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CS542 Class Challenge Report

a) Describe the architectures used in detail: layers, layer dimensions, dropout layers, etc. for both tasks. List the optimizer, loss function, parameters, and any regularization used in both tasks

<u>Task 1 (Binary Classification)</u>

```
True
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 7, 7, 512)         14714688
_________________________________________________________________
batch_normalization (BatchNo (None, 7, 7, 512)         2048
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 256)               6422784
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
_________________________________________________________________
activation (Activation)      (None, 1)                 0
=================================================================
Total params: 21,139,777
Trainable params: 6,424,065
Non-trainable params: 14,715,712
_________________________________________________________________
```

I decided to use the pretrained VGG16 Model on the ImageNet dataset for transfer learning. After the convolution layers of VGG16, I applied Batch Normalization and a Flatten Layer, Fully Connected Layer and Dropout Layer. Activations for the first and last fully Connected Layers are ReLU and sigmoid respectively.

The probability of the dropout layer is 0.3 and the number of units in the first connected layer is 256 and the last layer is 1 (for binary classification)

I applied several regularization techniques, Batch Normalization and Dropout, and L2 Kernal Regularization in the first fully connected Layer.

For compilation, I used the Adam Optimizer with a learning rate of 0.001, with the binary cross entropy loss function. The model is trained over 40 epochs with a batch size of 10, 10 steps per epoch for training and 2 steps per epoch for validation.

Task 2 (Categorical Classification):

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inception_v3 (Functional)    (None, 5, 5, 2048)        21802784
_________________________________________________________________
batch_normalization_94 (Batc (None, 5, 5, 2048)        8192
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
densefn (Dense)              (None, 256)               13107456
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 4)                 1028
_________________________________________________________________
activation_94 (Activation)   (None, 4)                 0
=================================================================
Total params: 34,919,460
Trainable params: 13,112,580
Non-trainable params: 21,806,880
_________________________________________________________________
```

I decided to use the pretrained InceptionV3 Model on the ImageNet dataset for transfer learning, freezing the first 300 layers and training the rest. After the convolution layers of VGG16, I applied Batch Normalization and a Flatten Layer, Fully Connected Layer and Dropout Layer. Activations for the first and last fully Connected Layers are ReLU and softmax respectively.

The probability of the dropout layer is 0.3 and the number of units in the first connected layer is 256 and the last layer is 4 (for categorical classification)

I applied several regularization techniques, Batch Normalization and Dropout.

For compilation, I used the Adam Optimizer with a learning rate of 0.001, with the categorical cross entropy loss function. The model is trained over 100 epochs with a batch size of 10, 10 steps per epoch for training and 5 steps per epoch for validation.

b) Comparison of the performance of different architectures for the second task and relating this to the architecture and parameter settings used.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 7, 7, 512)         14714688
_________________________________________________________________
batch_normalization (BatchNo (None, 7, 7, 512)         2048
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
densefn (Dense)              (None, 256)               6422784
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 4)                 1028
_________________________________________________________________
activation (Activation)      (None, 4)                 0
=================================================================
Total params: 21,140,548
Trainable params: 6,424,836
Non-trainable params: 14,715,712
_________________________________________________________________
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inception_v3 (Functional)    (None, 5, 5, 2048)        21802784
_________________________________________________________________
batch_normalization_94 (Batc (None, 5, 5, 2048)        8192
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
densefn (Dense)              (None, 256)               13107456
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 4)                 1028
_________________________________________________________________
activation_94 (Activation)   (None, 4)                 0
=================================================================
Total params: 34,919,460
Trainable params: 13,112,580
Non-trainable params: 21,806,880
_________________________________________________________________
```

I have used 2 different pre trained models (VGG16 and InceptionV3) for task2 and compared the various results between both.

