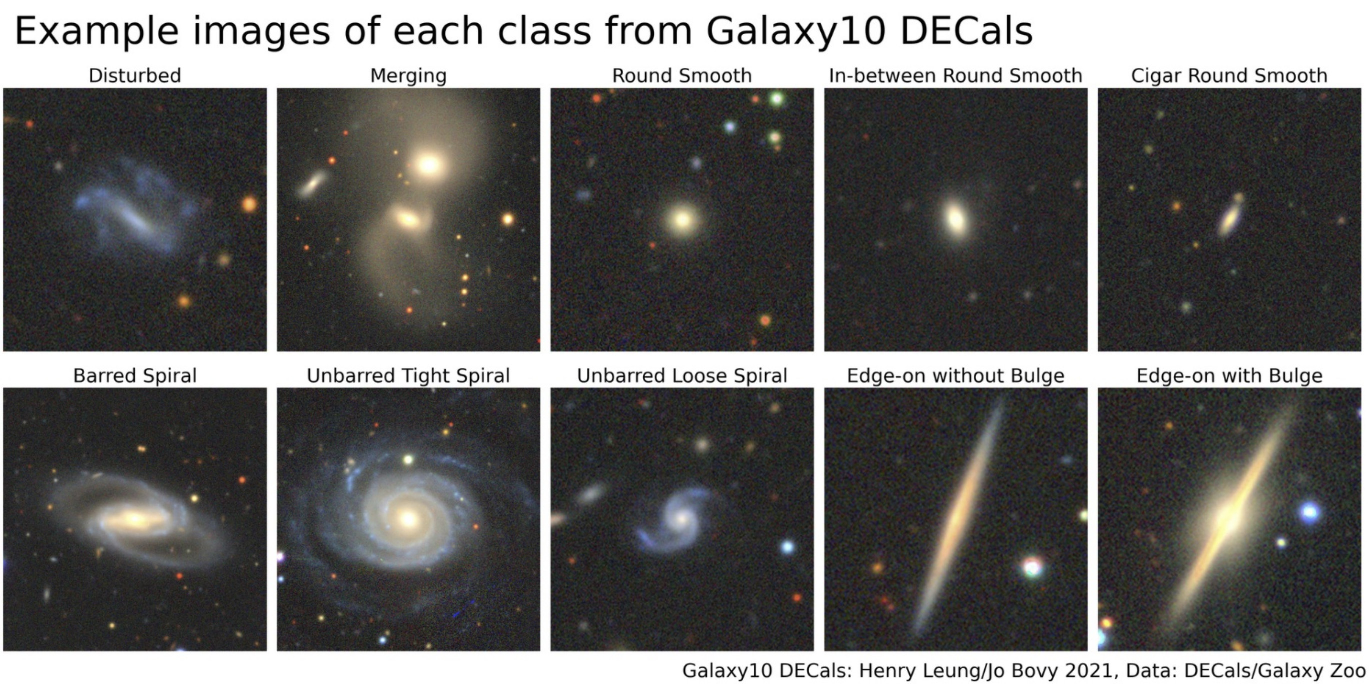
Galaxy Classification Using Convolutional Neural Network

Our night sky is filled with billions of galaxies, each with billions of stars. With new technoly we are able to make telescopes that can probe even the farthest of the galaxies that were born just after the big bang. But analysing all the night sky is very difficult so we have to pick out targets wisely. I propose a pipeline where the telescope data can be fed in and it will automatically classify the object based on their morphology or spectrum or anything that can be useful for the scientists. So here i have created the most crutial step of the pipeline, the classifier.

The original Galaxy10 dataset was created with Galaxy Zoo (GZ) Data Release 2 where volunteers classify ~270k of SDSS galaxy images where ~22k of those images were selected in 10 broad classes using volunteer votes. GZ later utilized images from DESI Legacy Imaging Surveys (DECals) with much better resolution and image quality. Galaxy10 DECals has combined all three (GZ DR2 with DECals images instead of SDSS images and DECals campaign ab, c) results in ~441k of unique galaxies covered by DECals where ~18k of those images were selected in 10 broad classes using volunteer votes with more rigorous filtering. Galaxy10 DECals had its 10 broad classes tweaked a bit so that each class is more distinct from each other and Edge-on Disk with Boxy Bulge class with only 17 images in original Galaxy10 was abandoned. The source code for this dataset is released under this repositary so you are welcome to play around if you like, otherwise you can use the compiled Galaxy10 DECals with dowload link below.

Galaxy10_DECals.h5: https://astro.utoronto.ca/~hleung/shared/Galaxy10/Galaxy10_DECals.h5

Galaxy10 DECals is a dataset contains 17736 256x256 pixels colored galaxy images (g, r and z band) separated in 10 classes. Galaxy10_DECals.h5 have columns images with shape (17736, 256, 256, 3), ans, ra, dec, redshift and pxscale in unit of arcsecond per pixel



Importing required library

In [2]:

```
!pip install h5py
```

```
Requirement already satisfied: h5py in c:\users\user\anaconda3\lib\site-packages (3.2.1)
Requirement already satisfied: numpy>=1.19.0 in c:\users\user\anaconda3\lib\site-packages
(from h5py) (1.20.3)
```

In [4]:

```python
import h5py
import numpy as np
from tensorflow.keras import utils
```

Collecting the Image data

The data is stored in .h5 file format. So here I am using h5py library to open the image data and storing it in a numpy array.

