxPooling2D)	(None, 4, 4, 256)	0	conv2d_75[0][0]
conv2d_76 (Conv2D)	(None, 4, 4, 512)	1180160	max_pooling2d_17[0][0]
conv2d_77 (Conv2D)	(None, 4, 4, 512)	2359808	conv2d_76[0][0]
conv2d_transpose_12 (Conv2DTran	(None, 8, 8, 64)	131136	conv2d_77[0][0]
concatenate_12 (Concatenate)	(None, 8, 8, 320)	0	conv2d_transpose_12[0][0] conv2d_75[0][0]
conv2d_78 (Conv2D)	(None, 8, 8, 256)	737536	concatenate_12[0][0]
conv2d_79 (Conv2D)	(None, 8, 8, 256)	590080	conv2d_78[0][0]
conv2d_transpose_13 (Conv2DTran	(None, 16, 16, 32)	32800	conv2d_79[0][0]
concatenate_13 (Concatenate)	(None, 16, 16, 160)	0	conv2d_transpose_13[0][0] conv2d_73[0][0]

Plot training and validation loss vs epoch

```
# set font size for all elements in plot
plt.rcParams.update({'font.size': 14})

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.show()

f = open("loss.txt","w") #opens file with name of "test.txt"
f1 = open("val_loss.txt","w")
f.write(str(history.history['loss']).strip('[]'))
f1.write(str(history.history['val_loss']).strip('[]'))
```

```
f.close()
f1.close()
```

Plot raw images + ground truth masks + detection masks for attached UNet model

```
for i in range(32):
  img = x[i]
  msk = y[i].squeeze()
  pred = model_attached.predict(np.expand_dims(img, 0)).squeeze()
  pred_mask = (pred >= 0.88).astype(np.float32) # pred >= threshold
  fig, ax = plt.subplots(1, 4, figsize=(15,60))
  [axi.set_axis_off() for axi in ax.ravel()]
  ax[0].imshow(img)
  ax[0].set_title('Image', fontsize=18)
  ax[1].imshow(msk, cmap = 'gray')
  ax[1].set_title('True Mask',fontsize=18)
  ax[2].imshow(pred, cmap = 'gray')
  ax[2].set_title('Prediction',fontsize=18)
  ax[3].imshow(pred_mask, cmap = 'gray')
  ax[3].set_title('Prediction w/ thresholding',fontsize=18)

total_msk_graphene = np.sum(y)
grd_graphene_to_whole_image = total_msk_graphene/(256*256*32)
grd_graphene_to_bg = total_msk_graphene/(256*256*32 - total_msk_graphene)
print(grd_graphene_to_whole_image)
print(grd_graphene_to_bg)
```

Evaluation Metrics Definition

```
def recall_m(y_true, y_pred):
    true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
```

```
    possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
    recall = true_positives / (possible_positives + K.epsilon())
    return recall

def precision_m(y_true, y_pred):
    true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
    predicted_positives = K.sum(K.round(K.clip(y_pred, 0, 1)))
    precision = true_positives / (predicted_positives + K.epsilon())
    return precision

def false_alarm_m(y_true, y_pred):
    false_positives = K.sum(K.round(K.clip((1 - y_true) * y_pred, 0, 1)))
    true_negatives = K.sum(K.round(K.clip((1 - y_true) * (1 - y_pred), 0, 1)))
    false_alarm = false_positives / (false_positives + true_negatives)
    return false_alarm

recall_m(msk,pred_mask)
```

```
<tf.Tensor: shape=(), dtype=float32, numpy=0.99715906>
```

```
def compute_recall_precision(dataset, threshold, model_name, model_name2 = None, sz = default_input_size[:2]):
    recall = 0
    precision = 0
    false_alarm = 0

    for im_id in dataset.image_ids:

        #get the mask
        mask = np.clip(np.sum(dataset.load_mask(im_id)[0], axis = -1, keepdims = True), a_min = 0, a_max = 1)
        mask = cv2.resize(mask.astype(np.float32), dsize = sz, interpolation = cv2.INTER_CUBIC)

        #preprocess the raw images
        raw = cv2.resize(dataset.load_image(im_id), dsize = sz, interpolation = cv2.INTER_CUBIC)
        pred = model_name.predict(np.expand_dims(raw/255., 0)).squeeze() # raw image (256,256,3), after expansi

        if model_name2 != None:
          pred = pred[:,:,None]*(raw/255.)
          pred = model_name2.predict(np.expand_dims(pred, 0)).squeeze() #pred(=raw image * pred mask ) (256,256
```

```
        # Threshold it to 0 or 1
        pred_mask = (pred >= threshold).astype(np.float32)
        recall += recall_m(mask,pred_mask)
        precision += precision_m(mask,pred_mask)
        false_alarm += false_alarm_m(mask,pred_mask)

    recall /= len(dataset.image_ids)
    precision /= len(dataset.image_ids)
    false_alarm /= len(dataset.image_ids)
    return (recall, precision, false_alarm)
```

```
rec_val_attached_value, prec_val_attached_values, false_ala_val_attached_value = compute_recall_precision(datas
print(rec_val_attached_value, prec_val_attached_values, false_ala_val_attached_value )
```

```
tf.Tensor(0.9505101, shape=(), dtype=float32) tf.Tensor(0.523563, shape=(), dtype=float32) tf.Tensor(0.026580
```

```
for j in range(57):
  raw = cv2.resize(dataset_val.load_image(j),
                        dsize=default_input_size[:2],
                        interpolation=cv2.INTER_CUBIC)/255
  mask = np.clip(np.sum(dataset_val.load_mask(j)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
  mask = cv2.resize(mask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
  mask[mask != 0 ] = 1

  # Ground truth monolayer
  mmask = np.clip(np.sum(dataset_val.load_mask(j)[0][:,:,[i for i in range(len(dataset_val.load_mask(j)[1])) if
  mmask = cv2.resize(mmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
  mmask[mmask != 0 ] = 1


  # Ground truth bilayer
  bmask = np.clip(np.sum(dataset_val.load_mask(j)[0][:,:,[i for i in range(len(dataset_val.load_mask(j)[1])) if
  bmask = cv2.resize(bmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
  bmask[bmask != 0 ] = 1


  print(j)
```

```
fig, ax = plt.subplots(1,4,figsize=(15,60))
[axi.set_axis_off() for axi in ax.ravel()]
ax[0].imshow(raw)
ax[0].set_title('Image',fontsize=18)
ax[1].imshow(mask,cmap='gray')
ax[1].set_title('Total Mask',fontsize=18)
ax[2].imshow(mmask,cmap='gray')
ax[2].set_title('Mono',fontsize=18)
ax[3].imshow(bmask,cmap='gray')
ax[3].set_title('Bilayer',fontsize=18)
plt.show()

```

SVM training data set

```
## Step 1. Create empty lists to store pixel values
R0 = [] # create 3 lists to store background pixel values
G0 = []
B0 = []
R1 = [] # create 3 lists to store monolayer pixel values
G1 = []
B1 = []
R2 = [] # create 3 lists to store bilayer pixel values
G2 = []
B2 = []


## Step 2. Load total ground truth RGB pixel intensities multiplied by UNet masks
for i in range(246):

   raw = cv2.resize(dataset_train.load_image(i), # Original raw images
                         dsize=default_input_size[:2],
                         interpolation=cv2.INTER_CUBIC)/255
   pred_mask = model_attached.predict(np.expand_dims(raw, 0)).squeeze() # predict masks from UNet
   graphene_pred = pred_mask[:,:,None] * raw
   graphene_pred = graphene_pred*(1 + np.sign(pred_mask[:,:,None]- 0.844))/2
```

```

#Ground truth monolayer
    mmask = np.clip(np.sum(dataset_train.load_mask(i)[0][:,:,[a for a in range(len(dataset_train.load_mask(i)[1
    mmask = cv2.resize(mmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
    mmask[mmask != 0 ] = 1
    raw = cv2.resize(dataset_train.load_image(i),
            dsize=default_input_size[:2],
            interpolation=cv2.INTER_CUBIC)/255
    img = raw
    graphene1 = mmask[:,:,None] * graphene_pred # Unet predicted monolayer mask

# Ground truth bilayer
    bmask = np.clip(np.sum(dataset_train.load_mask(i)[0][:,:,[b for b in range(len(dataset_train.load_mask(i)[1
    bmask = cv2.resize(bmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
    bmask[bmask != 0 ] = 1
    graphene2 = bmask[:,:,None] * graphene_pred # Unet predicted bilayer mask

# Combine the monolayer and bilayer ground truths
    graphene = np.append(graphene1, graphene2, axis = 0)
    r, g, b = cv2.split(graphene)
    fig = plt.figure()
    axis = fig.add_subplot(1, 1, 1, projection="3d")
    pixel_colors = graphene.reshape((np.shape(graphene)[0]*np.shape(graphene)[1], 3))

## Step 3. Plot the RGB distribution of total ground truth pixel intensities multiplied by UNet masks
    pix_c=[]
    R=[]
    G=[]
    B=[]
    r=r.flatten()
    g=g.flatten()
    b=b.flatten()
    for j in range(len(r)):
      if r[j]+g[j]+b[j] != 0:
        R.append(r[j])
        G.append(g[j])
        B.append(b[j])
        pix_c.append(pixel_colors[j])
    R=np.array(R)
```

```
  G=np.array(G)
  B=np.array(B)
  axis.scatter(R, G, B, facecolors =pix_c, marker=".")
  axis.set_xlabel("Red")
  axis.set_ylabel("Green")
  axis.set_zlabel("Blue")
  plt.show()

## Step 4. Prepare and store the background, monolayer and bilayer RGB pixel values separately
  # Monolayer
  r1, g1, b1 = cv2.split(graphene1) # monolayer RGB pixel intensities
  r1=r1.flatten()
  g1=g1.flatten()
  b1=b1.flatten()
  for j in range(len(r1)):
   if r1[j]+g1[j]+b1[j] != 0:
    R1.append(r1[j])
    G1.append(g1[j])
    B1.append(b1[j])
    pix_c.append(pixel_colors[j])

  # Bilayer
  r2, g2, b2 = cv2.split(graphene2) # graphene1 is monolayer
  r2=r2.flatten()
  g2=g2.flatten()
  b2=b2.flatten()
  for j in range(len(r1)):
   if r2[j]+g2[j]+b2[j] != 0:
    R2.append(r2[j])
    G2.append(g2[j])
    B2.append(b2[j])
    pix_c.append(pixel_colors[j])

  # for background
  mask = np.clip(np.sum(dataset_train.load_mask(i)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
  mask = cv2.resize(mask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
  # pre-process the mask
  mask[mask != 0 ] = 1
  background = (1 - mask)[:,:,None] * graphene_pred
```

```
    r0, g0, b0 = cv2.split(background) # graphene1 is monolayer
    r0=r0.flatten()
    g0=g0.flatten()
    b0=b0.flatten()
    for j in range(len(r0)):
      if r0[j]+g0[j]+b0[j] != 0:
        R0.append(r0[j])
        G0.append(g0[j])
        B0.append(b0[j])
        pix_c.append(pixel_colors[j])

## Step 5. Convert the RGB list to array
R1=np.array(R1)
G1=np.array(G1)
B1=np.array(B1)
result1 = np.ones(len(R1)) # monolayer

R2=np.array(R2)
G2=np.array(G2)
B2=np.array(B2)
result2 = 2*np.ones(len(R2)) # bilayer

R0=np.array(R0)
G0=np.array(G0)
B0=np.array(B0)
result0 = np.zeros(len(R0)) # background

## Step 6. Combine the RGB values of monolayer, bilayer and background for SVM input dataset
graphene_R_train = np.append(R0, R1)
graphene_R_train = np.append(graphene_R_train, R2)
graphene_G_train = np.append(G0, G1)
graphene_G_train = np.append(graphene_G_train,G2)
graphene_B_train = np.append(B0, B1)
graphene_B_train = np.append(graphene_B_train,B2)
result_train = np.append(result0, result1)
result_train = np.append(result_train, result2)
```

SVM testing data set

```
## similart process to SVM training dataset but here is for testing dataset
R0 = []
G0 = []
B0 = []
R1 = []
G1 = []
B1 = []
R2 = []
G2 = []
B2 = []
# print the ground truth monolayer distribution
for i in range(57):

    raw = cv2.resize(dataset_val.load_image(i),
                          dsize=default_input_size[:2],
                          interpolation=cv2.INTER_CUBIC)/255
    pred_mask = model_attached.predict(np.expand_dims(raw, 0)).squeeze()
    graphene_pred = pred_mask[:,:,None] * raw
    graphene_pred = graphene_pred*(1 + np.sign(pred_mask[:,:,None]- 0.844))/2
#Ground truth monolayer
    mmask = np.clip(np.sum(dataset_val.load_mask(i)[0][:,:,[a for a in range(len(dataset_val.load_mask(i)[1]))
    mmask = cv2.resize(mmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
    mmask[mmask != 0 ] = 1
    raw = cv2.resize(dataset_val.load_image(i),
            dsize=default_input_size[:2],
            interpolation=cv2.INTER_CUBIC)/255
    img = raw #x[i]
    graphene1 = mmask[:,:,None] * graphene_pred

# Ground truth bilayer

    bmask = np.clip(np.sum(dataset_val.load_mask(i)[0][:,:,[b for b in range(len(dataset_val.load_mask(i)[1]))
    bmask = cv2.resize(bmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
    bmask[bmask != 0 ] = 1
    graphene2 = bmask[:,:,None] * graphene_pred

    graphene = np.append(graphene1, graphene2,axis = 0)
```

```
r, g, b = cv2.split(graphene)
fig = plt.figure()
axis = fig.add_subplot(1, 1, 1, projection="3d")

pixel_colors = graphene.reshape((np.shape(graphene)[0]*np.shape(graphene)[1], 3))

pix_c=[]
R=[]
G=[]
B=[]
r=r.flatten()
g=g.flatten()
b=b.flatten()
for j in range(len(r)):
  if r[j]+g[j]+b[j] != 0:
    R.append(r[j])
    G.append(g[j])
    B.append(b[j])
    pix_c.append(pixel_colors[j])
R=np.array(R)
G=np.array(G)
B=np.array(B)
axis.scatter(R, G, B, facecolors =pix_c, marker=".")
axis.set_xlabel("Red")
axis.set_ylabel("Green")
axis.set_zlabel("Blue")
plt.show()

# for monolayer
r1, g1, b1 = cv2.split(graphene1) # graphene1 is monolayer
r1=r1.flatten()
g1=g1.flatten()
b1=b1.flatten()
for j in range(len(r1)):
  if r1[j]+g1[j]+b1[j] != 0:
    R1.append(r1[j])
    G1.append(g1[j])
    B1.append(b1[j])
    pix_c.append(pixel_colors[j])
```

```


    # for bilayer
    r2, g2, b2 = cv2.split(graphene2) # graphene1 is monolayer
    r2=r2.flatten()
    g2=g2.flatten()
    b2=b2.flatten()
    for j in range(len(r1)):
      if r2[j]+g2[j]+b2[j] != 0:
        R2.append(r2[j])
        G2.append(g2[j])
        B2.append(b2[j])
        pix_c.append(pixel_colors[j])

    # for background
    mask = np.clip(np.sum(dataset_val.load_mask(i)[0],axis=-1,keepdims=True),a_min=0,a_max=1)
    mask = cv2.resize(mask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
    # pre-process the mask
    mask[mask != 0 ] = 1
    background = (1 - mask)[:,:,None] * graphene_pred
    r0, g0, b0 = cv2.split(background) # graphene1 is monolayer
    r0=r0.flatten()
    g0=g0.flatten()
    b0=b0.flatten()
    for j in range(len(r0)):
      if r0[j]+g0[j]+b0[j] != 0:
        R0.append(r0[j])
        G0.append(g0[j])
        B0.append(b0[j])
        pix_c.append(pixel_colors[j])

R1=np.array(R1)
G1=np.array(G1)
B1=np.array(B1)
result1 = np.ones(len(R1))

R2=np.array(R2)
G2=np.array(G2)
B2=np.array(B2)
```

```
result2 = 2*np.ones(len(R2))

R0=np.array(R0)
G0=np.array(G0)
B0=np.array(B0)
result0 = np.zeros(len(R0))

graphene_R_val = np.append(R0, R1)
graphene_R_val = np.append(graphene_R_val, R2)
graphene_G_val = np.append(G0, G1)
graphene_G_val = np.append(graphene_G_val,G2)
graphene_B_val = np.append(B0, B1)
graphene_B_val = np.append(graphene_B_val,B2)
result_val = np.append(result0, result1)
result_val = np.append(result_val, result2)
```

```
# Preparing for the training dataset
from sklearn.svm import SVC
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm, datasets
from mpl_toolkits.mplot3d import Axes3D
from sklearn.model_selection import train_test_split

X_Train = np.stack((graphene_R_train, graphene_G_train, graphene_B_train), axis = 0)
X_Train = X_Train.transpose()

X_Test = np.stack((graphene_R_val, graphene_G_val, graphene_B_val), axis = 0)
X_Test = X_Test.transpose()

Y_Train = result_train
Y_Test = result_val
```

```
# Dataset Normalization
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X_Train = sc_X.fit_transform(X_Train)
X_Test = sc_X.transform(X_Test)
```

```
X_Test = sc_X.transform(X_Test)
```