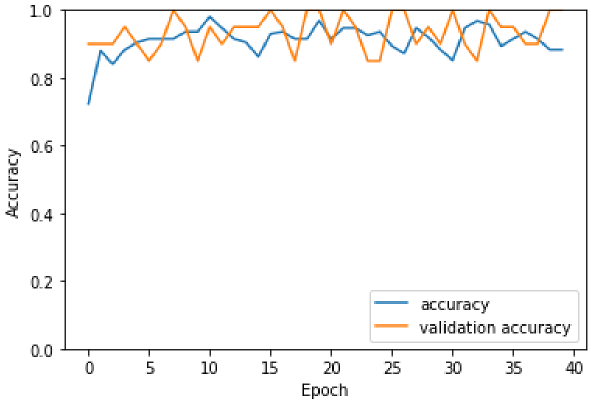
	VGG16	InceptionV3
Time taken per Epoch (seconds)	20-25	12 - 18
Time per Step	2-3 s/step	0.8-1s/step
Time taken	2359 seconds	1060 seconds
Total Parameters	21,140,548	34,919,460
Test Loss	1.2161	1.57811
Test Accuracy	0.5833	0.75

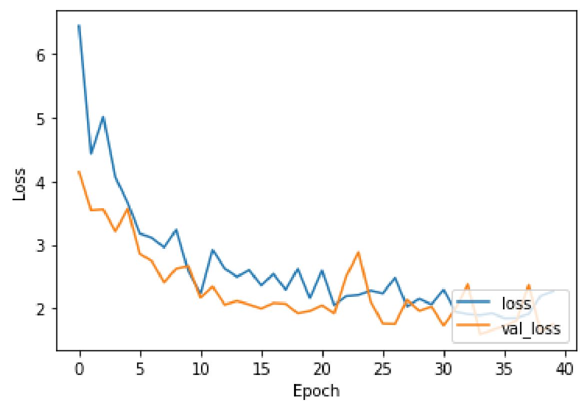
I used the same parameters settings between both architectures to get a fair comparison between both models for training and validation: Adam Optimizer, learning rate of 0.001, 100 epochs, 10 steps per epoch, batch size of 10, 5 steps per epoch for validation.

As you can see the time taken for VGG16 to run is approx. 2 times longer than that of InceptionV3, even though there are less parameters. In terms of results, the test loss of VGG16 (1.2161) is lower than InceptionV3 (1.578), but the accuracy of VGG16 (0.5833) is worse than that of InceptionV3 (0.75)

c) Plot and comment on the accuracy and the loss for both tasks

Task1:

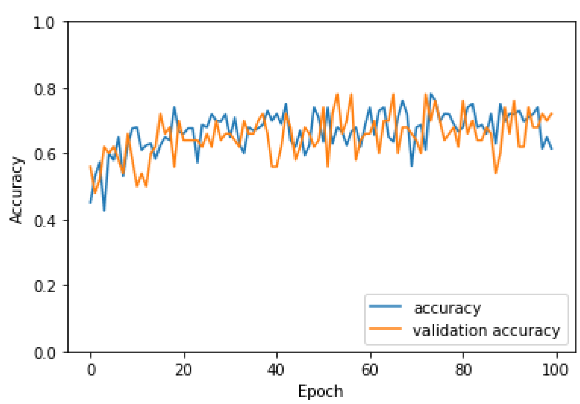


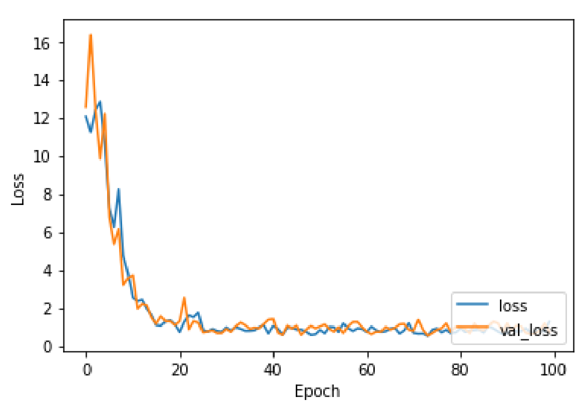


Test Loss: 1.7654
Test Accuracy: 1.0

The accuracy and validation accuracy for task 1 fluctuates between 0.85 and 1.0. The validation accuracy hits 1.0 several time while fitting the model. The loss and validation do fluctuate, however there is a decreasing gradient and starts to plateau around the 25^{th} epoch to around 1.0.

