# Image Segmentation Using U-Net (CNN)



https://www.tensorflow.org/tutorials/images/segmentation



This tutorial focuses on the task of image segmentation, using a modified U-Net whose paper can be found here: https://arxiv.org/pdf/1505.04597.pdf

The dataset that will be used for this tutorial is the Oxford-IIIT Pet Dataset, created by Parkhi *et al*. The dataset consists of images, their corresponding labels, and pixel-wise masks. The masks are basically labels for each pixel. Each pixel is given one of three categories :

- Class 1 : Pixel belonging to the pet.
- Class 2 : Pixel bordering the pet.
- Class 3 : None of the above/ Surrounding pixel.

```
!pip install git+https://github.com/tensorflow/examples.git
```

```
Collecting git+https://github.com/tensorflow/examples.git
  Cloning https://github.com/tensorflow/examples.git to /tmp/pip-req-build-jnr
  Running command git clone -q https://github.com/tensorflow/examples.git /tmp
Requirement already satisfied: absl-py in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (
Building wheels for collected packages: tensorflow-examples
  Building wheel for tensorflow-examples (setup.py) ... done
  Created wheel for tensorflow-examples: filename=tensorflow_examples-82efa2e0
  Stored in directory: /tmp/pip-ephem-wheel-cache-se57_tl0/wheels/83/64/b3/4c
Successfully built tensorflow-examples
Installing collected packages: tensorflow-examples
Successfully installed tensorflow-examples-82efa2e04c8bd356708af818ea922e215bb
```

```
import tensorflow as tf
```

```
from tensorflow_examples.models.pix2pix import pix2pix

import tensorflow_datasets as tfds

from IPython.display import clear_output
import matplotlib.pyplot as plt
```

## Download the Oxford-IIIT Pets dataset

The dataset is already included in TensorFlow datasets, all that is needed to do is download it. The segmentation masks are included in version 3+.

```
dataset, info = tfds.load('oxford_iiit_pet:3.*.*', with_info=True)
```

The following code performs a simple augmentation of flipping an image. In addition, image is normalized to [0,1]. Finally, as mentioned above the pixels in the segmentation mask are labeled either {1, 2, 3}. For the sake of convenience, let's subtract 1 from the segmentation mask, resulting in labels that are : {0, 1, 2}.

```
def normalize(input_image, input_mask):
  input_image = tf.cast(input_image, tf.float32) / 255.0
  input_mask -= 1
  return input_image, input_mask


@tf.function
def load_image_train(datapoint):
  input_image = tf.image.resize(datapoint['image'], (128, 128))
  input_mask = tf.image.resize(datapoint['segmentation_mask'], (128, 128))

  if tf.random.uniform(()) > 0.5:
    input_image = tf.image.flip_left_right(input_image)
    input_mask = tf.image.flip_left_right(input_mask)

  input_image, input_mask = normalize(input_image, input_mask)

  return input_image, input_mask
```

```
def load_image_test(datapoint):
  input_image = tf.image.resize(datapoint['image'], (128, 128))
  input_mask = tf.image.resize(datapoint['segmentation_mask'], (128, 128))

  input_image, input_mask = normalize(input_image, input_mask)

  return input_image, input_mask
```

The dataset already contains the required splits of test and train and so let's continue to use the same split.

```
TRAIN_LENGTH = info.splits['train'].num_examples
BATCH_SIZE = 64
BUFFER_SIZE = 1000
STEPS_PER_EPOCH = TRAIN_LENGTH // BATCH_SIZE
```

```
train = dataset['train'].map(load_image_train, num_parallel_calls=tf.data.AUTOTUNE)
test = dataset['test'].map(load_image_test)
```

```
train_dataset = train.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()
train_dataset = train_dataset.prefetch(buffer_size=tf.data.AUTOTUNE)
test_dataset = test.batch(BATCH_SIZE)
```