SVM training model

```
# use pickle to save the data for SVM
import pickle
```

```
## SVM training model
# from sklearn.preprocessing import StandardScaler
# sc_X = StandardScaler()
# X_Train = sc_X.fit_transform(X_Train)
# X_Test = sc_X.transform(X_Test)

# model_svm = svm.SVC(kernel='rbf',verbose=True)
# clf = model_svm.fit(X_Train, Y_Train)

## Save the model after training a model
#pickle.dump(clf, open(SVM_model_path , 'wb'))
```

```
## Load a trained model
clf1 = pickle.load(open(SVM_model_path, 'rb'))  # 'rb' for reading binary file

## Print the confusion metrics
y_pred = clf1.predict(X_Test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(Y_Test, y_pred))
print(classification_report(Y_Test, y_pred))
```

```
[[82733  7816 16146]
 [ 4476 18265  4452]
 [ 4976  6496 63390]]
              precision    recall  f1-score   support

         0.0       0.90      0.78      0.83    106695
         1.0       0.56      0.67      0.61     27193
         2.0       0.75      0.85      0.80     74862
```

```
    accuracy                           0.79    208750
   macro avg       0.74      0.76      0.75    208750
weighted avg       0.80      0.79      0.79    208750
```

Plot the SVM results

```
for h in range(57):
  raw1 = cv2.resize(dataset_val.load_image(h),
                      dsize=default_input_size[:2],
                      interpolation=cv2.INTER_CUBIC)/255

  pred_mask = model_attached.predict(np.expand_dims(raw1, 0)).squeeze()
  graphene_pred = pred_mask[:,:,None] * raw1
  graphene_pred = graphene_pred*(1 + np.sign(pred_mask[:,:,None]- 0.844))/2

  red = graphene_pred[:,:,0]
  green = graphene_pred[:,:,1]
  blue = graphene_pred[:,:,2]
  red=red.flatten()
  green = green.flatten()
  blue=blue.flatten()
  for j in range(len(red)):
    k = j%256
    i = j//256
    if red[j]+green[j]+blue[j] == 0:
      graphene_pred[i,k,:]=0
    else:
      x = np.array([red[j],green[j],blue[j]])
      x = np.expand_dims(x,0)
      x = sc_X.transform(x) # Perform mean and standard deviation on the x value
      y = clf1.predict(x)
      if y==0:
        graphene_pred[i,k,:]=0
      elif y==1:
        graphene_pred[i,k,:]=0
```

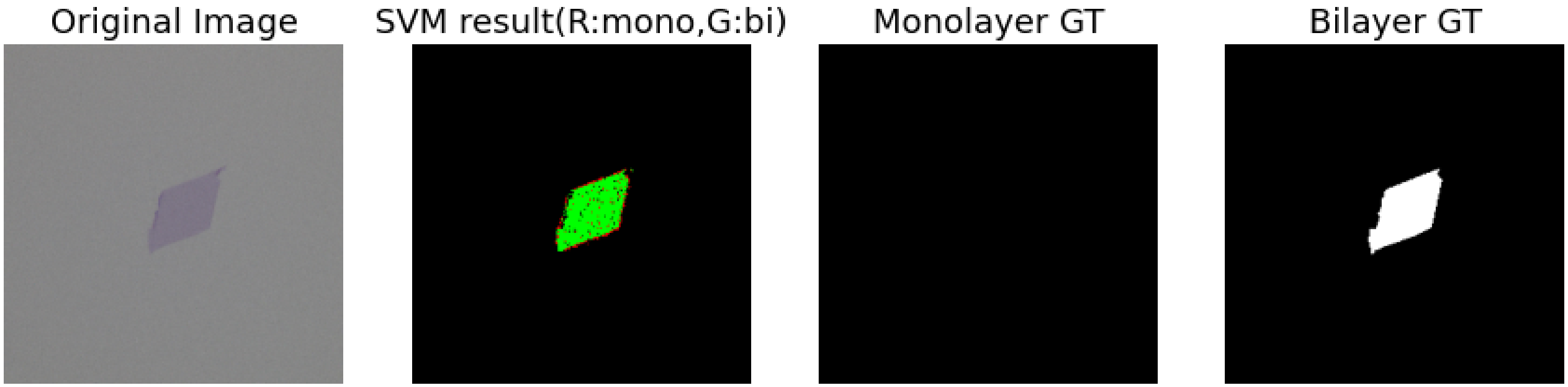
```
    graphene_pred[i,k,:]=0
    graphene_pred[i,k,0]=255
   elif y==2:
    graphene_pred[i,k,:]=0
    graphene_pred[i,k,1]=255


 # Ground truth monolayer
 mmask = np.clip(np.sum(dataset_val.load_mask(h)[0][:,:,[i for i in range(len(dataset_val.load_mask(h)[1])) if
 mmask = cv2.resize(mmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
 mmask[mmask != 0 ] = 1

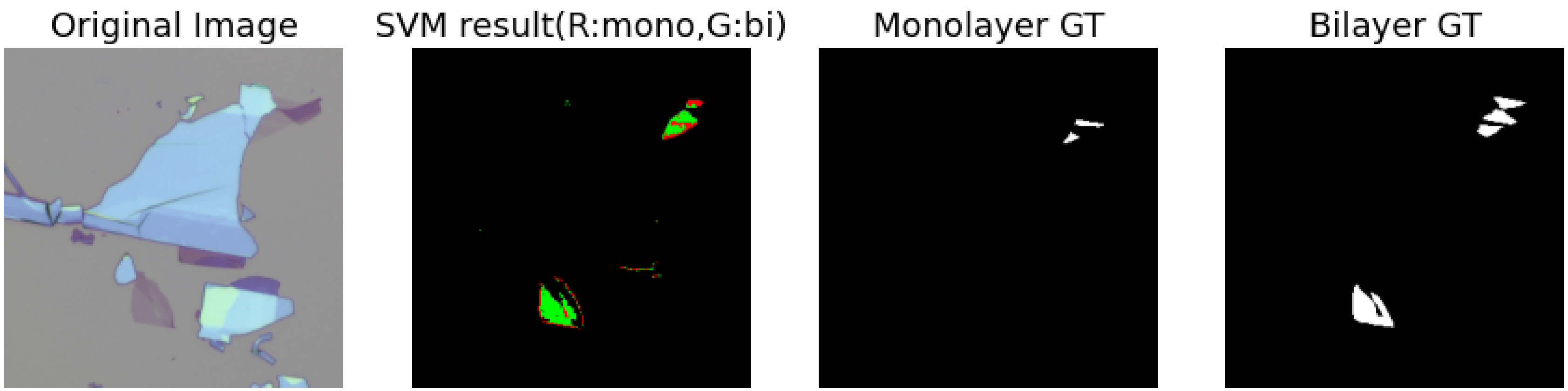
  # Ground truth bilayer
 bmask = np.clip(np.sum(dataset_val.load_mask(h)[0][:,:,[i for i in range(len(dataset_val.load_mask(h)[1])) if
 bmask = cv2.resize(bmask.astype(np.float32), dsize=default_input_size[:2], interpolation=cv2.INTER_CUBIC)
 bmask[bmask != 0 ] = 1

## Plot the images
 fig, ax = plt.subplots(1,4,figsize=(15,60))
 [axi.set_axis_off() for axi in ax.ravel()]
 ax[0].imshow(raw1)
 ax[0].set_title('Original Image',fontsize=18)
 ax[1].imshow(graphene_pred,cmap='gray')
 ax[1].set_title('SVM result(R:mono,G:bi)',fontsize=18)
 ax[2].imshow(mmask,cmap='gray')
 ax[2].set_title('Monolayer GT',fontsize=18)
 ax[3].imshow(bmask,cmap='gray')
 ax[3].set_title('Bilayer GT',fontsize=18)
 plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



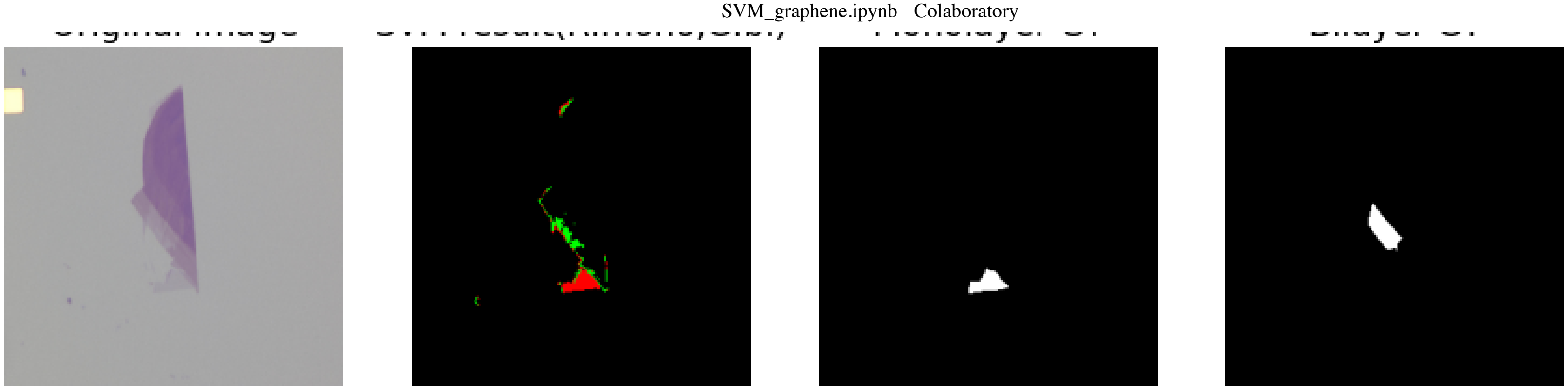

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



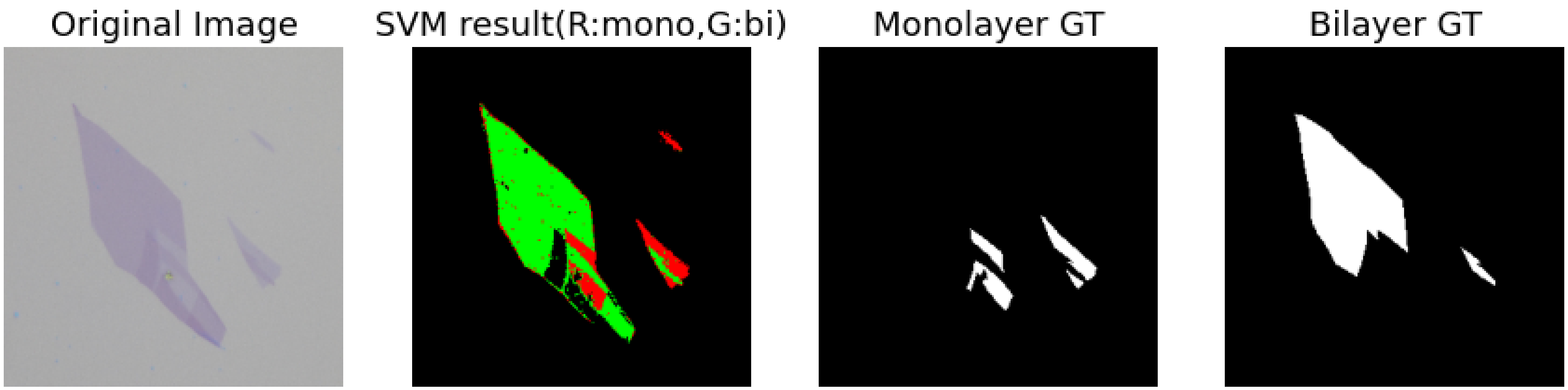

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```