In [41]:

```python
with h5py.File('../Data/Galaxy10_DECals.h5','r') as F:
    images = np.array(F['images'])
    labels = np.array(F['ans'])
```

In [6]:

```python
import PIL
import matplotlib.pyplot as plt
import random
```

Labels

In [7]:

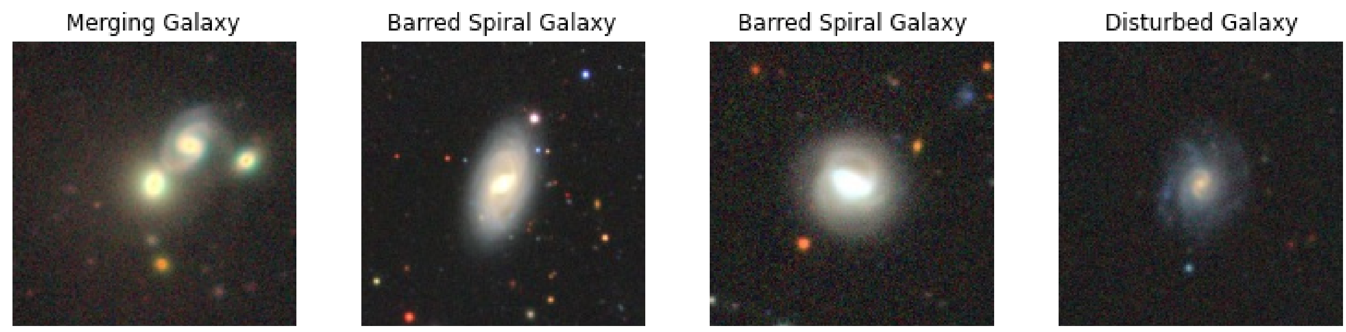
```python
label_names = ['Disturbed Galaxy',
               'Merging Galaxy',
               'Round Smooth Galaxy',
               'In-between Round Smooth Galaxy',
               'Cigar Shaped Smooth Galaxy',
               'Barred Spiral Galaxy',
               'Unbarred Tight Spiral Galaxy',
               'Unbarred Loose Spiral Galaxy',
               'Edge-on Galaxy without Bulge',
               'Edge-on Galaxy with Bulge'
              ]
```

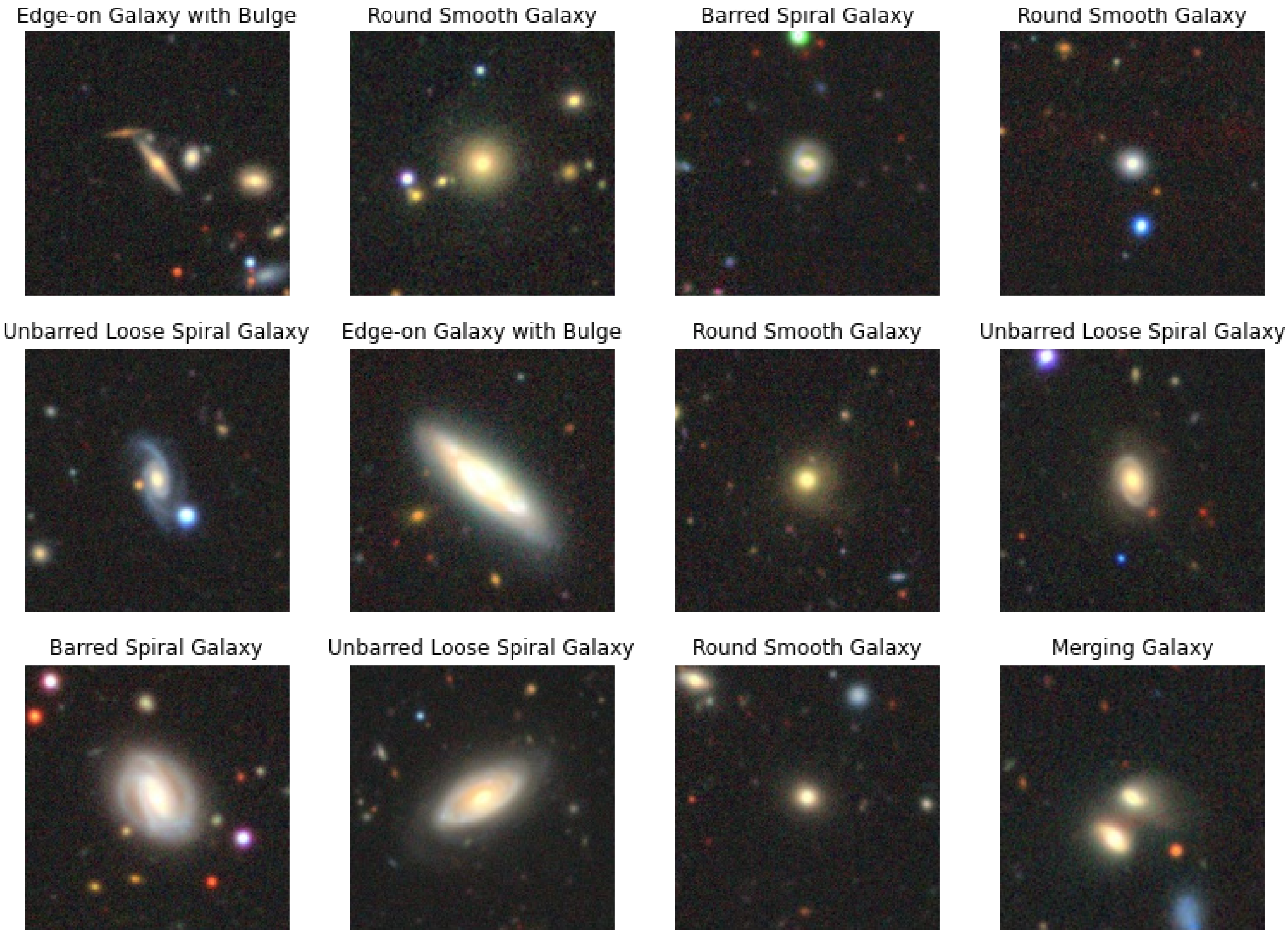
Data Visualization

Here I have selected 16 images randomly from the dataset and they are displayed using `matplotlib.pyplot.imshow`.

In [8]:

```python
plt.figure(figsize=(13,13))
for i in range(16):
    index = random.randint(0,17736)
    image = images[index]
    plt.subplot(4,4,i + 1)
    plt.imshow(image)
    plt.title(label_names[labels[index]])
    plt.axis('off')
```





In [9]:

```
labels.shape
```

Out[9]:

```
(17736,)
```

Spliting the data Into Test and Traning set

Here I have used sci-kit learn library to split the numpy data into training and testing set. The ratio of training and testing set is 5:1.