Task 2:



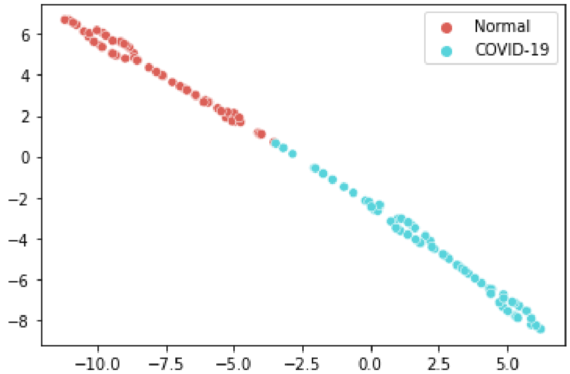


Test loss: 0.7389
Test accuracy: 0.75

The accuracy and validation accuracy for task 2 fluctuates between 0.5 and 0.7 after 20 epochs. For the loss and validation, there is a decreasing gradient and starts to plateau around the $30th^{th}$ epoch to around 1.0 from 12.

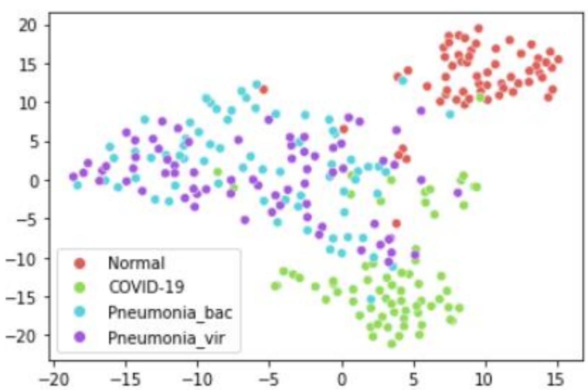
d) Plot and comment on the t-SNE visualizations

Task 1:



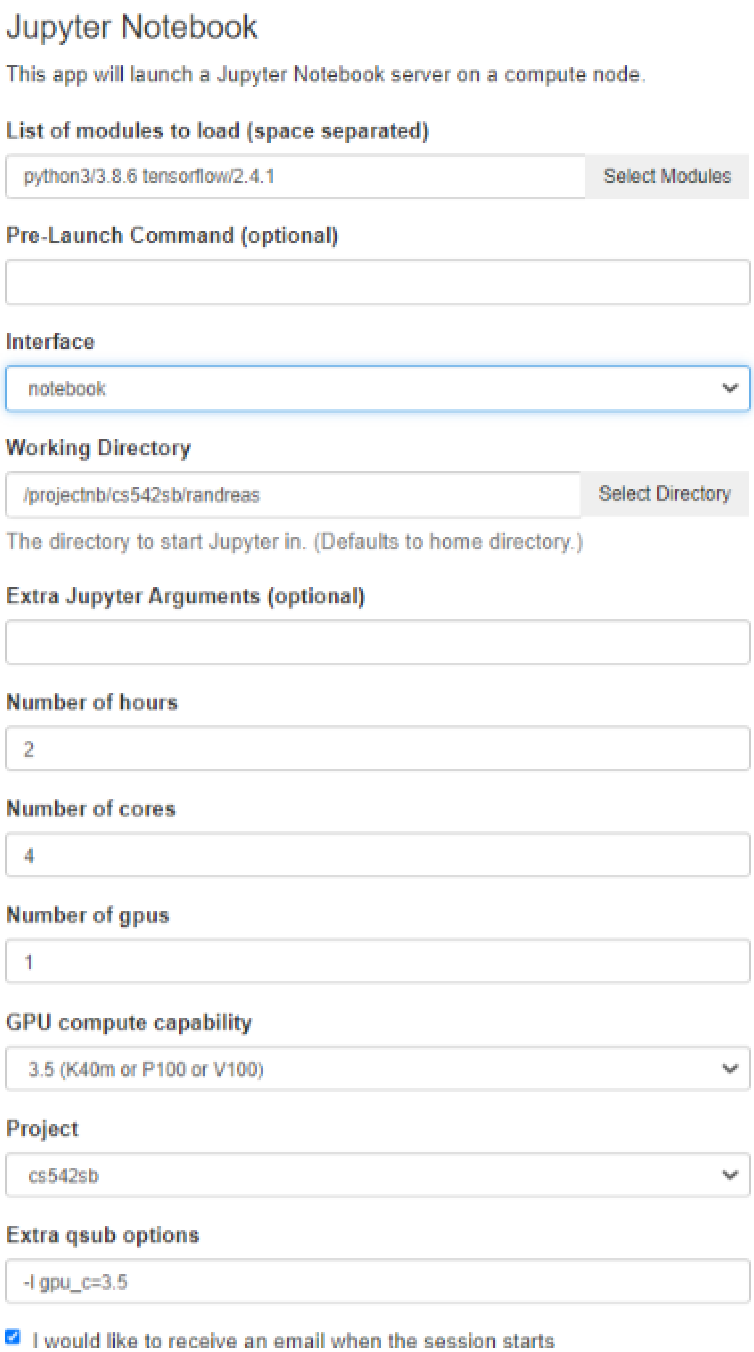
From the t-SNE plot of task 1, the COVID-19 and Normal Features are clearly separated into 2 different clusters. Meaning the Neural Network can differentiate the unique features between COVID-19 and Normal X-Rays.

Task 2:



However, when looking at the t-SNE plot of task 2, the model is able to differentiate between COVID-19, Normal and Pneumonia X-rays, but unable to differentiate between the 2 variants of Pneumonia (Bacterial and Viral). The top right (red) are mostly Normal Xray's, while bottom (yellow) is mainly COVID-19. However, the middle cluster is mixed with both Pneumonia bacterial and Pneumonia Viral, even though they are both in one cluster, a better model would have been able to separate these 2 variations. So, from this plot, my model is able to separate them into 3 distinct clusters instead of 4.

e) Bonus: Run the training on a GPU on the SCC cluster and include a CPU *vs.* GPU training time comparison by taking snapshots from your terminal



For Task1:

Running on local CPU

localhost:8888/notebooks/task1_template.ipynb

jupyter task1_template Last Checkpoint: 21 hours ago (autosaved)