```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

Original Image SVM result(R:mono,G:bi) Monolayer GT Bilayer GT

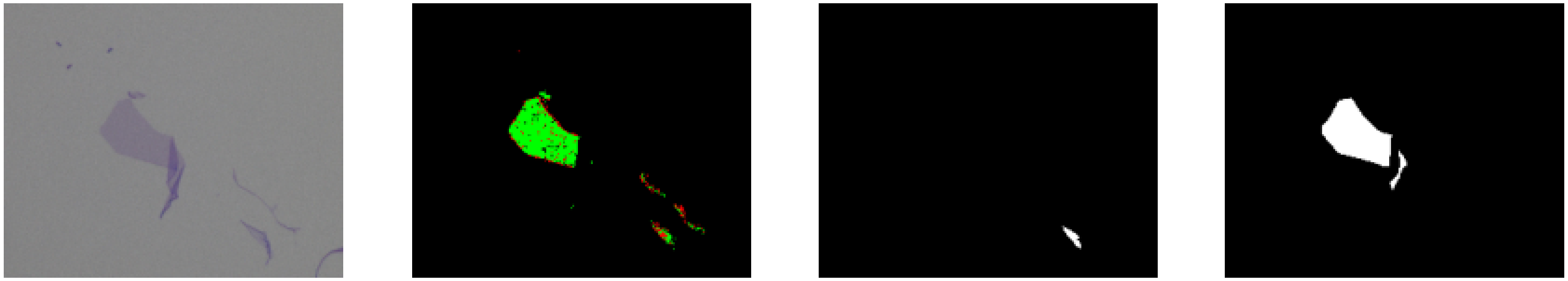


```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

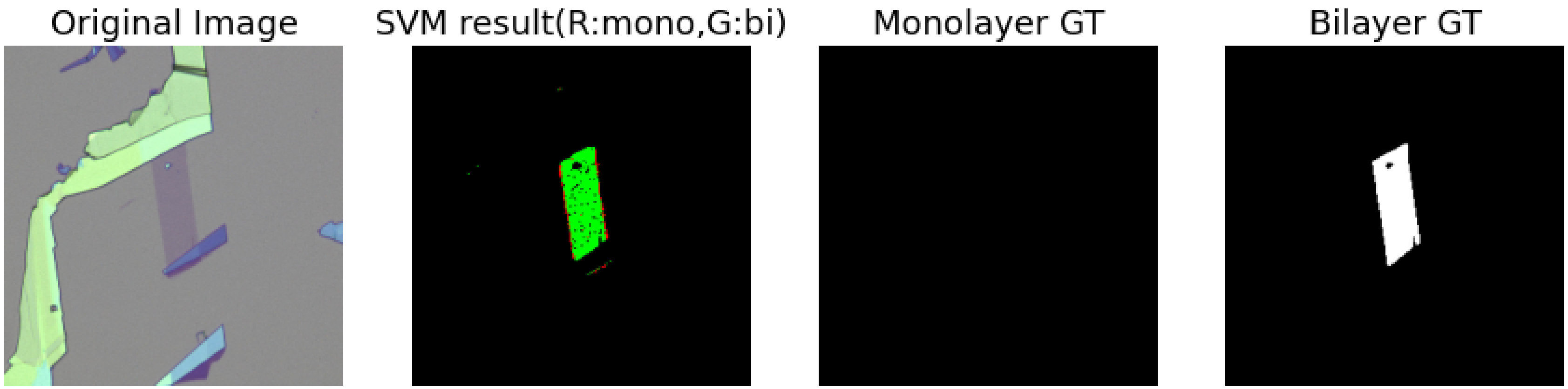



```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

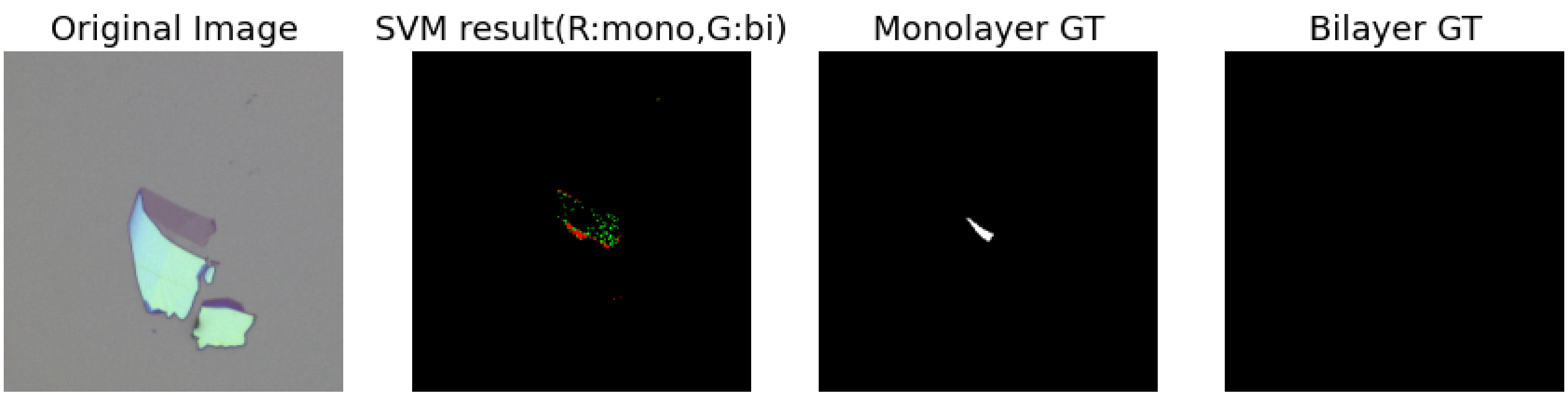

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



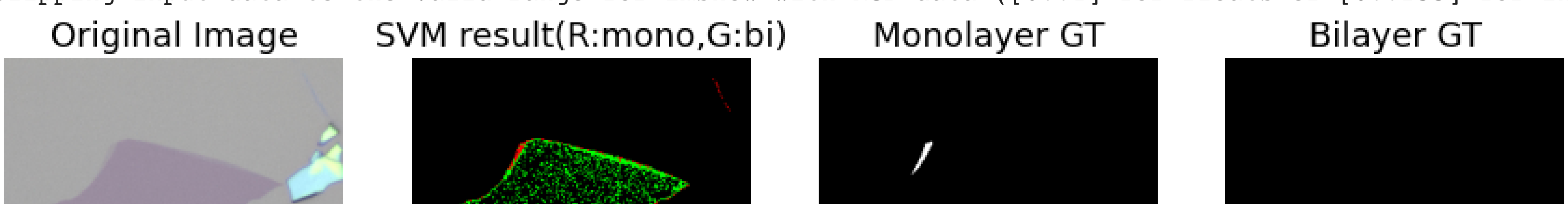
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



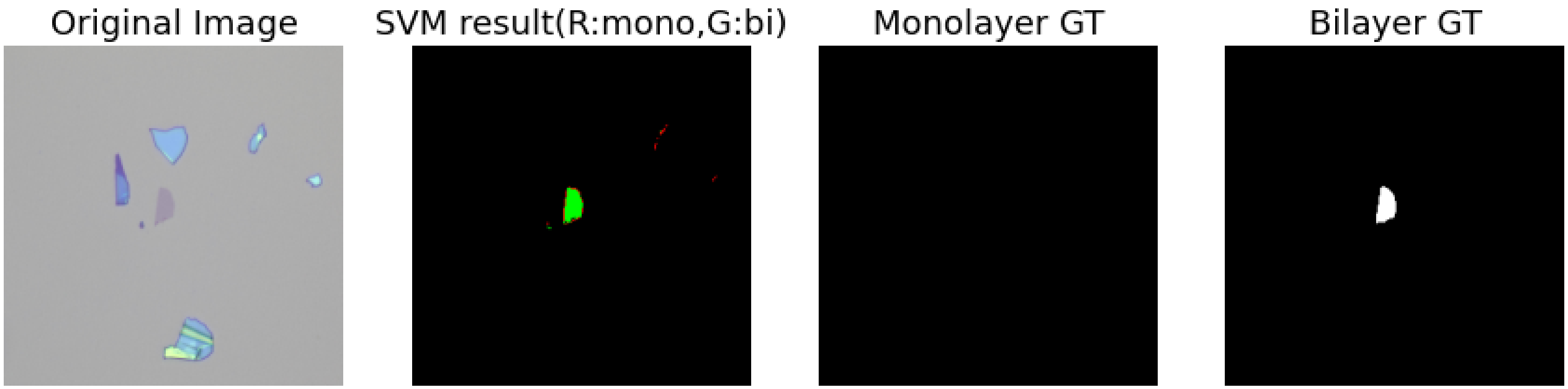
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



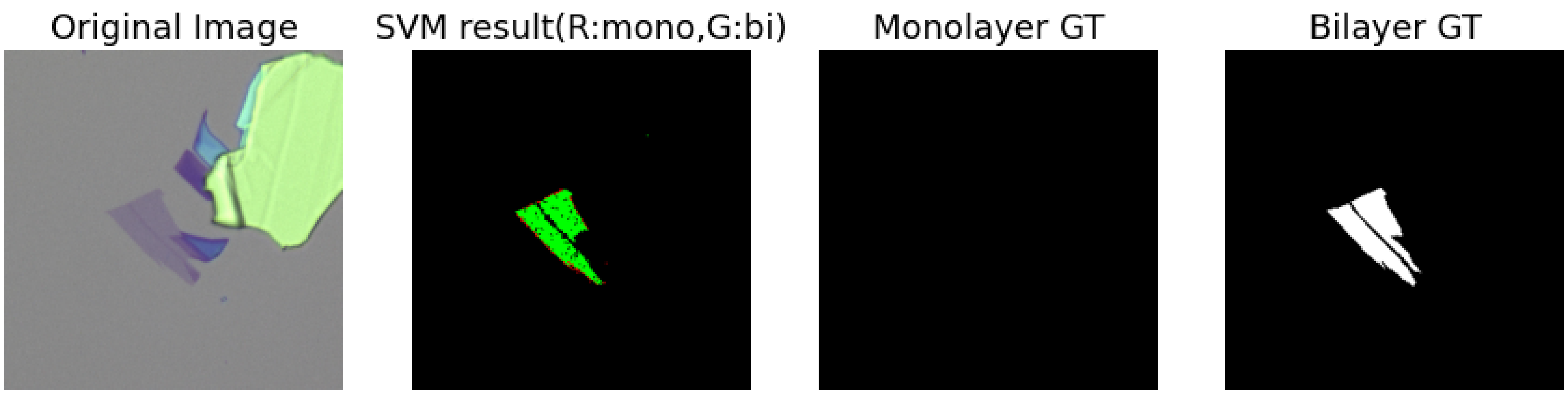
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

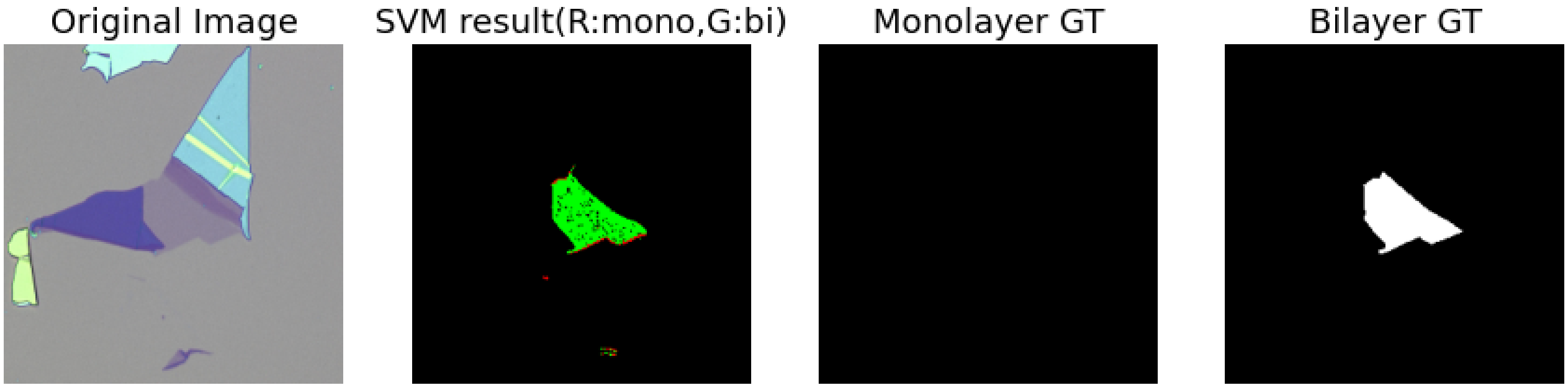


Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

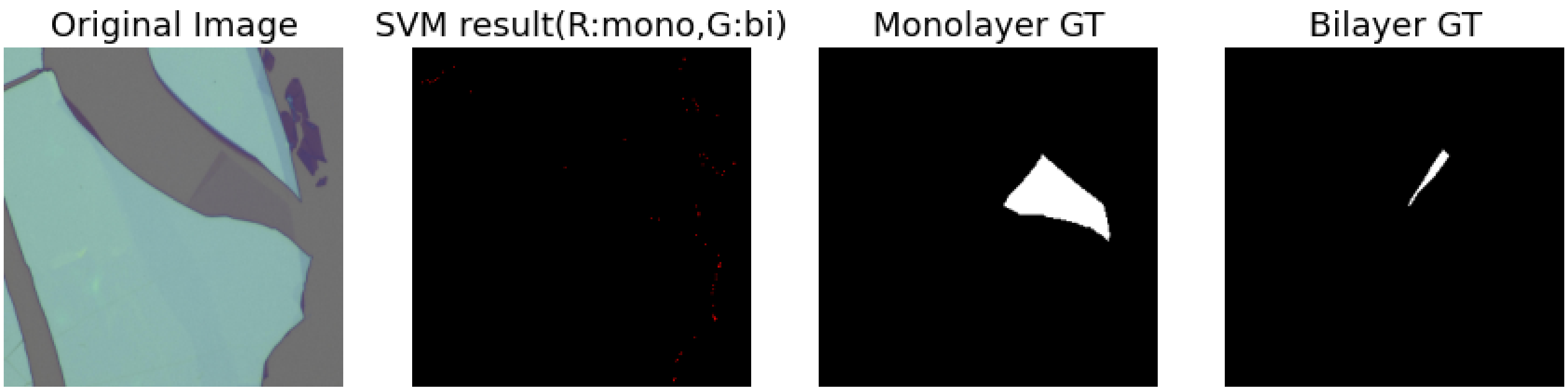


Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

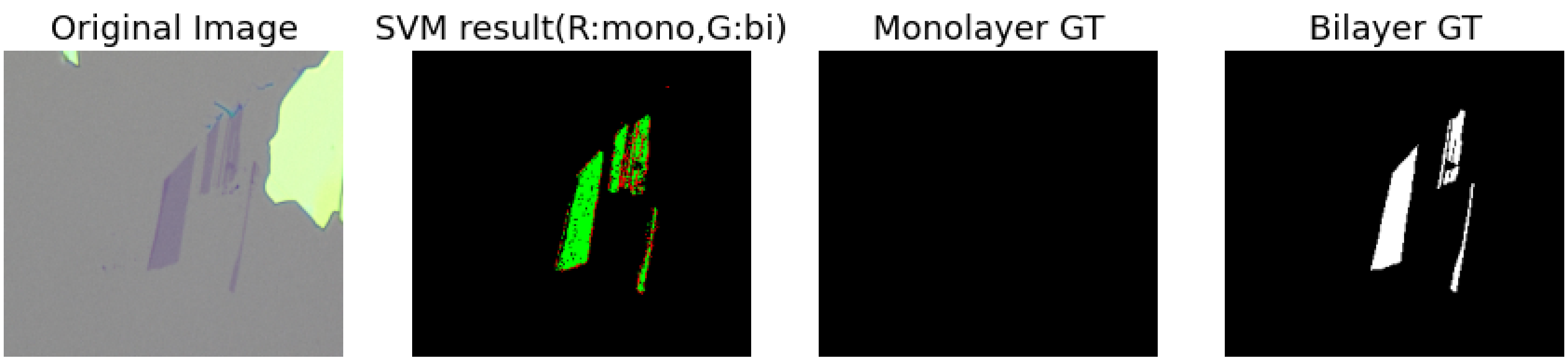
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