In [10]:

```
from sklearn.model_selection import train_test_split
```

In [11]:

```
train_idx, test_idx = train_test_split(np.arange(labels.shape[0]), test_size = 0.2)
```

In [12]:

```
train_images, train_labels, test_images, test_labels = images[train_idx], labels[train_i
dx], images[test_idx], labels[test_idx]
```

In [13]:

```
print(train_images.shape[0], test_images.shape[0])
```

```
14188 3548
```

In [14]:

```
images.shape
```

Out[14]:

Out[14]:

```
(17736, 256, 256, 3)
```

Preparing the dataset

In [42]:

```
import tensorflow as tf

img_height = 256
img_width = 256
```

In [18]:

```
class_names = label_names
```

In [19]:

```
train_dataset = tf.data.Dataset.from_tensor_slices((train_images, train_labels))
test_dataset = tf.data.Dataset.from_tensor_slices((test_images, test_labels))
```

In [20]:

```
BATCH_SIZE = 50
SHUFFLE_BUFFER_SIZE = 1000
```

In [21]:

```
train_dataset = train_dataset.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)
test_dataset = test_dataset.batch(BATCH_SIZE)
```

In [22]:

```
EPOCHS = 5
```

Standardise the data

The RGB channel values are in the `[0, 255]` range. This is not ideal for a neural network; in general we should seek to make your input values small.

Here, I have standardize values to be in the `[0, 1]` range by using `tf.keras.layers.Rescaling`:

In [23]:

```
AUTOTUNE = tf.data.AUTOTUNE

train_dataset = train_dataset.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.cache().prefetch(buffer_size=AUTOTUNE)
```

In [24]:

```
from tensorflow.keras import layers
normalization_layer = layers.Rescaling(1./255)
```

In [25]:

```
normalized_dataset = train_dataset.map(lambda x,y: (normalization_layer(x),y))
images_batch, labels_batch = next(iter(normalized_dataset))
```

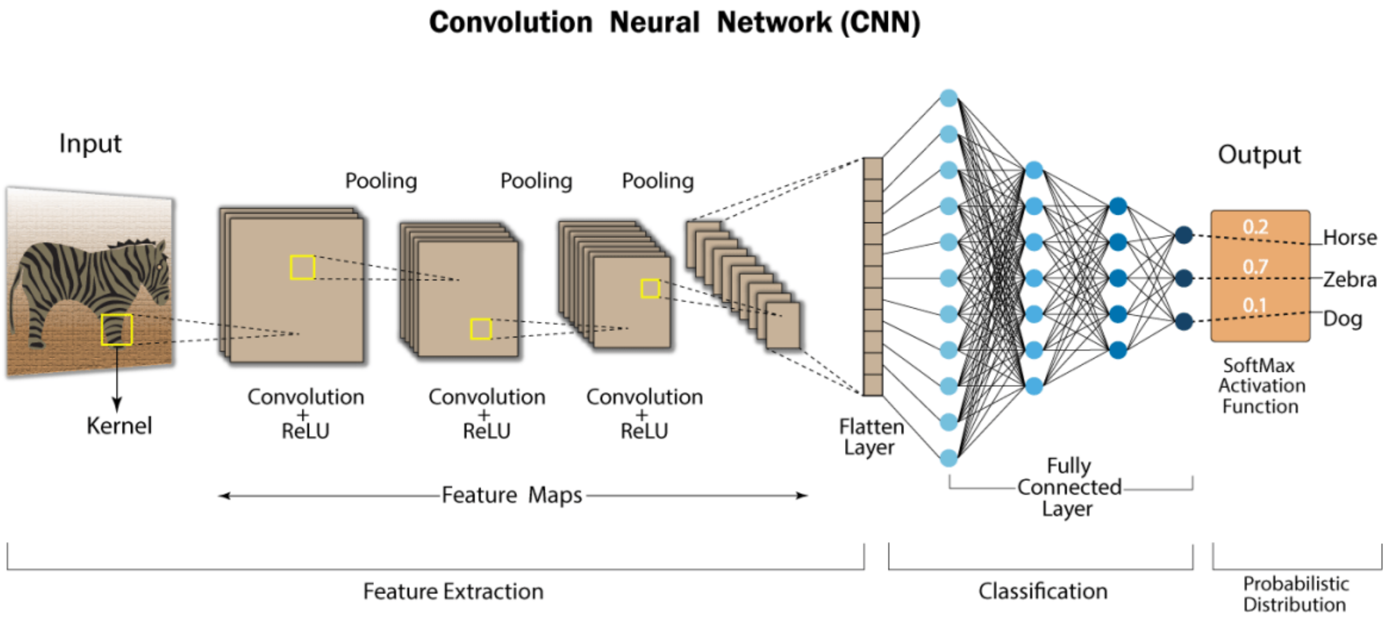
In [26]:

```
num_classes = len(class_names)
```

Creating the model

The Sequential model consists of three convolution blocks (`tf.keras.layers.Conv2D`) with a max pooling layer (`tf.keras.layers.MaxPooling2D`) in each of them. There's a fully-connected layer (`tf.keras.layers.Dense`) with 128 units on top of it that is activated by a ReLU activation function (`'relu'`). This model has not been tuned for high accuracy—the goal of this tutorial is to show a standard approach.

Below is an image to understand how neural network works, but instead of classifying animals we are classifying galaxies.



In [28]:

```
from tensorflow.keras.models import Sequential
model = Sequential([
    layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
    layers.Conv2D(16, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(32, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(64, 3, padding='same', activation='relu'),
    #layers.MaxPooling2D(),
    #layers.Conv2D(128, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(num_classes)
])
```

In [25]:

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

Summary of the model

Here you can se all the hidden layers and their shapes, and total numbers of parameters after each layers is also shown.

In [26]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_1 (Rescaling)     (None, 256, 256, 3)       0
```

```
 conv2d (Conv2D)             (None, 256, 256, 16)      448

 max_pooling2d (MaxPooling2D  (None, 128, 128, 16)     0
 )

 conv2d_1 (Conv2D)           (None, 128, 128, 32)      4640

 max_pooling2d_1 (MaxPooling  (None, 64, 64, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 64, 64, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 32, 32, 64)       0
 2D)

 flatten (Flatten)           (None, 65536)             0

 dense (Dense)               (None, 128)               8388736

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 8,413,610
Trainable params: 8,413,610
Non-trainable params: 0
_________________________________________________________________
```

Training the model

I haved trained the model for 5 epochs to see how the model behaves.

In [27]:

```
EPOCHS = 5
history = model.fit(
    train_dataset,
    validation_data = test_dataset,
    epochs = EPOCHS
)
```