Logout

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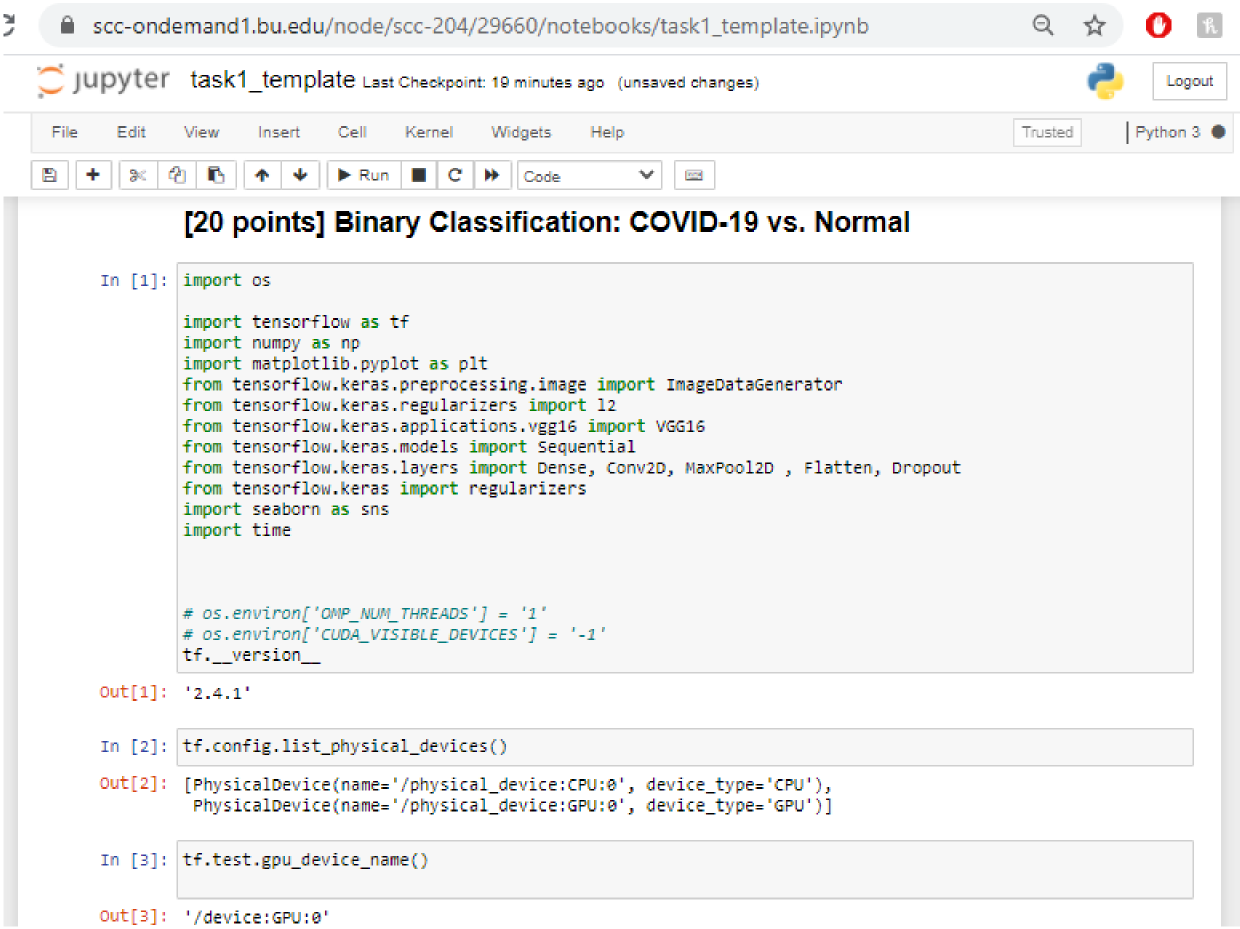
Run Markdown