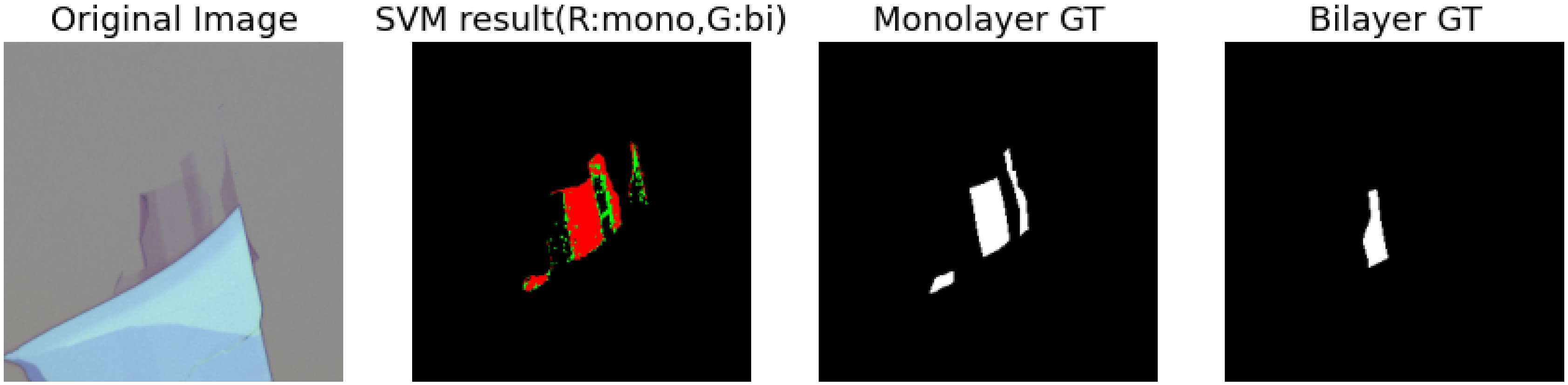

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



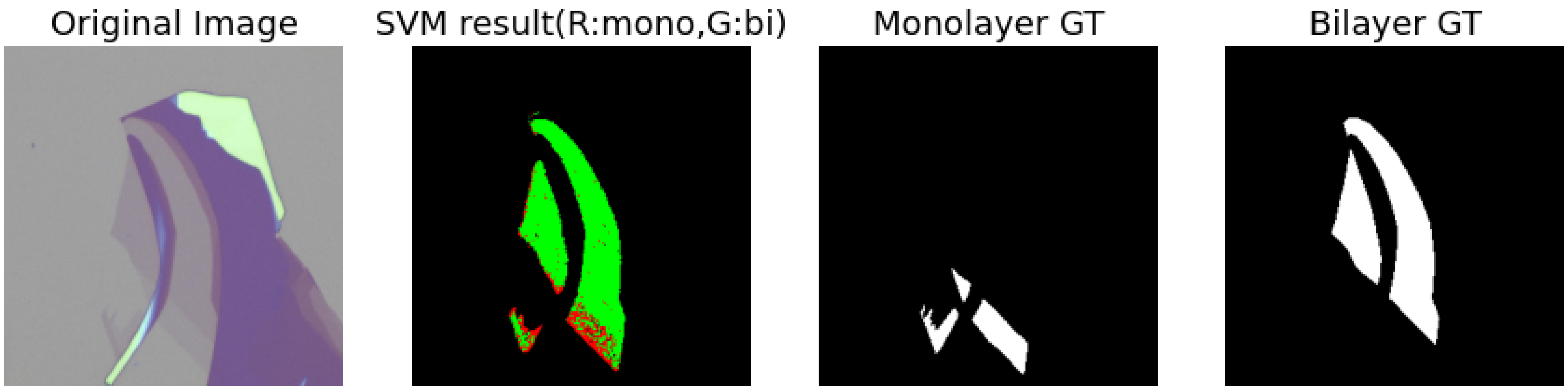

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



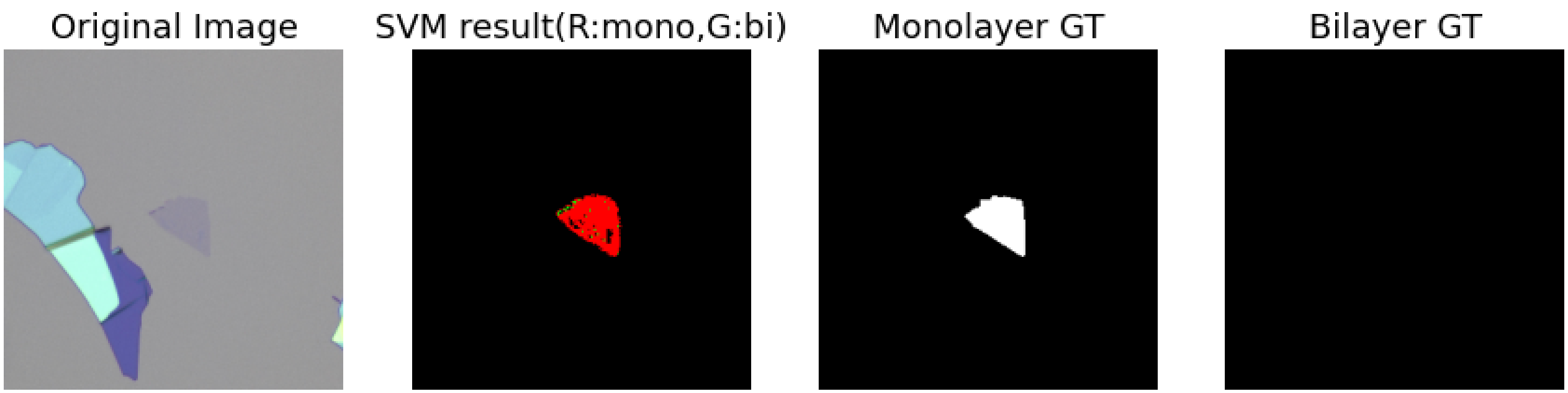
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



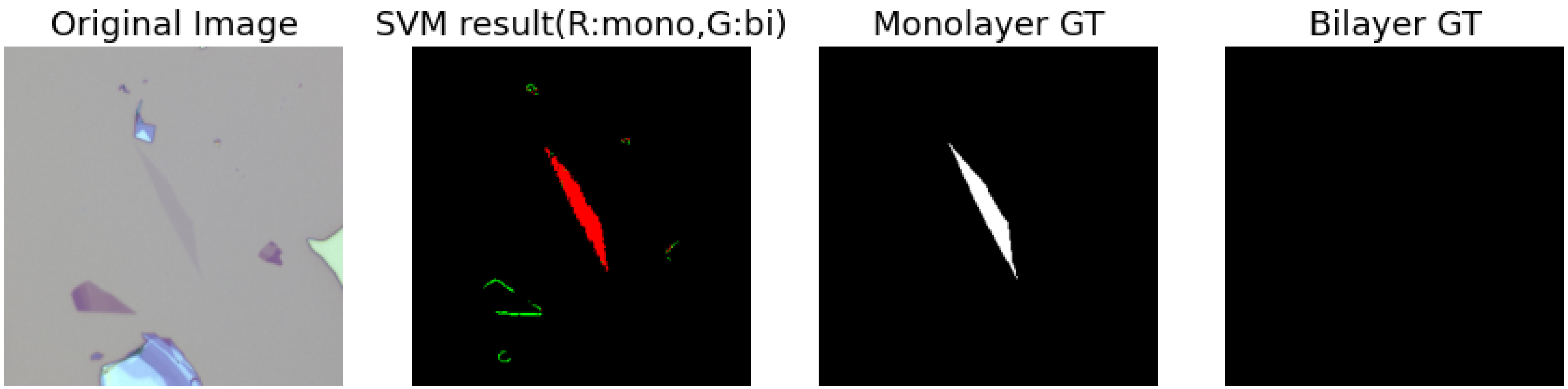
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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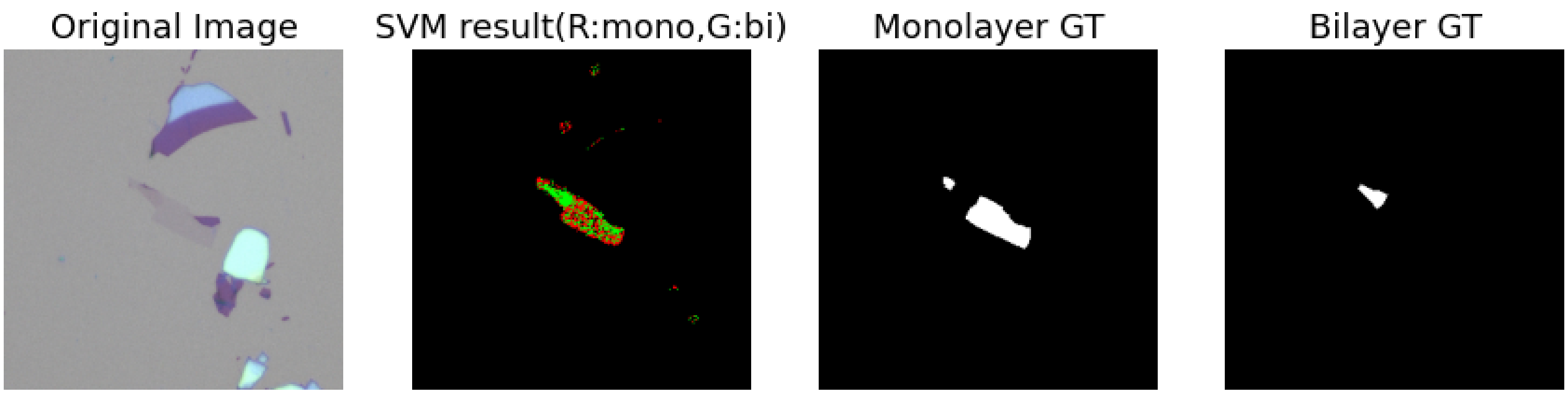


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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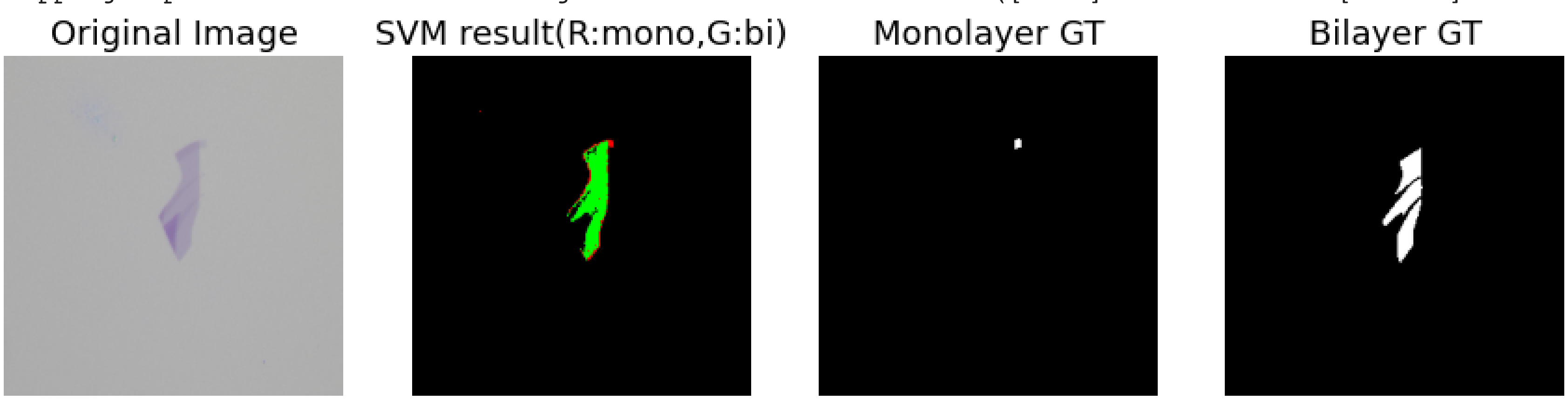