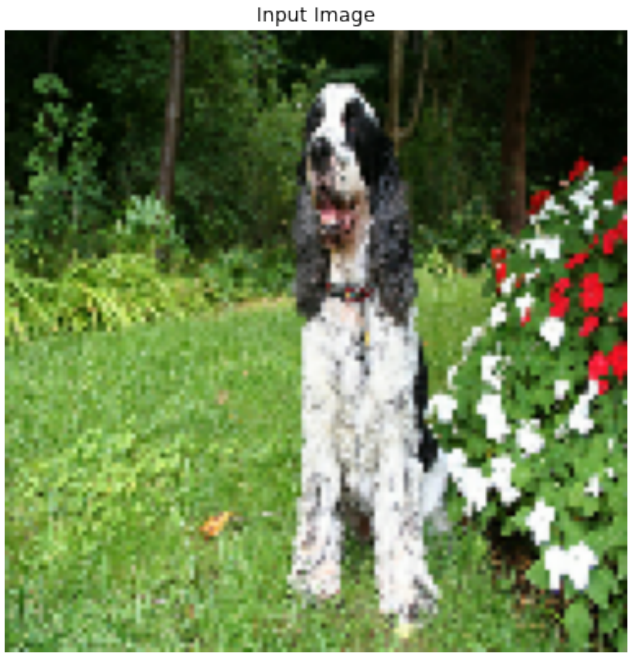
Let's take a look at an image example and it's correponding mask from the dataset.

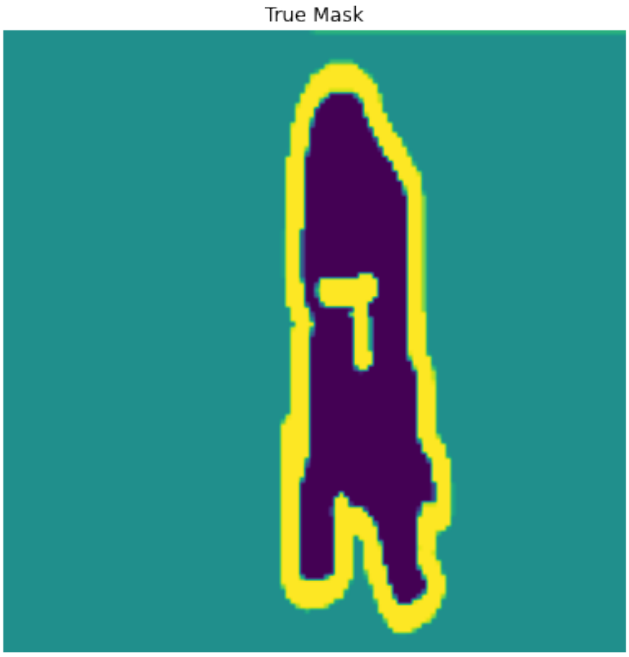
```
def display(display_list):
  plt.figure(figsize=(15, 15))

  title = ['Input Image', 'True Mask', 'Predicted Mask']

  for i in range(len(display_list)):
    plt.subplot(1, len(display_list), i+1)
    plt.title(title[i])
    plt.imshow(tf.keras.preprocessing.image.array_to_img(display_list[i]))
    plt.axis('off')
  plt.show()
```

```
for image, mask in train.take(2):
  sample_image, sample_mask = image, mask
display([sample_image, sample_mask])
```




## Define the model

The model being used here is a modified U-Net. A U-Net consists of an encoder (downsampler) and decoder (upsampler). In-order to learn robust features, and reduce the number of trainable parameters, a pretrained model can be used as the encoder. Thus, the encoder for this task will be a pretrained MobileNetV2 model, whose intermediate outputs will be used, and the decoder will be the upsample block already implemented in TensorFlow Examples in the Pix2pix tutorial.

The reason to output three channels is because there are three possible labels for each pixel. Think of this as multi-classification where each pixel is being classified into three classes.

```
OUTPUT_CHANNELS = 3
```

As mentioned, the encoder will be a pretrained MobileNetV2 model which is prepared and ready to use in [tf.keras.applications](). The encoder consists of specific outputs from intermediate layers in the model. Note that the encoder will not be trained during the training process.

```
base_model = tf.keras.applications.MobileNetV2(input_shape=[128, 128, 3], include_t

# Use the activations of these layers
layer_names = [
    'block_1_expand_relu',   # 64x64
    'block_3_expand_relu',   # 32x32
    'block_6_expand_relu',   # 16x16
    'block_13_expand_relu',  # 8x8
    'block_16_project',      # 4x4
]
base_model_outputs = [base_model.get_layer(name).output for name in layer_names]

# Create the feature extraction model
down_stack = tf.keras.Model(inputs=base_model.input, outputs=base_model_outputs)

down_stack.trainable = False
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicat
9412608/9406464 [==============================] - 0s 0us/step
```