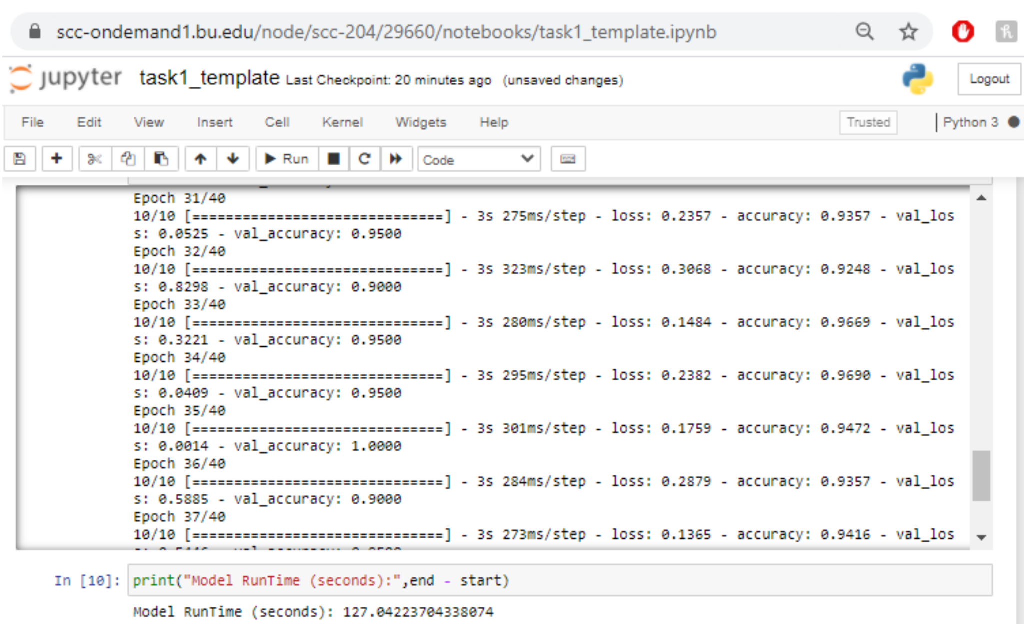
```
    x = train_batches,
    epochs=NUM_EPOCHS,
    validation_data= valid_batches,
    steps_per_epoch = STEP_SIZE_TRAIN,
    batch_size=BATCH_SIZE,
    validation_steps = STEP_SIZE_VALID
)

end = time.time()
```

```
10/10 [==============================] - 16s 2s/step - loss: 1.7893 - accuracy: 0.9690 - val_loss:
1.5917 - val_accuracy: 1.0000
Epoch 35/40
10/10 [==============================] - 16s 2s/step - loss: 1.9637 - accuracy: 0.8682 - val_loss:
1.6573 - val_accuracy: 0.9500
Epoch 36/40
10/10 [==============================] - 16s 2s/step - loss: 1.7845 - accuracy: 0.9442 - val_loss:
1.7199 - val_accuracy: 0.9500
Epoch 37/40
10/10 [==============================] - 16s 2s/step - loss: 1.8672 - accuracy: 0.9439 - val_loss:
1.8049 - val_accuracy: 0.9000
Epoch 38/40
10/10 [==============================] - 16s 2s/step - loss: 2.0210 - accuracy: 0.9002 - val_loss:
2.3667 - val_accuracy: 0.9000
Epoch 39/40
10/10 [==============================] - 16s 2s/step - loss: 2.2281 - accuracy: 0.9226 - val_loss:
1.6307 - val_accuracy: 1.0000
Epoch 40/40
10/10 [==============================] - 16s 2s/step - loss: 2.1520 - accuracy: 0.9146 - val_loss:
1.7534 - val_accuracy: 1.0000
```

```
In [8]: print("Model RunTime (seconds):",end - start)

Model RunTime (seconds): 748.4690515995026
```

Running on SCC using 1 GPU





Task2: Running on Local CPU

localhost:8888/notebooks/task2_template_currBest2.ipynb

jupyter task2_template_currBest2 (autosaved)

Logout

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Run Code

```
acy: 0.6960 - val_loss: 0.8479 - val_accuracy: 0.6000
Epoch 98/100
10/10 [==============================] - 9s 911ms/step - loss: 0.7446 - accur
acy: 0.7295 - val_loss: 0.5946 - val_accuracy: 0.7400
Epoch 99/100
10/10 [==============================] - 10s 1s/step - loss: 0.8301 - accurac
y: 0.6734 - val_loss: 0.9250 - val_accuracy: 0.6200
Epoch 100/100
10/10 [==============================] - 10s 1s/step - loss: 0.6043 - accurac
y: 0.6999 - val_loss: 0.8843 - val_accuracy: 0.6000
```