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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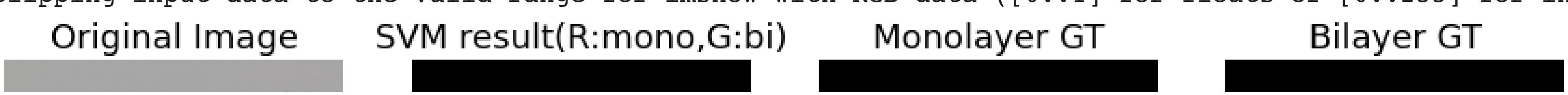
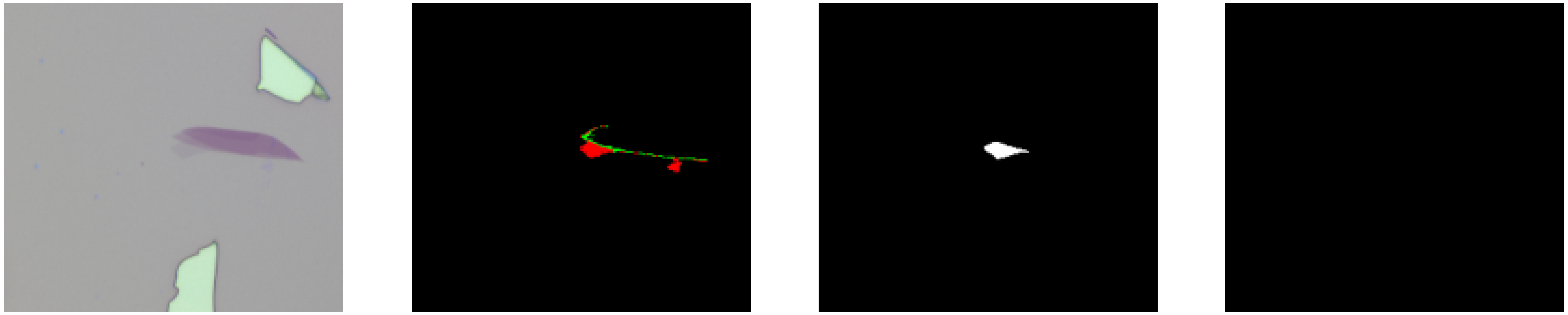
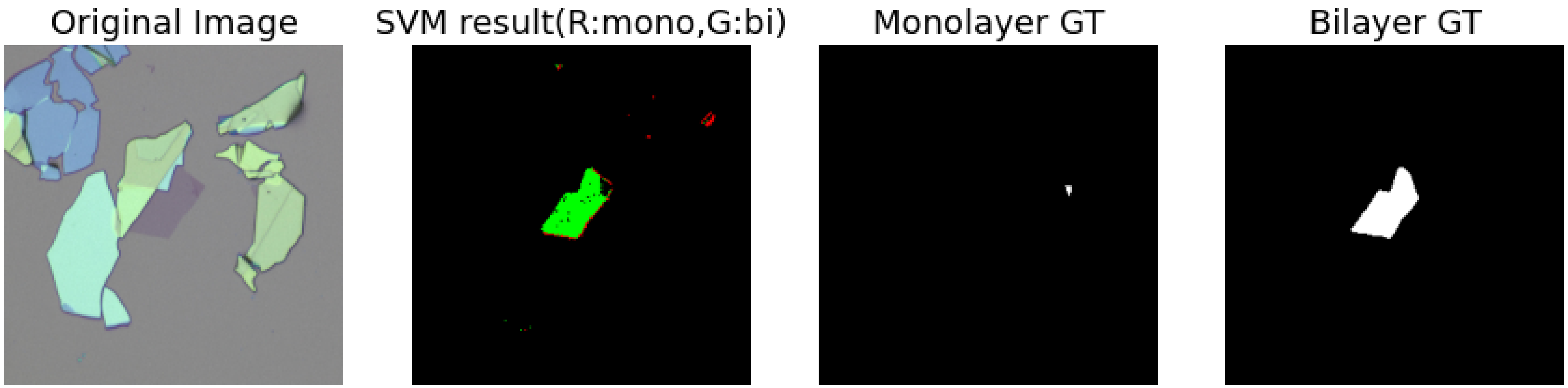
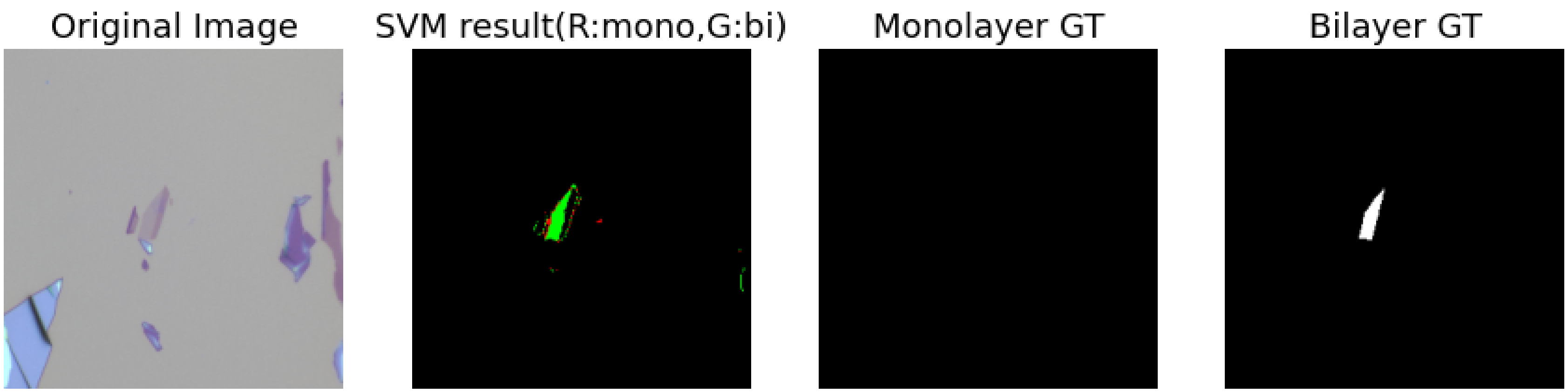




Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

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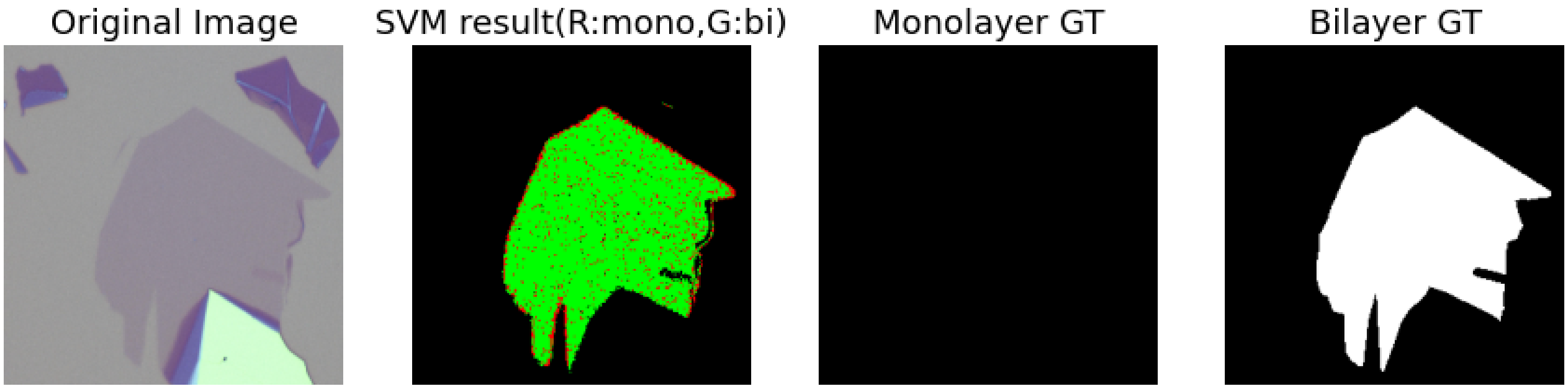


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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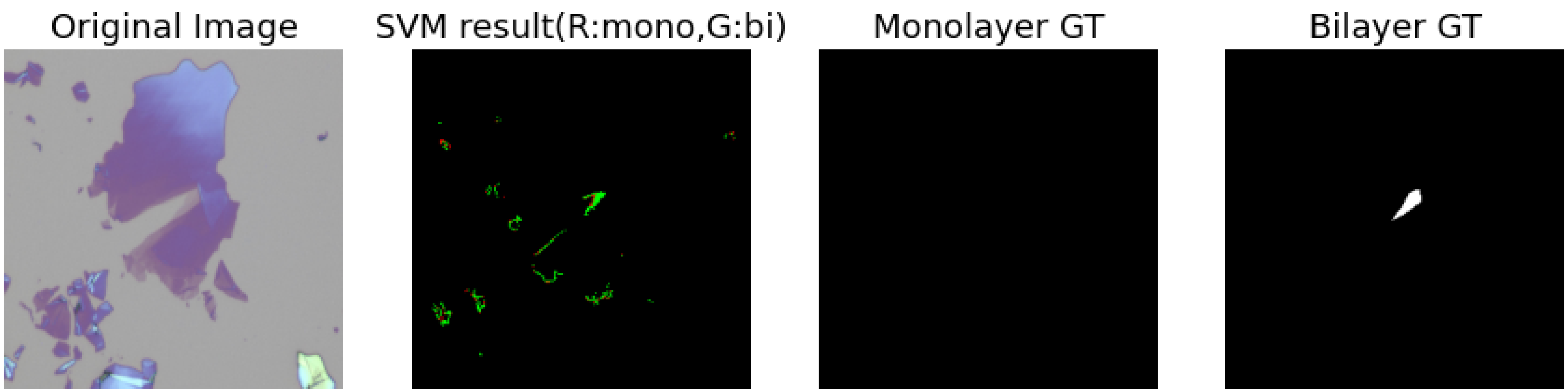


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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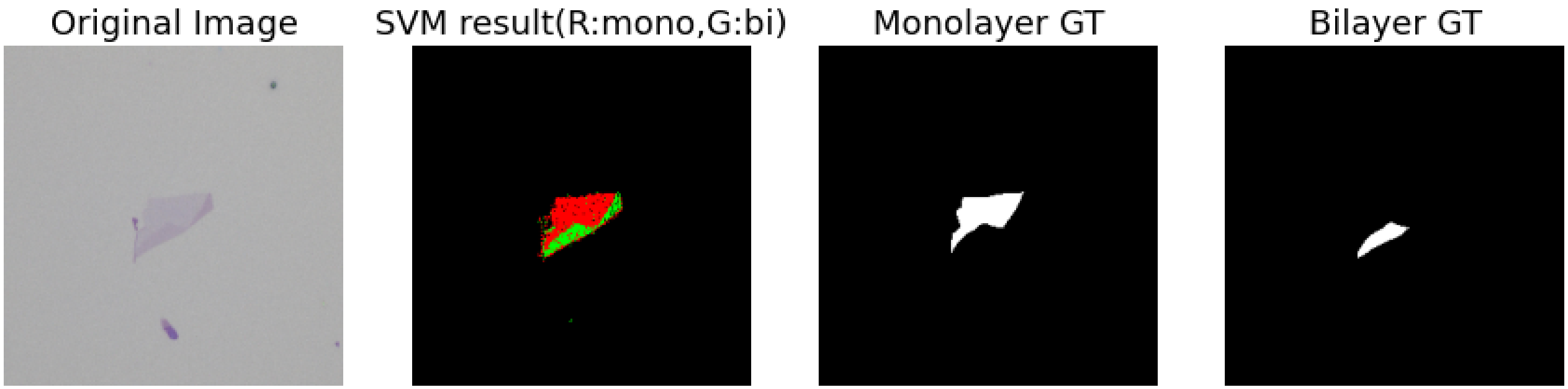
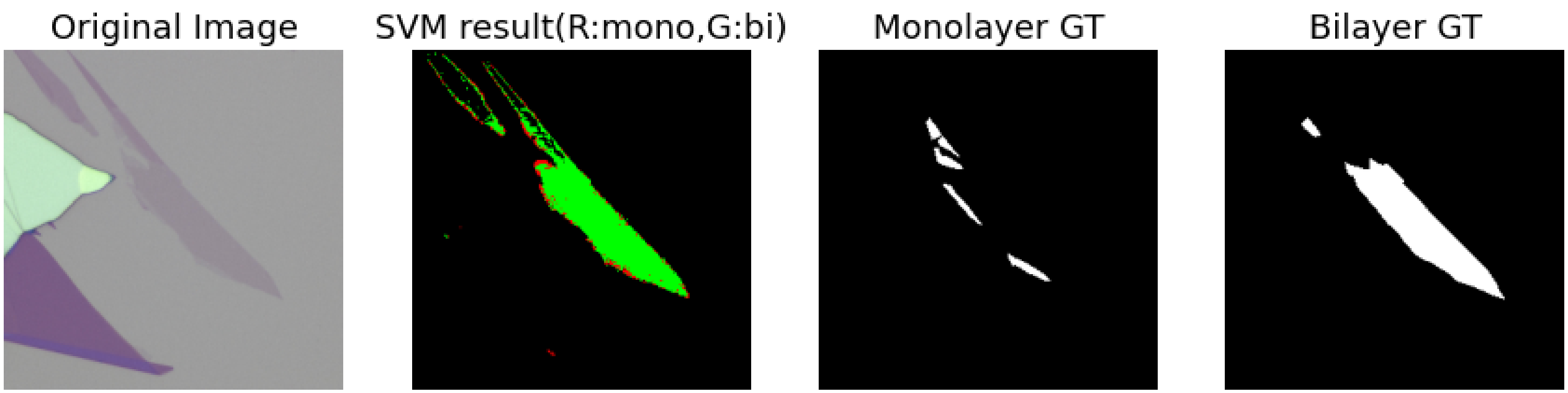
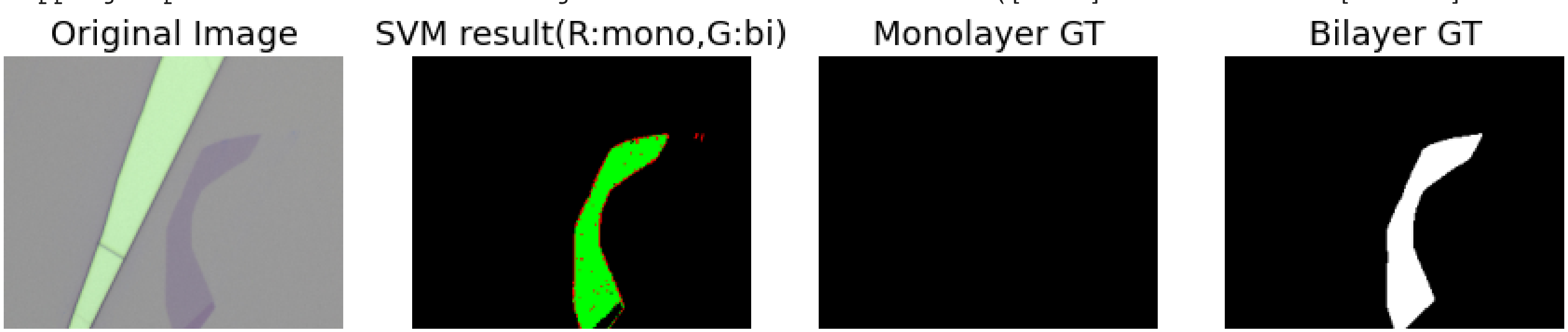


Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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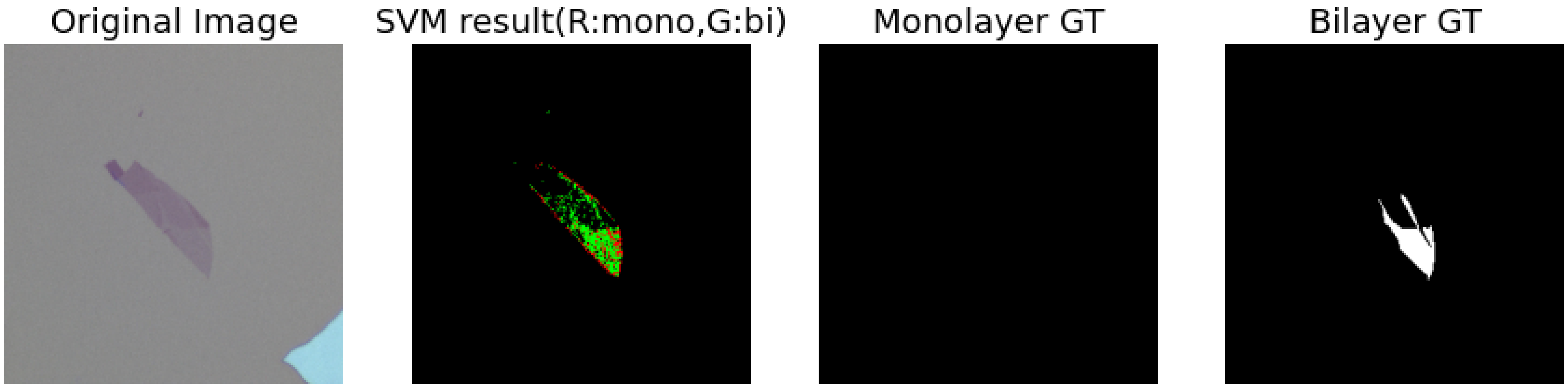


```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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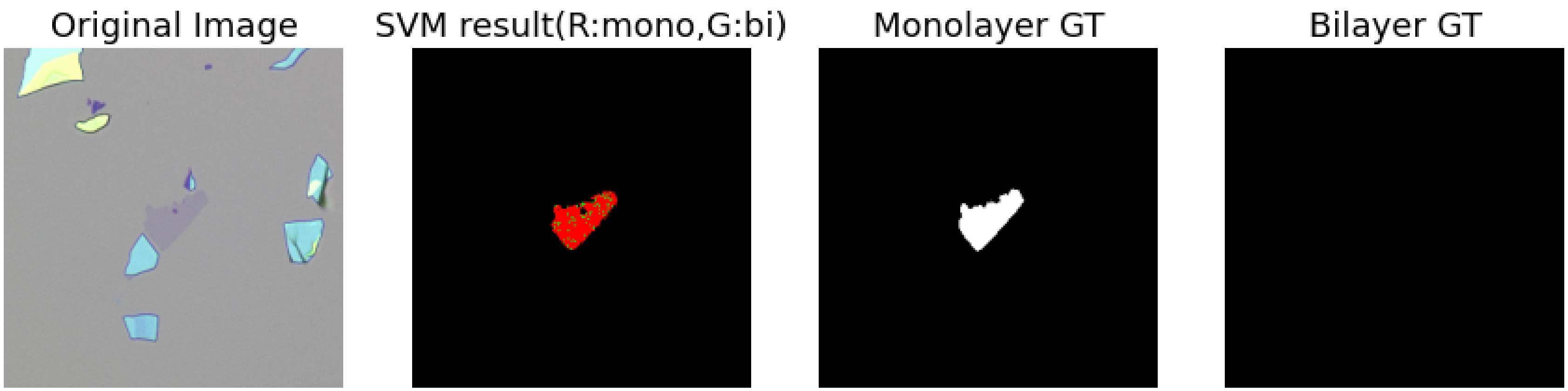


```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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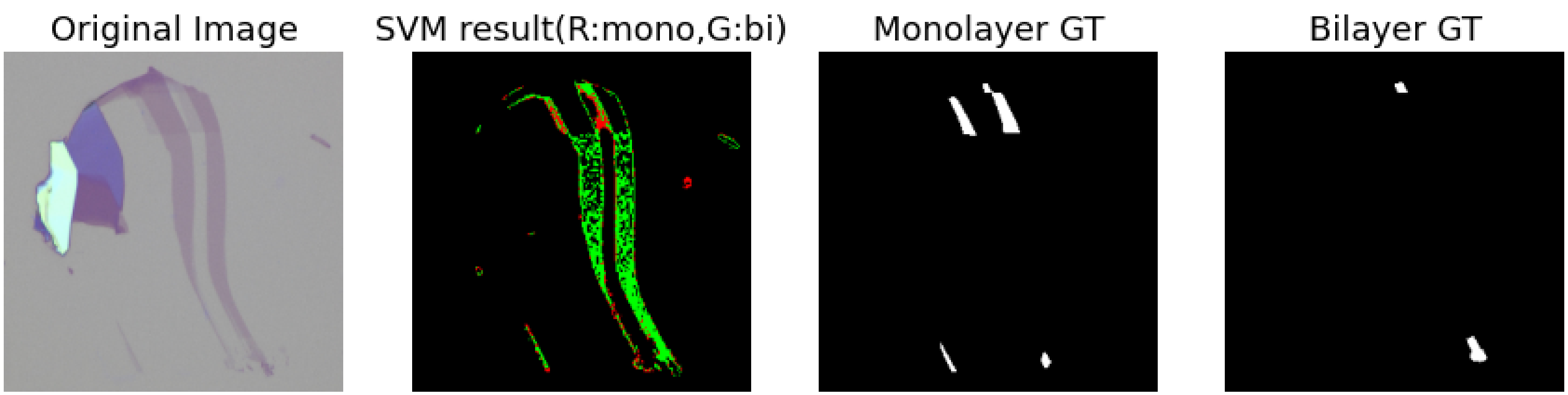
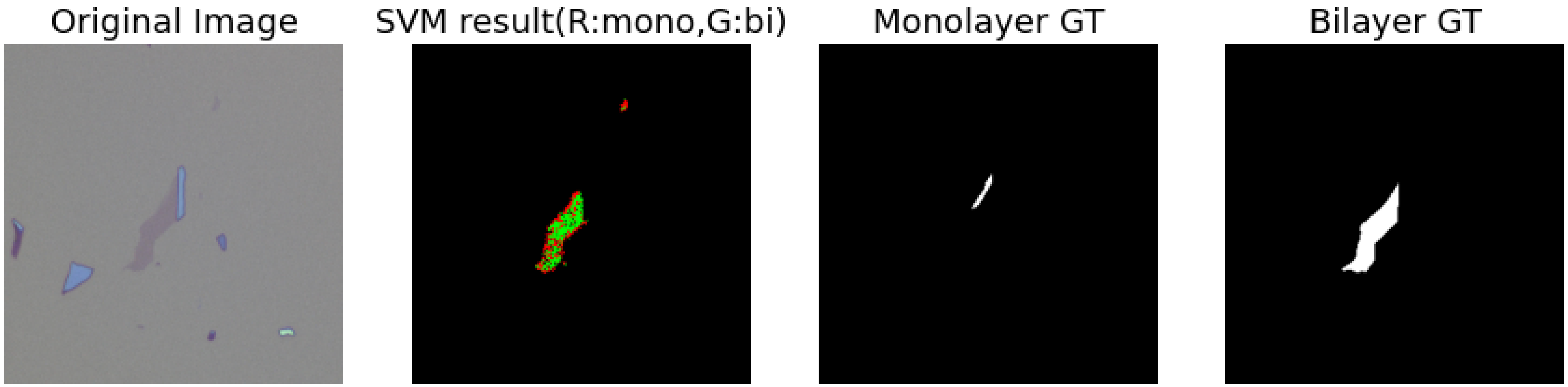
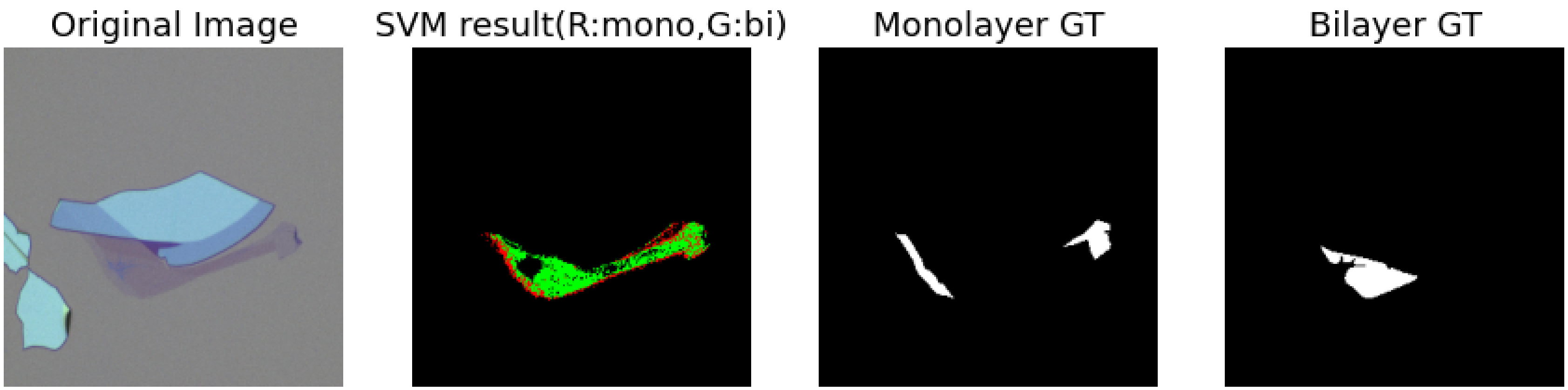


Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



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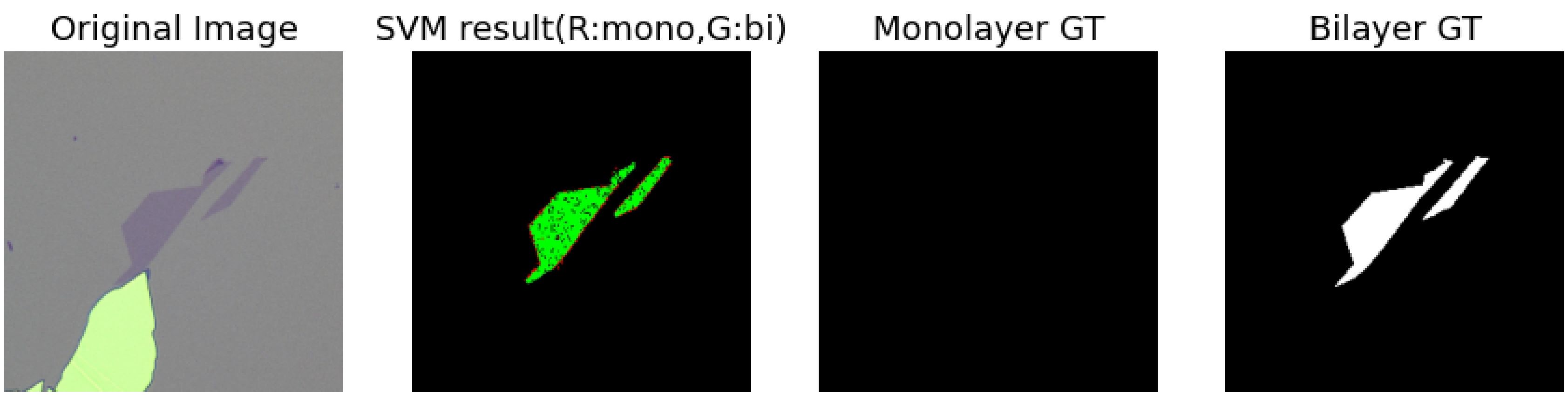
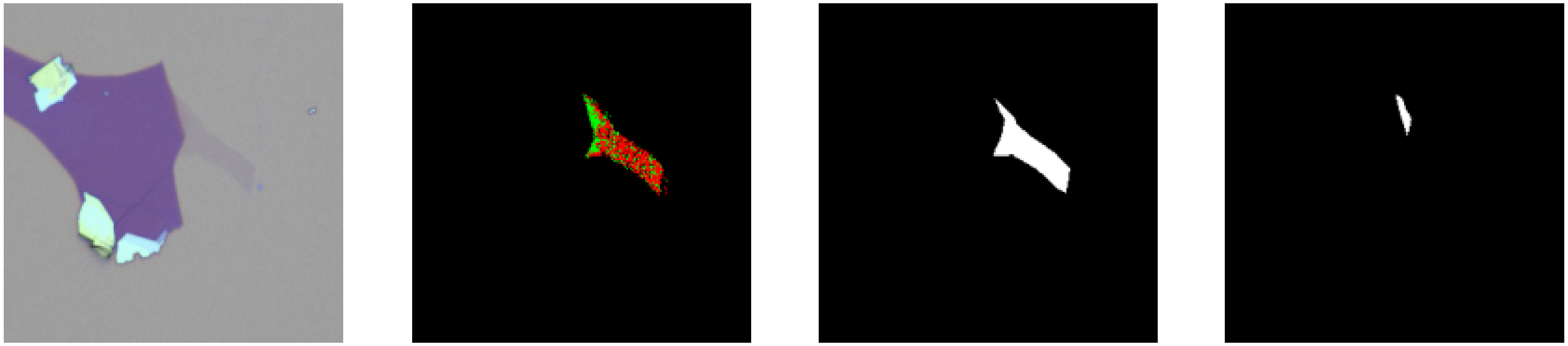
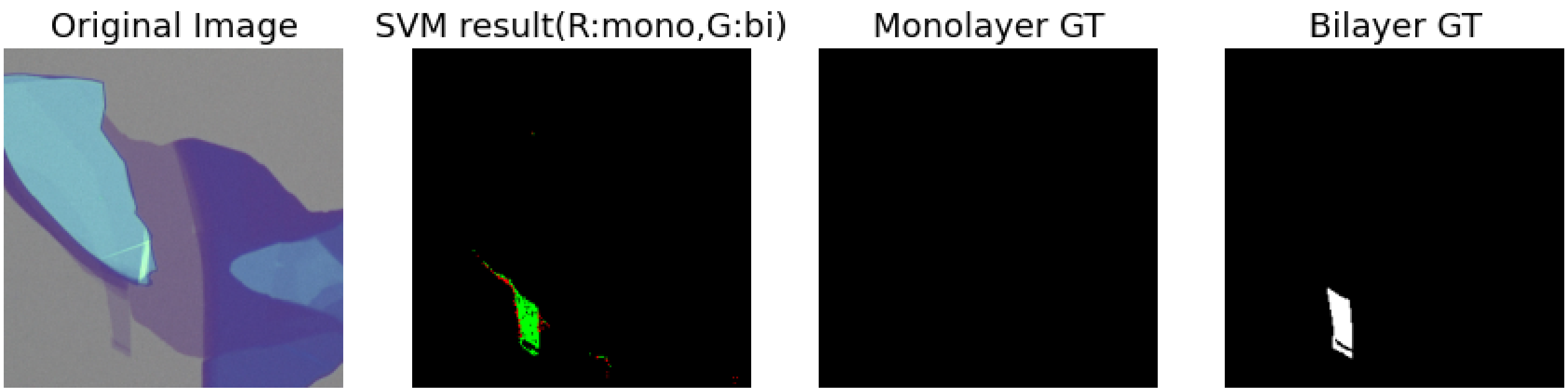


Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Original Image SVM result(R:mono,G:bi) Monolayer GT Bilayer GT



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



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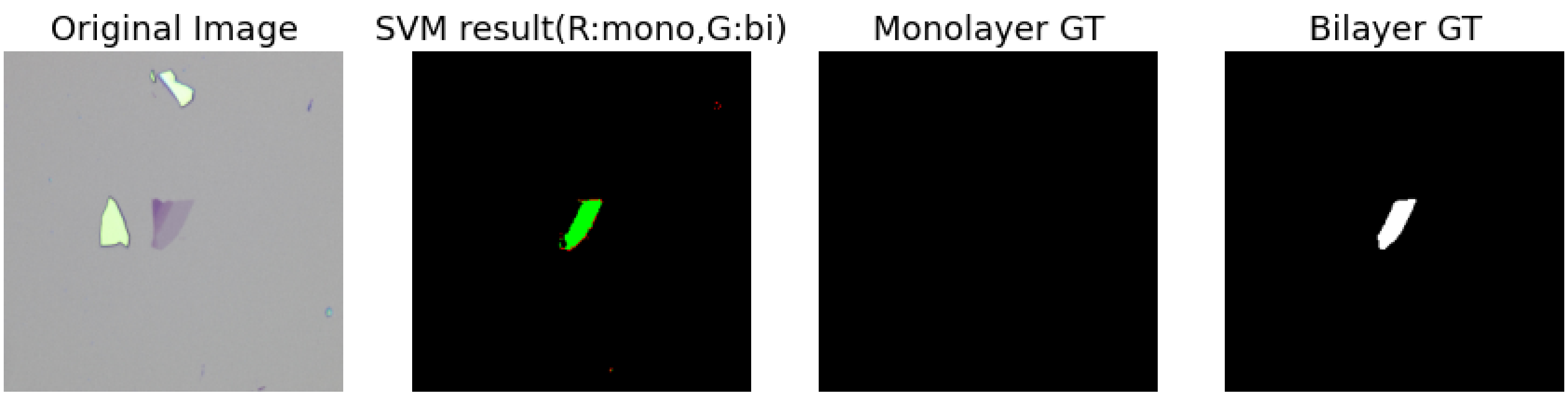
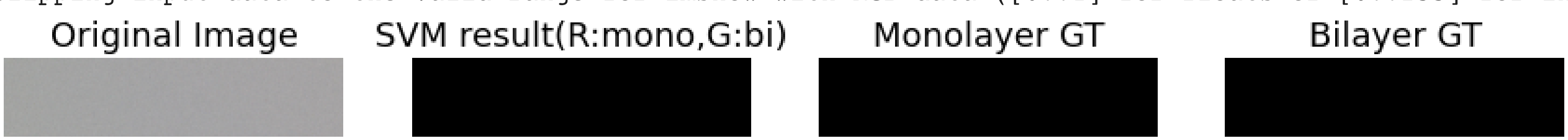
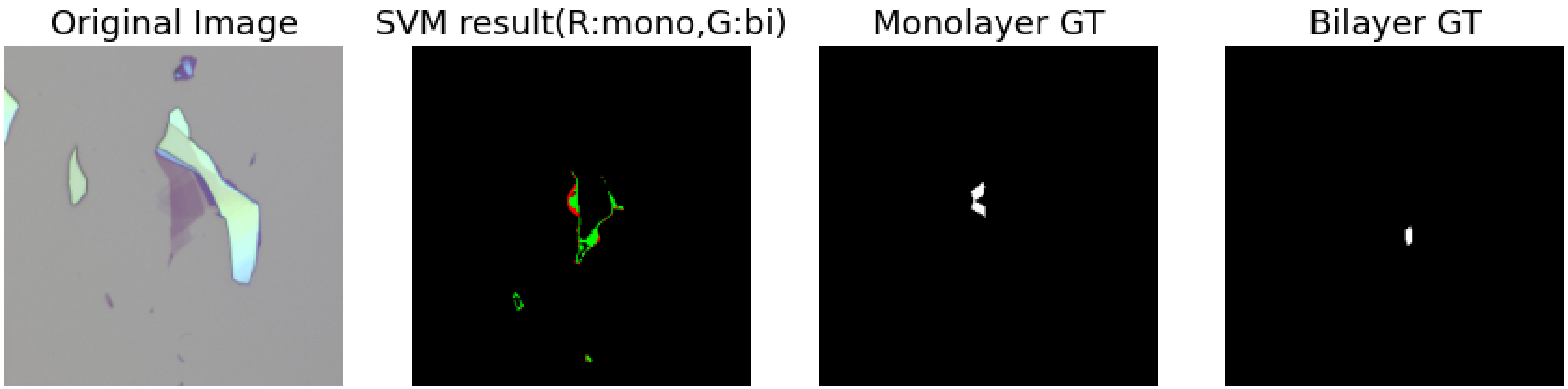


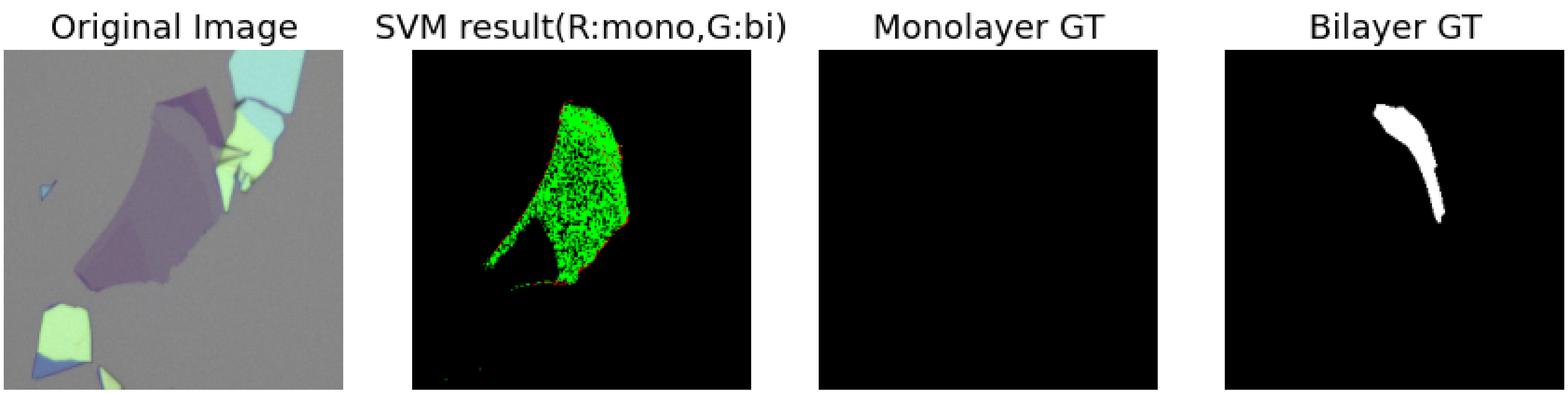
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



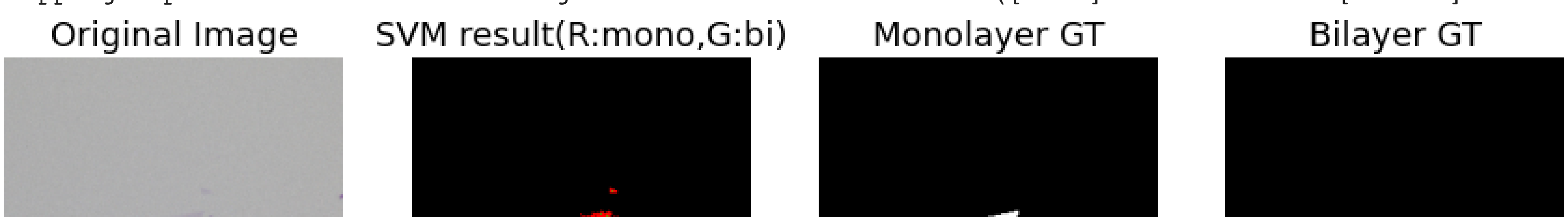
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



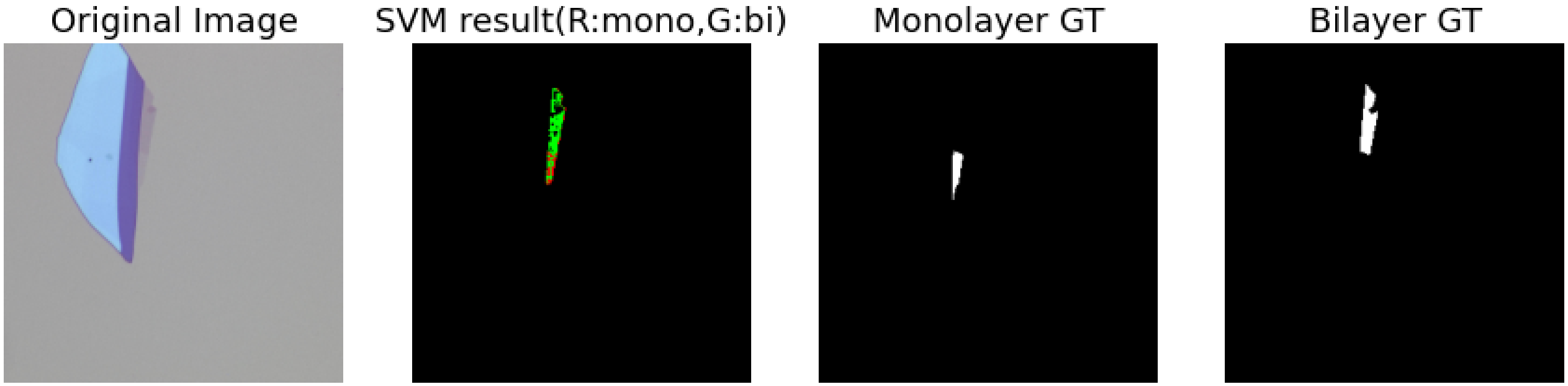
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



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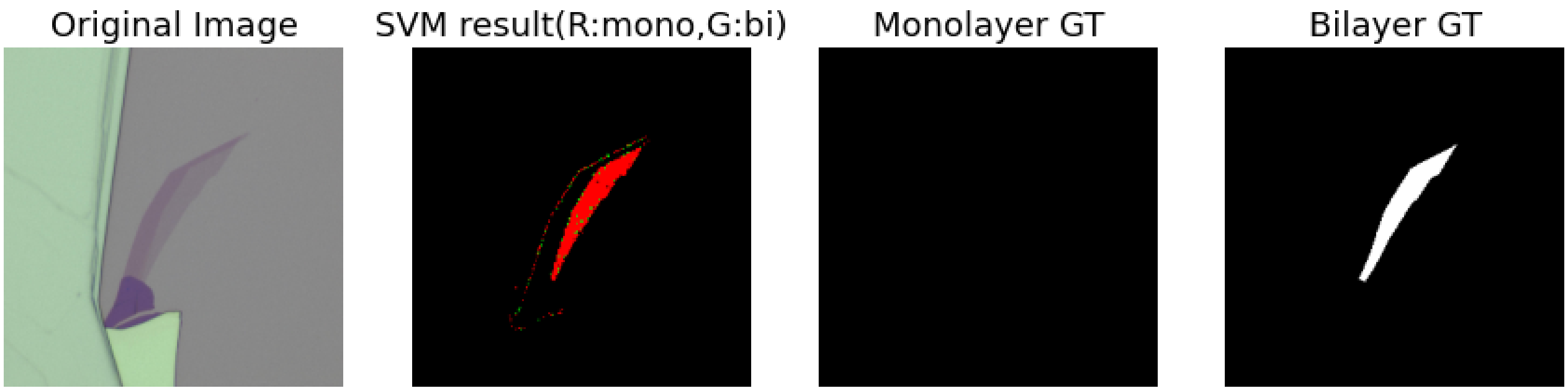

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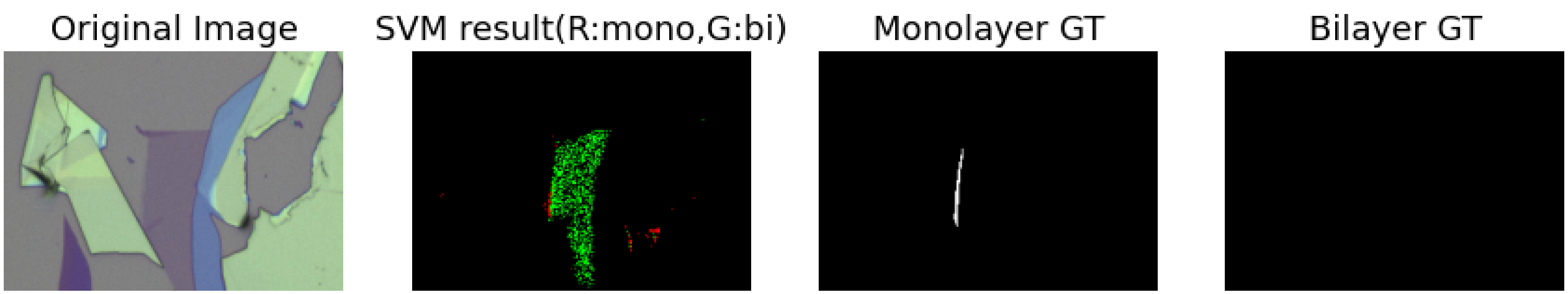

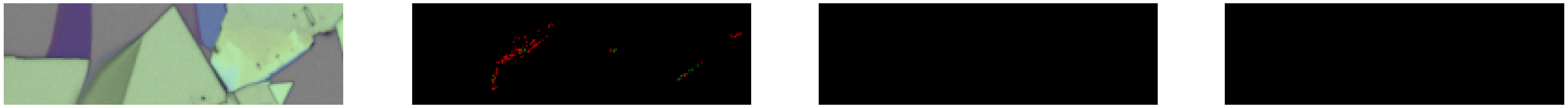

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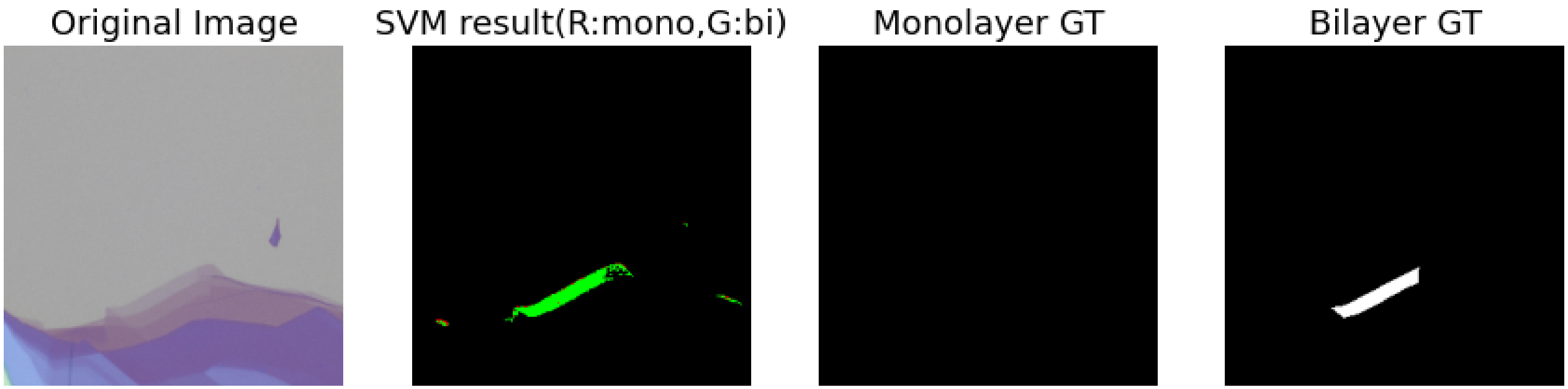