The decoder/upsampler is simply a series of upsample blocks implemented in TensorFlow examples: https://www.tensorflow.org/tutorials/generative/pix2pix

```
up_stack = [
    pix2pix.upsample(512, 3),  # 4x4 -> 8x8
    pix2pix.upsample(256, 3),  # 8x8 -> 16x16
    pix2pix.upsample(128, 3),  # 16x16 -> 32x32
    pix2pix.upsample(64, 3),   # 32x32 -> 64x64
]
```

```
def unet_model(output_channels):
  inputs = tf.keras.layers.Input(shape=[128, 128, 3])

  # Downsampling through the model
  skips = down_stack(inputs)
  x = skips[-1]
  skips = reversed(skips[:-1])

  # Upsampling and establishing the skip connections
  for up, skip in zip(up_stack, skips):
    x = up(x)
    concat = tf.keras.layers.Concatenate()
    x = concat([x, skip])

  # This is the last layer of the model
  last = tf.keras.layers.Conv2DTranspose(
      output_channels, 3, strides=2,
      padding='same')  #64x64 -> 128x128

  x = last(x)

  return tf.keras.Model(inputs=inputs, outputs=x)
```

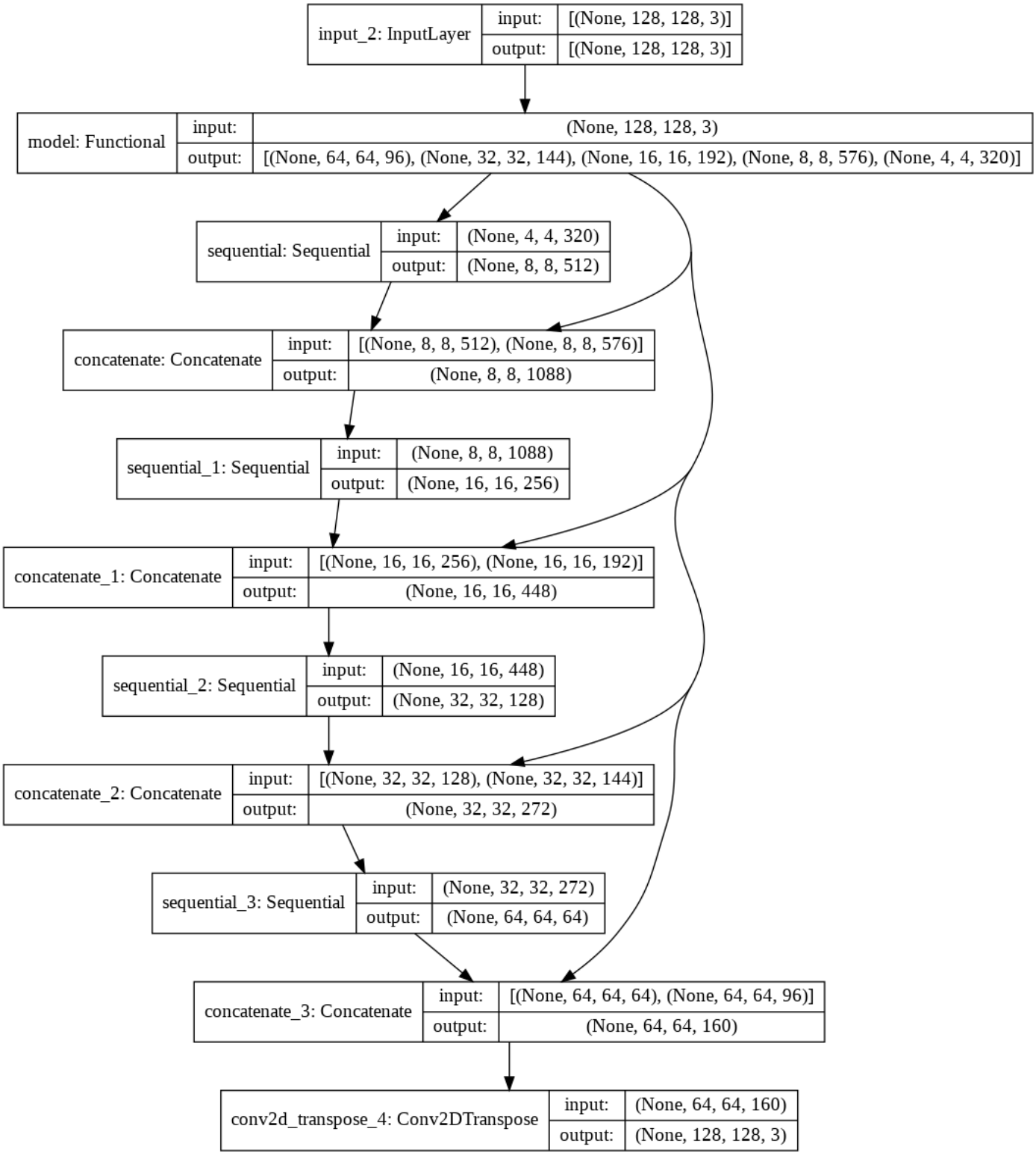
## Train the model

Now, all that is left to do is to compile and train the model. The loss being used here is `losses.SparseCategoricalCrossentropy(from_logits=True)`. The reason to use this loss function is because the network is trying to assign each