```
Epoch 1/5
284/284 [==============================] - 20s 49ms/step - loss: 2.0042 - accuracy: 0.244
7 - val_loss: 1.7909 - val_accuracy: 0.3174
Epoch 2/5
284/284 [==============================] - 13s 44ms/step - loss: 1.6224 - accuracy: 0.400
7 - val_loss: 1.4915 - val_accuracy: 0.4501
Epoch 3/5
284/284 [==============================] - 13s 44ms/step - loss: 1.2760 - accuracy: 0.538
9 - val_loss: 1.4778 - val_accuracy: 0.4749
Epoch 4/5
284/284 [==============================] - 13s 44ms/step - loss: 1.0344 - accuracy: 0.632
4 - val_loss: 1.3889 - val_accuracy: 0.5172
Epoch 5/5
284/284 [==============================] - 13s 45ms/step - loss: 0.8017 - accuracy: 0.719
8 - val_loss: 1.4810 - val_accuracy: 0.5285
```

Visualising the training results

In [28]:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = range(EPOCHS)
```

```
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Overfitting

In the plots above, the training accuracy is increasing linearly over time, whereas validation accuracy stalls around 60% in the training process. Also, the difference in accuracy between training and validation accuracy is noticeable—a sign of overfitting.

When there are a small number of training examples, the model sometimes learns from noises or unwanted details from training examples—to an extent that it negatively impacts the performance of the model on new examples. This phenomenon is known as overfitting. It means that the model will have a difficult time generalizing on a new dataset.

There are multiple ways to fight overfitting in the training process.

- **Data Augmentation**
- **Dropout layer.**

Testing the results

Here I have used a barred spiral galaxy image and the model is able to pridict it correctly, But not always. We need to improve the model.

In [29]:

```
from tensorflow import keras
from tensorflow.keras import utils
barred_spiral_img = tf.keras.utils.load_img('../Data/new_test_data/barred_spiral_test1.pn
g', target_size = (img_height, img_width))
PIL.Image.open('../Data/new_test_data/barred_spiral_test1.png')
```

Out[29]:

In [30]:

```
img_array = tf.keras.utils.img_to_array(barred_spiral_img)
img_array = tf.expand_dims(img_array, 0)
```

In [31]:

```
prediction = model.predict(img_array)
```

In [32]:

```
score = tf.nn.softmax(prediction[0])
```

In [33]:

```
for i in score: print(i)
```

```
tf.Tensor(0.07197627, shape=(), dtype=float32)
tf.Tensor(0.059918653, shape=(), dtype=float32)
tf.Tensor(0.0040735723, shape=(), dtype=float32)
tf.Tensor(0.0020373825, shape=(), dtype=float32)
tf.Tensor(4.951063e-06, shape=(), dtype=float32)
tf.Tensor(0.77023846, shape=(), dtype=float32)
tf.Tensor(0.0071348613, shape=(), dtype=float32)
```

```
tf.Tensor(0.0071348013, shape=(), dtype=float32)
tf.Tensor(0.08411451, shape=(), dtype=float32)
tf.Tensor(8.2698214e-05, shape=(), dtype=float32)
tf.Tensor(0.00041850048, shape=(), dtype=float32)
```

In [34]:

```
print('This galaxy is most likely to be a ' + str(class_names[np.argmax(score)]) + '.')
```

```
This galaxy is most likely to be a Barred Spiral Galaxy.
```

Data Augmentation

Overfitting generally occurs when there are a small number of training examples. Data augmentation takes the approach of generating additional training data from your existing examples by augmenting them using random transformations that yield believable-looking images. This helps expose the model to more aspects of the data and generalize better.

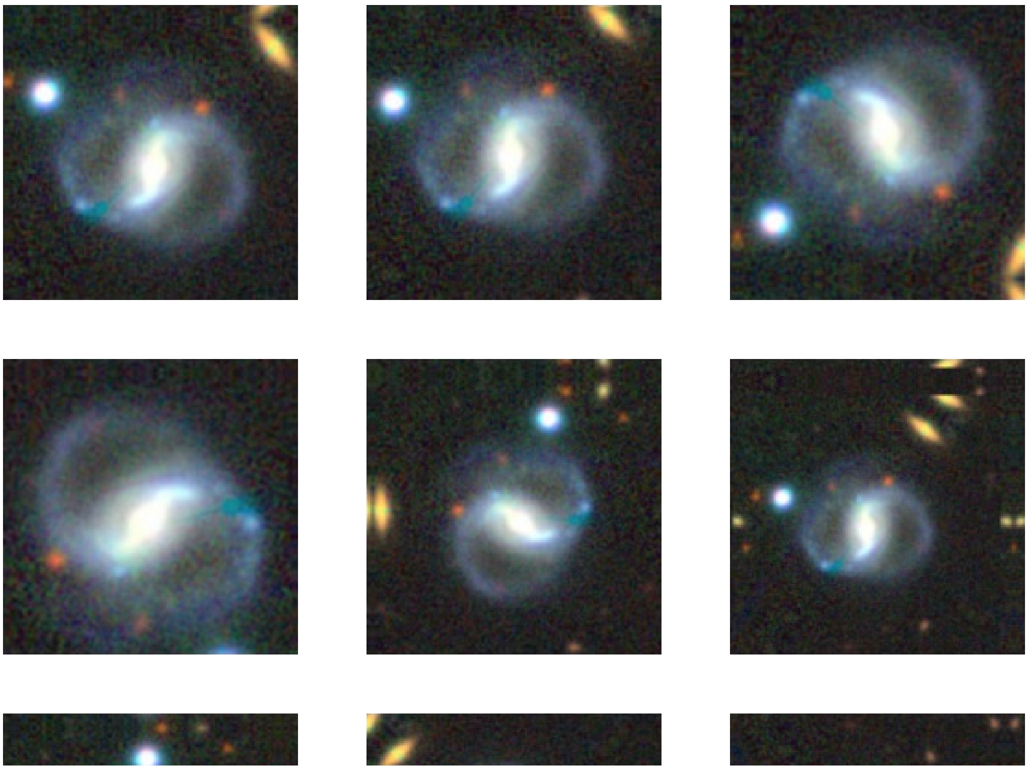
I will implement data augmentation using the following Keras preprocessing layers: `tf.keras.layers.RandomFlip`**,** `tf.keras.layers.RandomRotation`**,** `tf.keras.layers.RandomTranslation`**, and** `tf.keras.layers.RandomZoom`**. These can be included inside your model like other layers, and run on the GPU.**

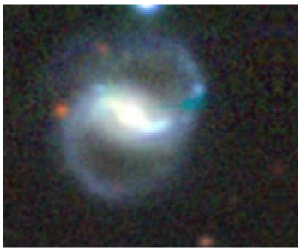
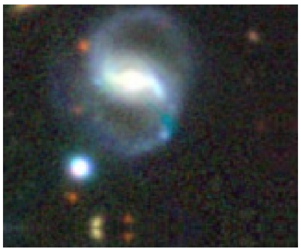
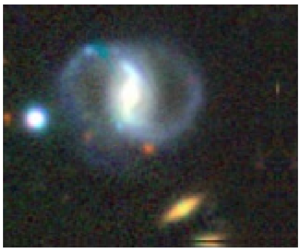
In [29]:

```
zoom_factor = (-0.1,0.5)
data_augmentation = Sequential([
    layers.RandomFlip('horizontal_and_vertical',input_shape=(img_height, img_width, 3)),
    layers.RandomRotation(0.5),
    #layers.RandomZoom(height_factor=zoom_factor, width_factor=zoom_factor),
    layers.RandomZoom((-0.5,0.1),fill_mode='wrap'),
    layers.RandomTranslation(0.08,0.08)#, fill_mode='wrap')
])
```

In [40]:

```
plt.figure(figsize=(10, 10))
for images, _ in train_dataset.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```



Dropout

In [37]:

```
model = Sequential([
    data_augmentation,
    layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
    layers.Conv2D(16, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(32, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(64, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(128, 3, padding='same', activation='relu'),
    layers.MaxPooling2D(),
    layers.Dropout(0.2),
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(num_classes)
])
```

In [38]:

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

In [39]:

```
EPOCHS = 100
```

In [40]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_1 (Sequential)   (None, 256, 256, 3)       0

 rescaling_2 (Rescaling)     (None, 256, 256, 3)       0

 conv2d_3 (Conv2D)           (None, 256, 256, 16)      448

 max_pooling2d_3 (MaxPooling  (None, 128, 128, 16)     0
 2D)

 conv2d_4 (Conv2D)           (None, 128, 128, 32)      4640

 max_pooling2d_4 (MaxPooling  (None, 64, 64, 32)       0
 2D)

 conv2d_5 (Conv2D)           (None, 64, 64, 64)        18496

 max_pooling2d_5 (MaxPooling  (None, 32, 32, 64)       0
 2D)

 conv2d_6 (Conv2D)           (None, 32, 32, 128)       73856
```

```
 conv2d_6 (Conv2D)           (None, 32, 32, 128)       73856

 max_pooling2d_6 (MaxPooling  (None, 16, 16, 128)      0
 2D)

 dropout (Dropout)           (None, 16, 16, 128)       0

 flatten_1 (Flatten)         (None, 32768)             0

 dense_2 (Dense)             (None, 256)               8388864

 flatten_2 (Flatten)         (None, 256)               0

 dense_3 (Dense)             (None, 128)               32896

 dense_4 (Dense)             (None, 10)                1290

=================================================================
Total params: 8,520,490
Trainable params: 8,520,490
Non-trainable params: 0
_________________________________________________________________
```

In [41]:

```
history = model.fit(train_dataset,
                   validation_data= test_dataset,
                   epochs=EPOCHS)
```

```
Epoch 1/100
284/284 [==============================] - 19s 60ms/step - loss: 1.9943 - accuracy: 0.250
5 - val_loss: 1.8324 - val_accuracy: 0.3126
Epoch 2/100
284/284 [==============================] - 16s 57ms/step - loss: 1.6606 - accuracy: 0.377
1 - val_loss: 1.4974 - val_accuracy: 0.4462
Epoch 3/100
284/284 [==============================] - 16s 58ms/step - loss: 1.4607 - accuracy: 0.453
8 - val_loss: 1.4886 - val_accuracy: 0.4346
Epoch 4/100
284/284 [==============================] - 16s 57ms/step - loss: 1.3698 - accuracy: 0.492
2 - val_loss: 1.3908 - val_accuracy: 0.4963
Epoch 5/100
284/284 [==============================] - 16s 58ms/step - loss: 1.2978 - accuracy: 0.524
5 - val_loss: 1.3375 - val_accuracy: 0.5025
Epoch 6/100
284/284 [==============================] - 16s 57ms/step - loss: 1.2314 - accuracy: 0.552
2 - val_loss: 1.1787 - val_accuracy: 0.5753
Epoch 7/100
284/284 [==============================] - 17s 59ms/step - loss: 1.1405 - accuracy: 0.587
0 - val_loss: 1.0567 - val_accuracy: 0.6198
Epoch 8/100
284/284 [==============================] - 17s 59ms/step - loss: 1.0823 - accuracy: 0.612
8 - val_loss: 1.0248 - val_accuracy: 0.6370
Epoch 9/100
284/284 [==============================] - 16s 57ms/step - loss: 1.0062 - accuracy: 0.642
7 - val_loss: 0.9466 - val_accuracy: 0.6719
Epoch 10/100
284/284 [==============================] - 16s 58ms/step - loss: 0.9776 - accuracy: 0.656
3 - val_loss: 0.9351 - val_accuracy: 0.6702
Epoch 11/100
284/284 [==============================] - 16s 58ms/step - loss: 0.9364 - accuracy: 0.671
1 - val_loss: 1.0565 - val_accuracy: 0.6234
Epoch 12/100
284/284 [==============================] - 16s 57ms/step - loss: 0.9026 - accuracy: 0.684
1 - val_loss: 0.9389 - val_accuracy: 0.6719
Epoch 13/100
284/284 [==============================] - 16s 58ms/step - loss: 0.8915 - accuracy: 0.685
5 - val_loss: 0.8972 - val_accuracy: 0.6843
Epoch 14/100
284/284 [==============================] - 16s 58ms/step - loss: 0.8698 - accuracy: 0.695
8 - val_loss: 0.8073 - val_accuracy: 0.7145
Epoch 15/100
```