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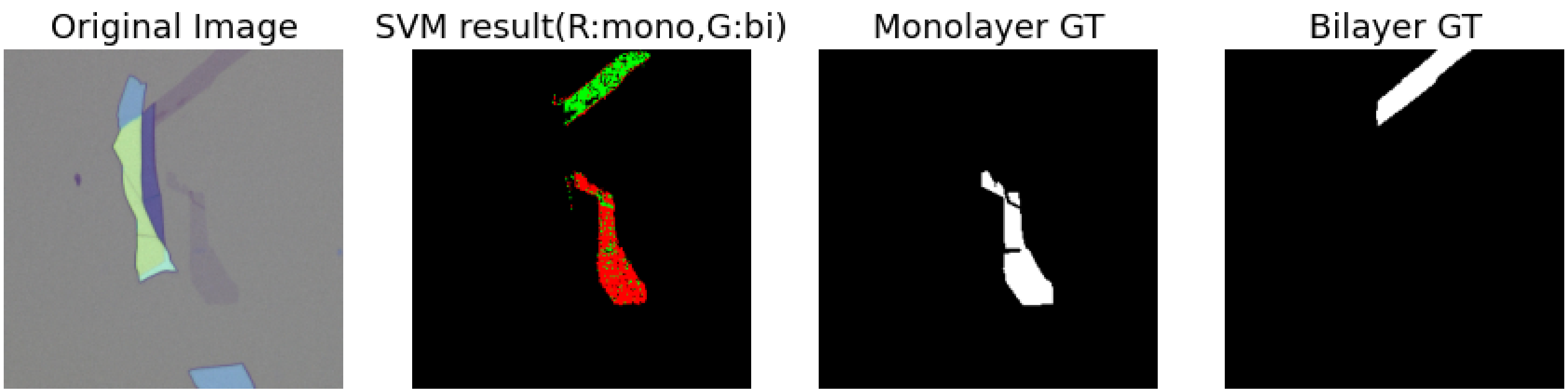

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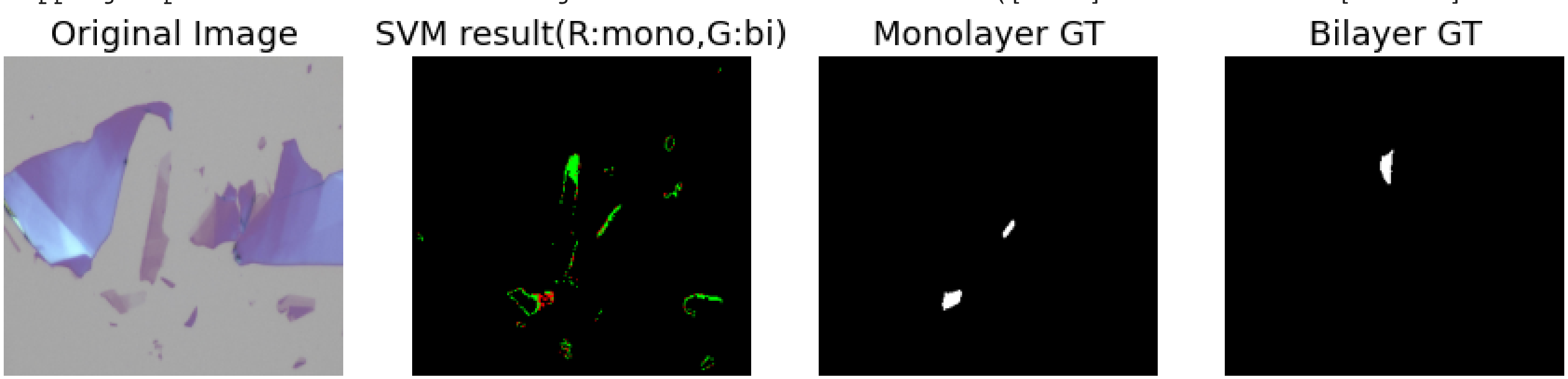

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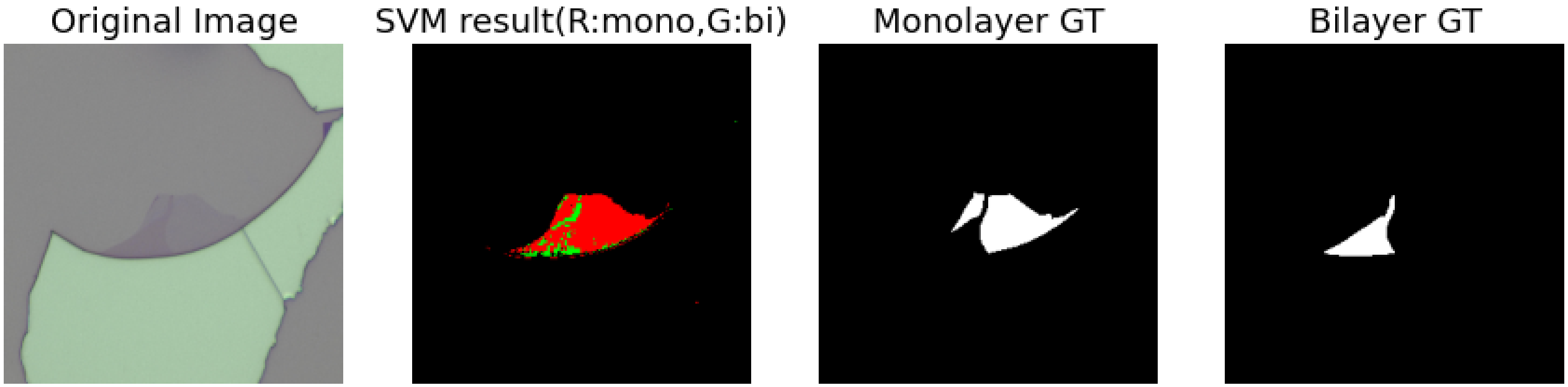

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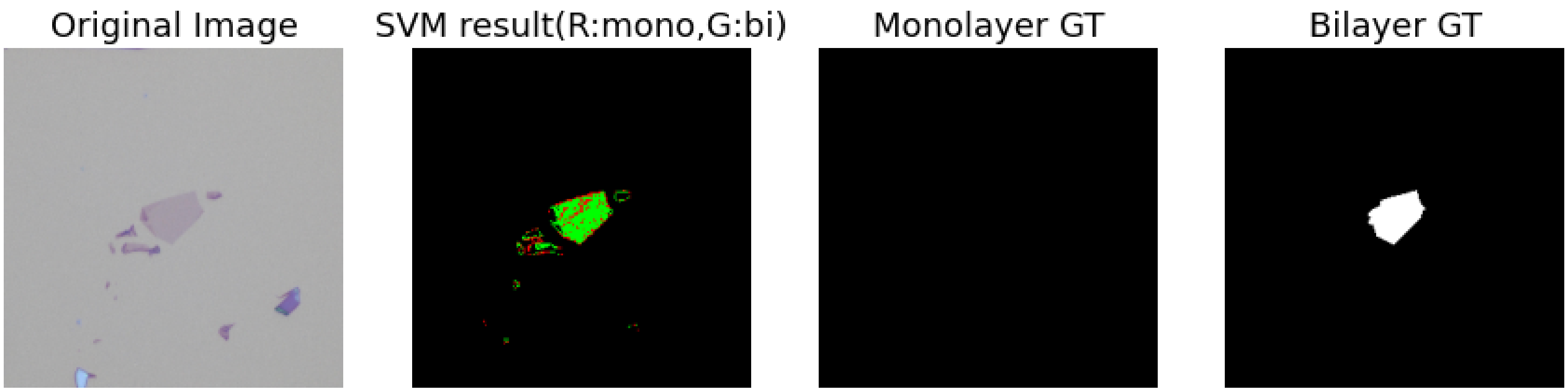

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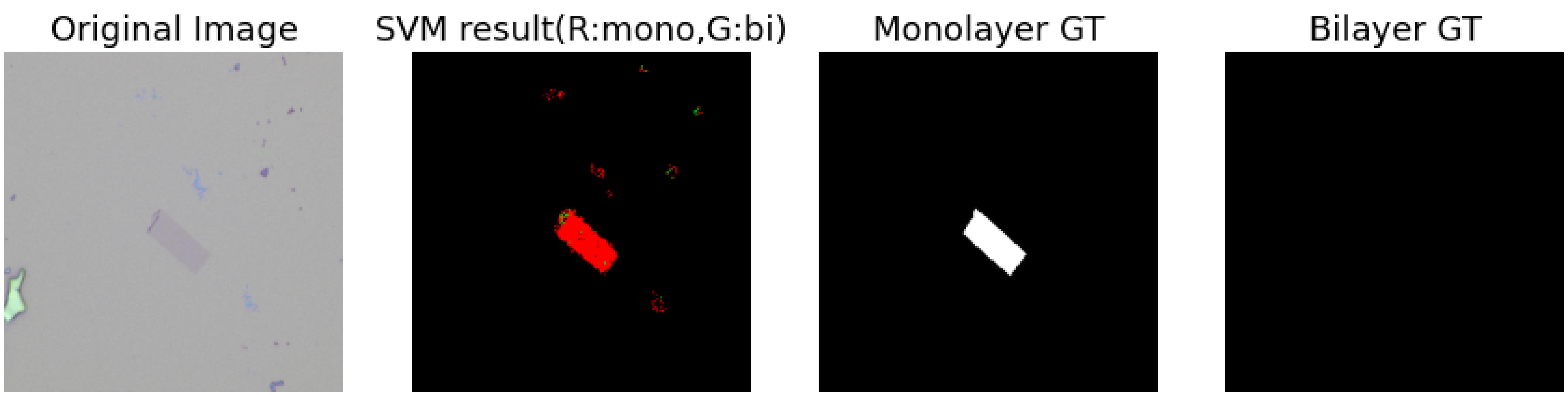

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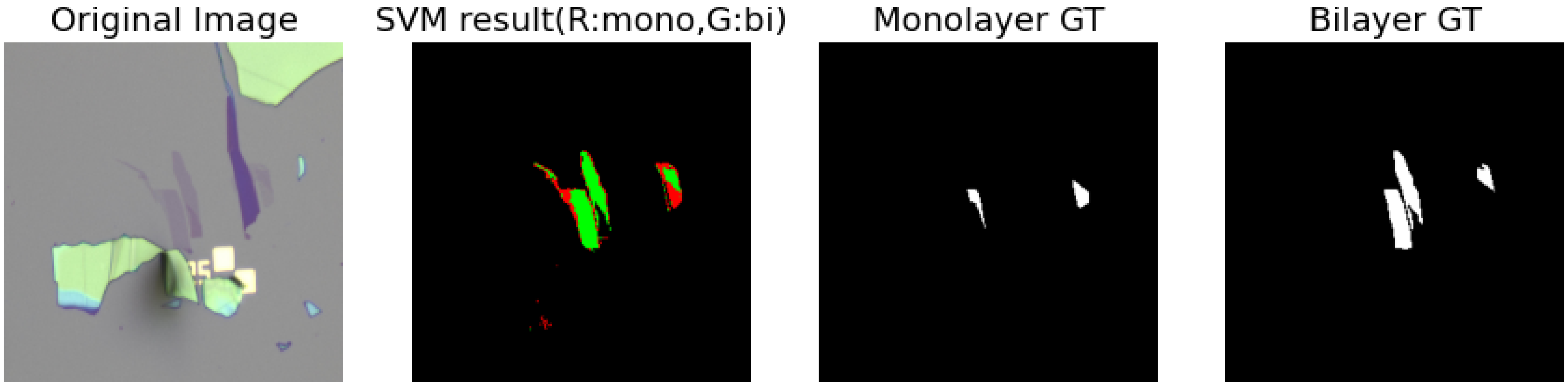


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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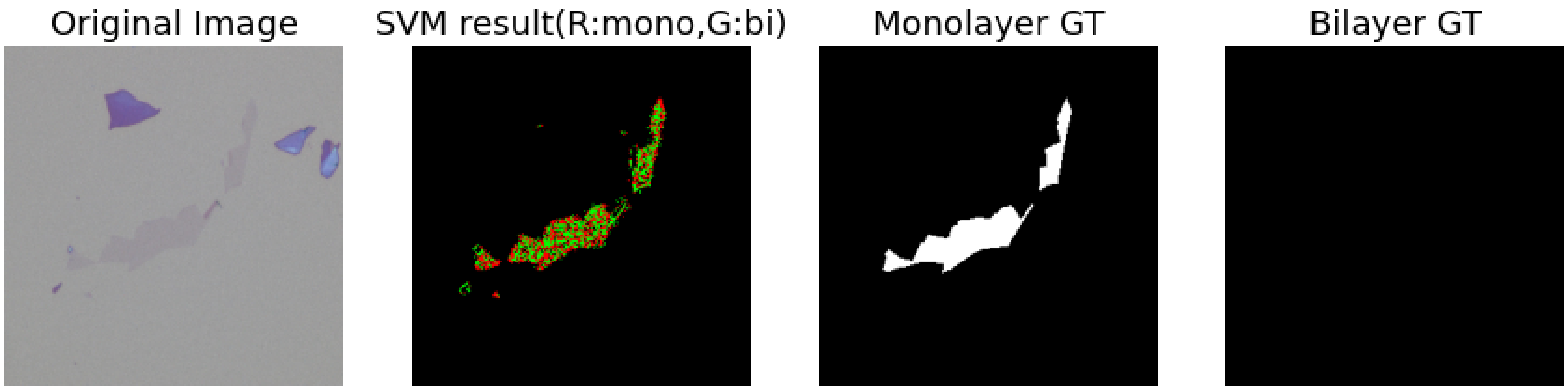


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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
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