pixel a label, just like multi-class prediction. In the true segmentation mask, each pixel has either a {0,1,2}. The network here is outputting three channels. Essentially, each channel is trying to learn to predict a class, and `losses.SparseCategoricalCrossentropy(from_logits=True)` is the recommended loss for such a scenario. Using the output of the network, the label assigned to the pixel is the channel with the highest value. This is what the create_mask function is doing.

```
model = unet_model(OUTPUT_CHANNELS)
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Have a quick look at the resulting model architecture:

```
tf.keras.utils.plot_model(model, show_shapes=True)
```

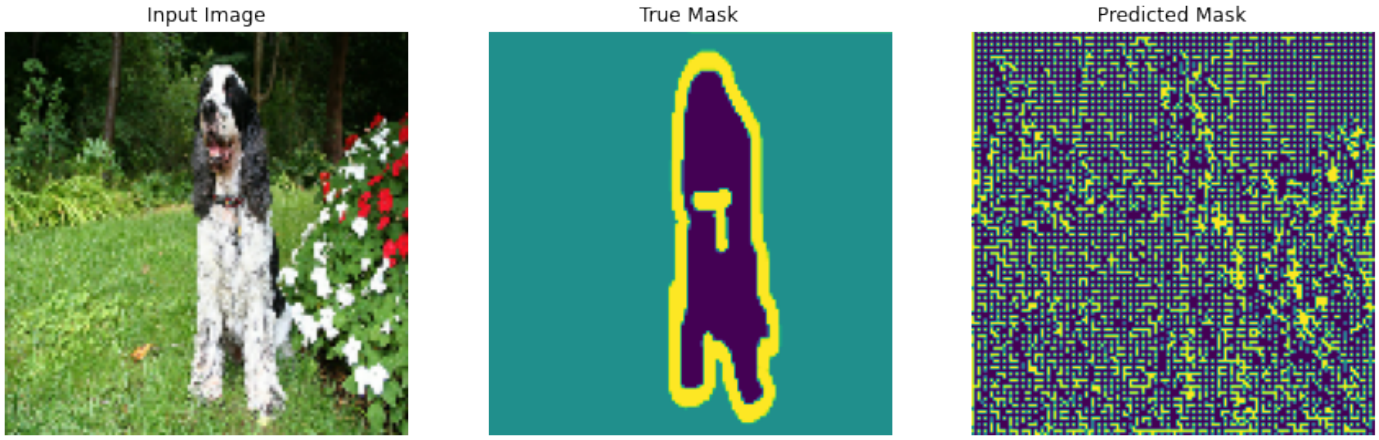


Let's try out the model to see what it predicts before training.

```
def create_mask(pred_mask):
  pred_mask = tf.argmax(pred_mask, axis=-1)
  pred_mask = pred_mask[..., tf.newaxis]
  return pred_mask[0]


def show_predictions(dataset=None, num=2):
  if dataset:
    for image, mask in dataset.take(num):
      pred_mask = model.predict(image)
      display([image[0], mask[0], create_mask(pred_mask)])
  else:
    display([sample_image, sample_mask,
             create_mask(model.predict(sample_image[tf.newaxis, ...]))])
```