```
284/284 [==============================] - 16s 57ms/step - loss: 0.8608 - accuracy: 0.699
0 - val_loss: 0.8737 - val_accuracy: 0.6908
Epoch 16/100
284/284 [==============================] - 16s 58ms/step - loss: 0.8342 - accuracy: 0.710
8 - val_loss: 0.7918 - val_accuracy: 0.7252
Epoch 17/100
284/284 [==============================] - 16s 58ms/step - loss: 0.8382 - accuracy: 0.708
4 - val_loss: 0.8312 - val_accuracy: 0.7134
Epoch 18/100
284/284 [==============================] - 16s 57ms/step - loss: 0.8208 - accuracy: 0.712
5 - val_loss: 0.8034 - val_accuracy: 0.7103
Epoch 19/100
284/284 [==============================] - 16s 58ms/step - loss: 0.8000 - accuracy: 0.719
8 - val_loss: 0.7638 - val_accuracy: 0.7283
Epoch 20/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7873 - accuracy: 0.723
6 - val_loss: 0.7911 - val_accuracy: 0.7275
Epoch 21/100
284/284 [==============================] - 16s 58ms/step - loss: 0.7922 - accuracy: 0.723
6 - val_loss: 0.8206 - val_accuracy: 0.7066
Epoch 22/100
284/284 [==============================] - 16s 58ms/step - loss: 0.7693 - accuracy: 0.732
8 - val_loss: 0.7656 - val_accuracy: 0.7325
Epoch 23/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7663 - accuracy: 0.731
1 - val_loss: 0.7168 - val_accuracy: 0.7497
Epoch 24/100
284/284 [==============================] - 16s 58ms/step - loss: 0.7605 - accuracy: 0.732
6 - val_loss: 0.6867 - val_accuracy: 0.7630
Epoch 25/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7606 - accuracy: 0.737
4 - val_loss: 0.7477 - val_accuracy: 0.7410
Epoch 26/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7391 - accuracy: 0.743
1 - val_loss: 0.7636 - val_accuracy: 0.7356
Epoch 27/100
284/284 [==============================] - 16s 58ms/step - loss: 0.7460 - accuracy: 0.738
9 - val_loss: 0.7563 - val_accuracy: 0.7444
Epoch 28/100
284/284 [==============================] - 16s 58ms/step - loss: 0.7384 - accuracy: 0.737
2 - val_loss: 0.7704 - val_accuracy: 0.7418
Epoch 29/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7229 - accuracy: 0.750
2 - val_loss: 0.7855 - val_accuracy: 0.7266
Epoch 30/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7243 - accuracy: 0.750
7 - val_loss: 0.6959 - val_accuracy: 0.7610
Epoch 31/100
284/284 [==============================] - 17s 59ms/step - loss: 0.7193 - accuracy: 0.751
3 - val_loss: 0.7416 - val_accuracy: 0.7362
Epoch 32/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7179 - accuracy: 0.749
6 - val_loss: 0.6834 - val_accuracy: 0.7596
Epoch 33/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7061 - accuracy: 0.754
9 - val_loss: 0.6591 - val_accuracy: 0.7675
Epoch 34/100
284/284 [==============================] - 16s 57ms/step - loss: 0.7047 - accuracy: 0.755
5 - val_loss: 0.6575 - val_accuracy: 0.7765
Epoch 35/100
284/284 [==============================] - 16s 56ms/step - loss: 0.7041 - accuracy: 0.756
1 - val_loss: 0.6487 - val_accuracy: 0.7754
Epoch 36/100
284/284 [==============================] - 16s 57ms/step - loss: 0.6906 - accuracy: 0.755
8 - val_loss: 0.6476 - val_accuracy: 0.7740
Epoch 37/100
284/284 [==============================] - 18s 63ms/step - loss: 0.6845 - accuracy: 0.763
3 - val_loss: 0.7185 - val_accuracy: 0.7466
Epoch 38/100
284/284 [==============================] - 18s 62ms/step - loss: 0.6854 - accuracy: 0.760
0 - val_loss: 0.6829 - val_accuracy: 0.7582
Epoch 39/100
```

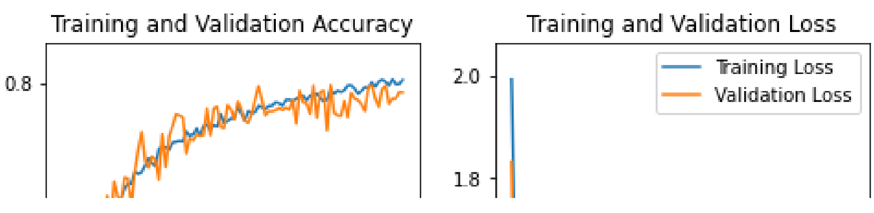
```
284/284 [==============================] - 17s 59ms/step - loss: 0.6828 - accuracy: 0.761
0 - val_loss: 0.6975 - val_accuracy: 0.7565
Epoch 40/100
284/284 [==============================] - 17s 60ms/step - loss: 0.6824 - accuracy: 0.765
6 - val_loss: 0.6842 - val_accuracy: 0.7610
Epoch 41/100
284/284 [==============================] - 17s 61ms/step - loss: 0.6882 - accuracy: 0.759
9 - val_loss: 0.6943 - val_accuracy: 0.7599
Epoch 42/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6627 - accuracy: 0.767
3 - val_loss: 0.6877 - val_accuracy: 0.7604
Epoch 43/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6714 - accuracy: 0.768
5 - val_loss: 0.6208 - val_accuracy: 0.7807
Epoch 44/100
284/284 [==============================] - 17s 59ms/step - loss: 0.6729 - accuracy: 0.764
2 - val_loss: 0.6468 - val_accuracy: 0.7604
Epoch 45/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6615 - accuracy: 0.768
0 - val_loss: 0.6372 - val_accuracy: 0.7807
Epoch 46/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6658 - accuracy: 0.766
8 - val_loss: 0.6231 - val_accuracy: 0.7821
Epoch 47/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6541 - accuracy: 0.776
4 - val_loss: 0.6657 - val_accuracy: 0.7666
Epoch 48/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6495 - accuracy: 0.769
4 - val_loss: 0.6753 - val_accuracy: 0.7658
Epoch 49/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6536 - accuracy: 0.771
2 - val_loss: 0.6315 - val_accuracy: 0.7830
Epoch 50/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6534 - accuracy: 0.773
1 - val_loss: 0.6324 - val_accuracy: 0.7802
Epoch 51/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6466 - accuracy: 0.773
1 - val_loss: 0.6493 - val_accuracy: 0.7725
Epoch 52/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6367 - accuracy: 0.782
1 - val_loss: 0.6161 - val_accuracy: 0.7858
Epoch 53/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6413 - accuracy: 0.777
0 - val_loss: 0.6303 - val_accuracy: 0.7804
Epoch 54/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6445 - accuracy: 0.771
6 - val_loss: 0.6459 - val_accuracy: 0.7714
Epoch 55/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6366 - accuracy: 0.778
8 - val_loss: 0.6468 - val_accuracy: 0.7697
Epoch 56/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6306 - accuracy: 0.777
3 - val_loss: 0.6397 - val_accuracy: 0.7762
Epoch 57/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6301 - accuracy: 0.777
8 - val_loss: 0.6298 - val_accuracy: 0.7872
Epoch 58/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6260 - accuracy: 0.782
6 - val_loss: 0.5936 - val_accuracy: 0.7976
Epoch 59/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6268 - accuracy: 0.781
8 - val_loss: 0.6049 - val_accuracy: 0.7872
Epoch 60/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6243 - accuracy: 0.780
4 - val_loss: 0.6380 - val_accuracy: 0.7754
Epoch 61/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6248 - accuracy: 0.782
4 - val_loss: 0.6213 - val_accuracy: 0.7787
Epoch 62/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6209 - accuracy: 0.782
8 - val_loss: 0.6150 - val_accuracy: 0.7785
Epoch 63/100
```

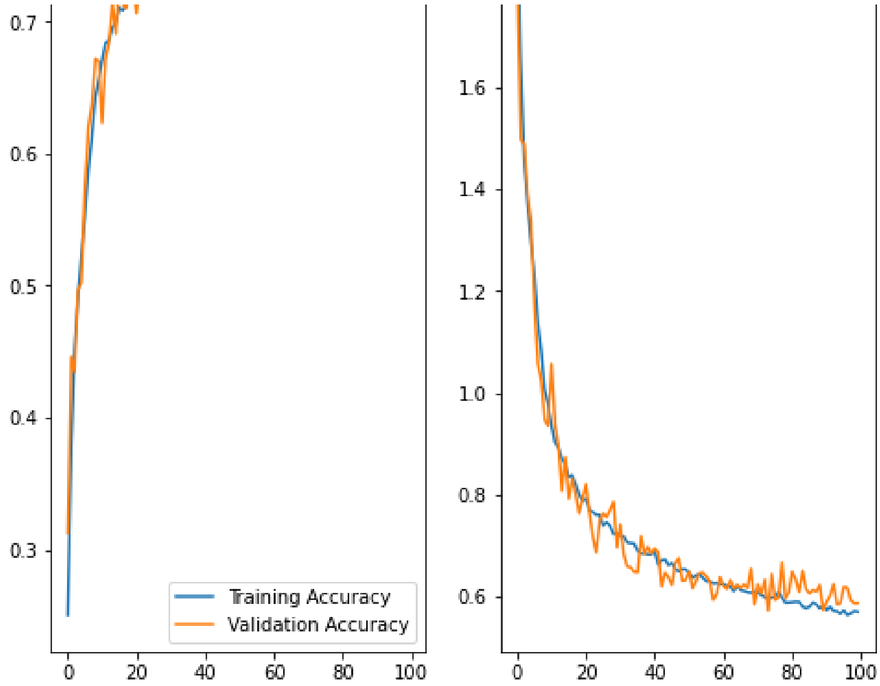
```
284/284 [==============================] - 17s 59ms/step - loss: 0.6202 - accuracy: 0.785
4 - val_loss: 0.6322 - val_accuracy: 0.7796
Epoch 64/100
284/284 [==============================] - 16s 57ms/step - loss: 0.6105 - accuracy: 0.784
5 - val_loss: 0.6160 - val_accuracy: 0.7810
Epoch 65/100
284/284 [==============================] - 16s 57ms/step - loss: 0.6212 - accuracy: 0.782
8 - val_loss: 0.6229 - val_accuracy: 0.7796
Epoch 66/100
284/284 [==============================] - 16s 56ms/step - loss: 0.6128 - accuracy: 0.787
1 - val_loss: 0.6167 - val_accuracy: 0.7813
Epoch 67/100
284/284 [==============================] - 16s 57ms/step - loss: 0.6111 - accuracy: 0.787
3 - val_loss: 0.6239 - val_accuracy: 0.7799
Epoch 68/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6084 - accuracy: 0.786
4 - val_loss: 0.6170 - val_accuracy: 0.7866
Epoch 69/100
284/284 [==============================] - 16s 58ms/step - loss: 0.6074 - accuracy: 0.788
0 - val_loss: 0.6549 - val_accuracy: 0.7692
Epoch 70/100
284/284 [==============================] - 16s 58ms/step - loss: 0.6097 - accuracy: 0.789
4 - val_loss: 0.5852 - val_accuracy: 0.7943
Epoch 71/100
284/284 [==============================] - 16s 58ms/step - loss: 0.6080 - accuracy: 0.790
3 - val_loss: 0.6243 - val_accuracy: 0.7855
Epoch 72/100
284/284 [==============================] - 16s 58ms/step - loss: 0.6028 - accuracy: 0.786
9 - val_loss: 0.6059 - val_accuracy: 0.7841
Epoch 73/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5994 - accuracy: 0.790
2 - val_loss: 0.6334 - val_accuracy: 0.7768
Epoch 74/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5952 - accuracy: 0.791
0 - val_loss: 0.5726 - val_accuracy: 0.7982
Epoch 75/100
284/284 [==============================] - 17s 59ms/step - loss: 0.5985 - accuracy: 0.791
8 - val_loss: 0.6444 - val_accuracy: 0.7737
Epoch 76/100
284/284 [==============================] - 18s 62ms/step - loss: 0.5987 - accuracy: 0.788
5 - val_loss: 0.5933 - val_accuracy: 0.7931
Epoch 77/100
284/284 [==============================] - 17s 58ms/step - loss: 0.6092 - accuracy: 0.786
2 - val_loss: 0.5981 - val_accuracy: 0.7943
Epoch 78/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5978 - accuracy: 0.787
4 - val_loss: 0.6671 - val_accuracy: 0.7641
Epoch 79/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5880 - accuracy: 0.795
2 - val_loss: 0.5966 - val_accuracy: 0.7985
Epoch 80/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5882 - accuracy: 0.791
8 - val_loss: 0.6077 - val_accuracy: 0.7776
Epoch 81/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5889 - accuracy: 0.794
2 - val_loss: 0.6490 - val_accuracy: 0.7754
Epoch 82/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5898 - accuracy: 0.793
1 - val_loss: 0.6343 - val_accuracy: 0.7751
Epoch 83/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5894 - accuracy: 0.794
5 - val_loss: 0.6090 - val_accuracy: 0.7864
Epoch 84/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5803 - accuracy: 0.798
2 - val_loss: 0.6500 - val_accuracy: 0.7740
Epoch 85/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5770 - accuracy: 0.798
2 - val_loss: 0.6145 - val_accuracy: 0.7923
Epoch 86/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5802 - accuracy: 0.795
7 - val_loss: 0.6062 - val_accuracy: 0.7883
Epoch 87/100
```