```
show_predictions()
```

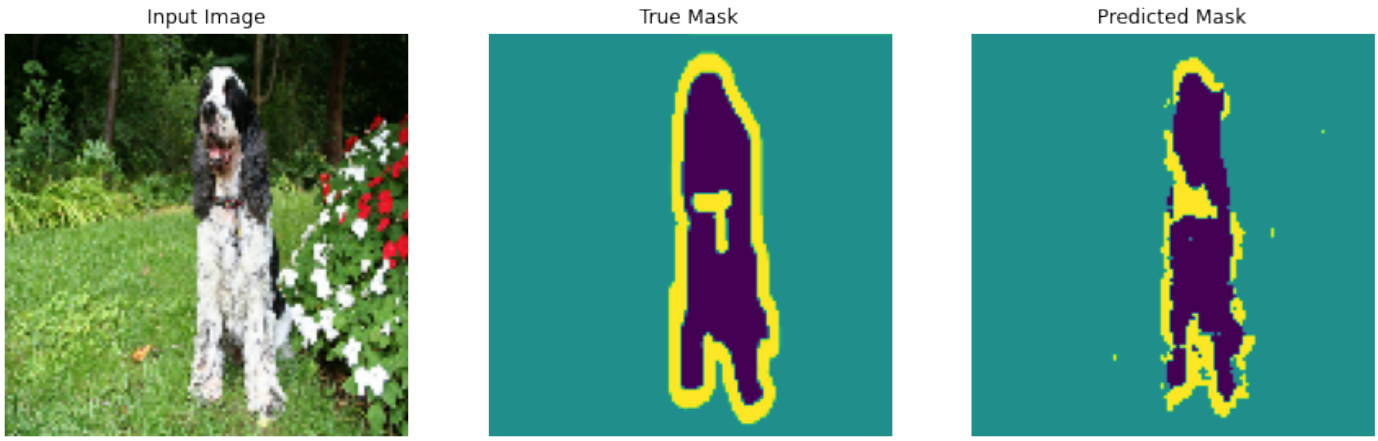



Let's observe how the model improves while it is training. To accomplish this task, a callback function is defined below.

```
class DisplayCallback(tf.keras.callbacks.Callback):
  def on_epoch_end(self, epoch, logs=None):
    clear_output(wait=True)
    show_predictions()
    print ('\nSample Prediction after epoch {}\n'.format(epoch+1))
```

```
EPOCHS = 20
VAL_SUBSPLITS = 5
VALIDATION_STEPS = info.splits['test'].num_examples//BATCH_SIZE//VAL_SUBSPLITS

model_history = model.fit(train_dataset, epochs=EPOCHS,
                          steps_per_epoch=STEPS_PER_EPOCH,
                          validation_steps=VALIDATION_STEPS,
                          validation_data=test_dataset,
                          callbacks=[DisplayCallback()])
```

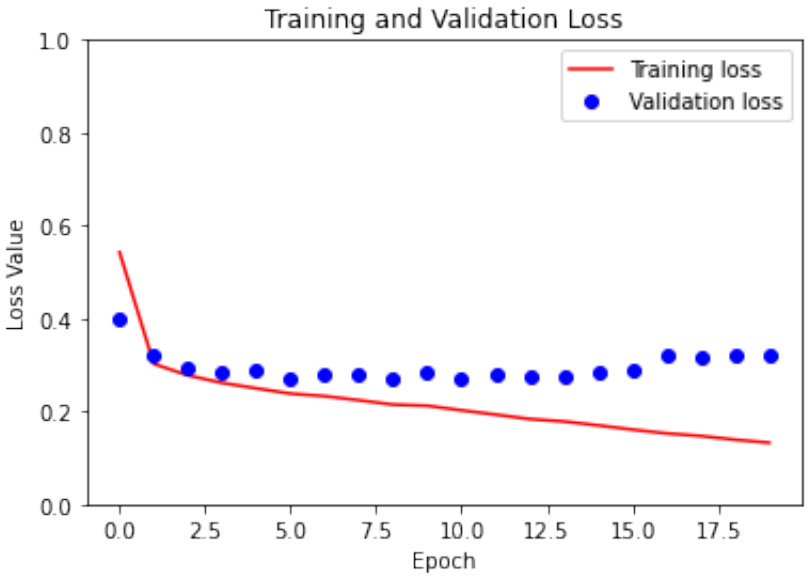



Sample Prediction after epoch 20

```
loss = model_history.history['loss']
val_loss = model_history.history['val_loss']

epochs = range(EPOCHS)

plt.figure()
plt.plot(epochs, loss, 'r', label='Training loss')
plt.plot(epochs, val_loss, 'bo', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss Value')
plt.ylim([0, 1])
plt.legend()
plt.show()
```




## Make predictions

Let's make some predictions. In the interest of saving time, the number of epochs was kept small, but you may set this higher to achieve more accurate results.

```
show_predictions(test_dataset, 3)
```


Input Image
True Mask
Predicted Mask
Input Image
True Mask
Predicted Mask
Input Image
True Mask
Predicted Mask