```
284/284 [==============================] - 16s 58ms/step - loss: 0.5881 - accuracy: 0.791
9 - val_loss: 0.6129 - val_accuracy: 0.7869
Epoch 88/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5846 - accuracy: 0.794
1 - val_loss: 0.6099 - val_accuracy: 0.7835
Epoch 89/100
284/284 [==============================] - 17s 58ms/step - loss: 0.5767 - accuracy: 0.796
9 - val_loss: 0.6226 - val_accuracy: 0.7787
Epoch 90/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5823 - accuracy: 0.796
2 - val_loss: 0.5737 - val_accuracy: 0.7968
Epoch 91/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5737 - accuracy: 0.800
6 - val_loss: 0.5902 - val_accuracy: 0.7982
Epoch 92/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5799 - accuracy: 0.797
2 - val_loss: 0.6021 - val_accuracy: 0.7883
Epoch 93/100
284/284 [==============================] - 17s 59ms/step - loss: 0.5721 - accuracy: 0.801
0 - val_loss: 0.6244 - val_accuracy: 0.7818
Epoch 94/100
284/284 [==============================] - 17s 58ms/step - loss: 0.5713 - accuracy: 0.802
6 - val_loss: 0.5846 - val_accuracy: 0.7951
Epoch 95/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5666 - accuracy: 0.800
8 - val_loss: 0.5867 - val_accuracy: 0.7982
Epoch 96/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5731 - accuracy: 0.798
3 - val_loss: 0.6190 - val_accuracy: 0.7841
Epoch 97/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5640 - accuracy: 0.802
9 - val_loss: 0.6175 - val_accuracy: 0.7880
Epoch 98/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5673 - accuracy: 0.799
1 - val_loss: 0.5932 - val_accuracy: 0.7883
Epoch 99/100
284/284 [==============================] - 16s 58ms/step - loss: 0.5717 - accuracy: 0.799
3 - val_loss: 0.5865 - val_accuracy: 0.7931
Epoch 100/100
284/284 [==============================] - 17s 58ms/step - loss: 0.5702 - accuracy: 0.802
4 - val_loss: 0.5872 - val_accuracy: 0.7928
```

In [42]:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = range(EPOCHS)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```





In [43]:

```
prediction = model.predict(img_array)
```

In [44]:

```
score = tf.nn.softmax(prediction[0])
for i in score: print(i)
```

```
tf.Tensor(0.031662643, shape=(), dtype=float32)
tf.Tensor(1.3360906e-05, shape=(), dtype=float32)
tf.Tensor(1.7445062e-05, shape=(), dtype=float32)
tf.Tensor(9.918027e-09, shape=(), dtype=float32)
tf.Tensor(1.1274198e-11, shape=(), dtype=float32)
tf.Tensor(0.96132505, shape=(), dtype=float32)
tf.Tensor(6.0916893e-05, shape=(), dtype=float32)
tf.Tensor(0.006852181, shape=(), dtype=float32)
tf.Tensor(7.145125e-07, shape=(), dtype=float32)
tf.Tensor(6.769257e-05, shape=(), dtype=float32)
```

In [45]:

```
print('This galaxy is most likely to be a ' + str(class_names[np.argmax(score)]) + '.')
```

```
This galaxy is most likely to be a Barred Spiral Galaxy.
```

In [48]:

```
i = 5
test_img = tf.keras.utils.load_img(f'../Data/new_test_data/galaxy_test_{i}.png', target_s
ize = (img_height, img_width))
disp_img = PIL.Image.open(f'../Data/new_test_data/galaxy_test_{i}.png')
#disp_img.resize((img_height, img_width))
size = (img_height, img_width)
disp_img.thumbnail(size, PIL.Image.ANTIALIAS)
disp_img
```

Out[48]:

In [141]:

```
img_array = tf.keras.utils.img_to_array(test_img)
img_array = tf.expand_dims(img_array, 0)
img_array.shape
```

Out[141]:

```
TensorShape([1, 256, 256, 3])
```

In [142]:

```
prediction = model.predict(img_array)
```

In [143]:

```
score = tf.nn.softmax(prediction[0])
for i in score: print(i)
```

```
tf.Tensor(0.029760612, shape=(), dtype=float32)
tf.Tensor(0.00096607377, shape=(), dtype=float32)
tf.Tensor(0.0001968926, shape=(), dtype=float32)
tf.Tensor(0.0004474812, shape=(), dtype=float32)
tf.Tensor(0.0014142577, shape=(), dtype=float32)
tf.Tensor(0.6551534, shape=(), dtype=float32)
tf.Tensor(0.010337954, shape=(), dtype=float32)
tf.Tensor(0.051949665, shape=(), dtype=float32)
tf.Tensor(0.10332805, shape=(), dtype=float32)
tf.Tensor(0.14644569, shape=(), dtype=float32)
```

In [144]:

```
print('This galaxy is most likely to be a ' + str(class_names[np.argmax(score)]) + '.')
```

```
This galaxy is most likely to be a Barred Spiral Galaxy.
```

In [107]:

```
class_names
```

Out[107]:

```
['Disturbed Galaxy',
 'Merging Galaxy',
 'Round Smooth Galaxy',
 'In-between Round Smooth Galaxy',
 'Cigar Shaped Smooth Galaxy',
 'Barred Spiral Galaxy',
 'Unbarred Tight Spiral Galaxy',
 'Unbarred Loose Spiral Galaxy',
 'Edge-on Galaxy without Bulge',
 'Edge-on Galaxy with Bulge']
```

In [ ]:

```

```

In [ ]:

```

```