In [8]:
```
print("Model RunTime (seconds):",end - start)
```

```
Model RunTime (seconds): 1060.2564942836761
```

Task2: Running on GPU on the SCC

scc-ondemand1.bu.edu/node/scc-204/4461/notebooks/task2_template_currBest.ipynb

jupyter task2_template_currBest Last Checkpoint: Last Monday at 7:37 PM (unsaved changes)

Logout

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Run Code

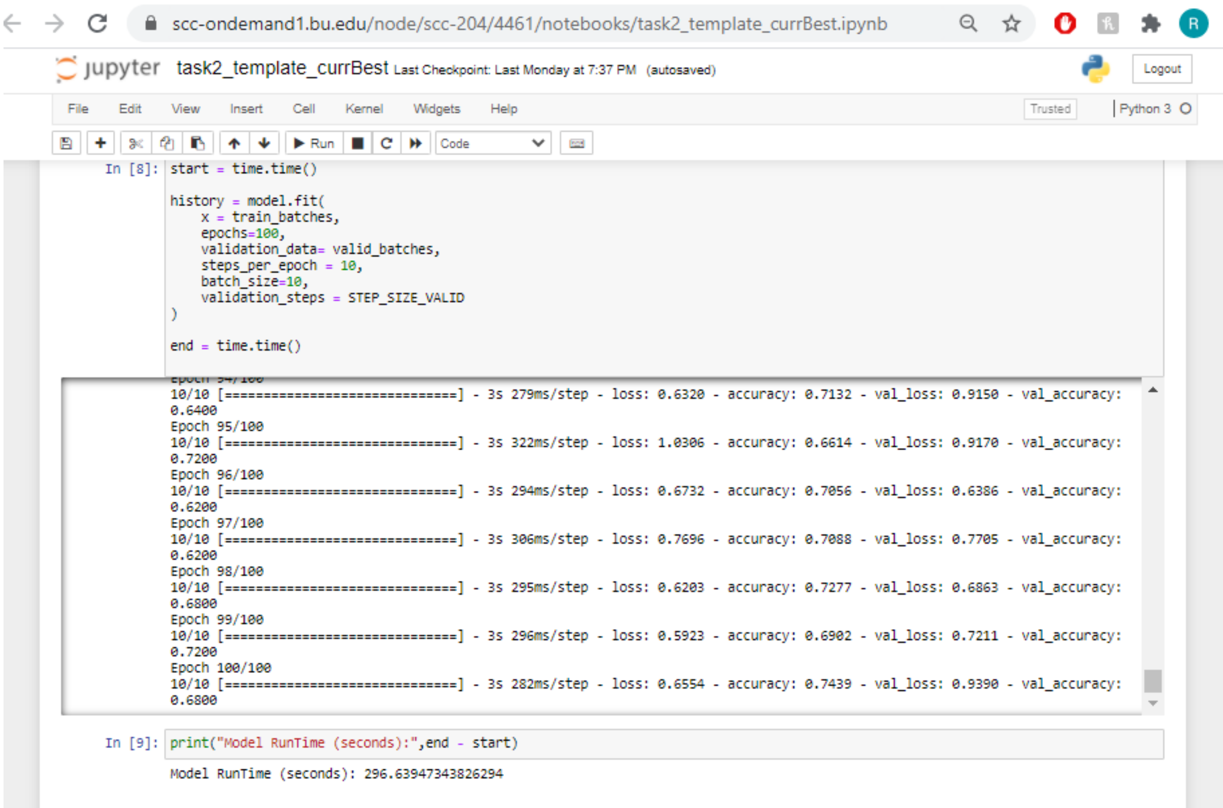
[20 points] Multi-class Classification

In [1]:
```
import os

import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPool2D , Flatten, Dropout
import seaborn as sns
from sklearn.manifold import TSNE
import tensorflow.keras.models as models
import seaborn as sns
from tensorflow.keras.regularizers import l2
import time

# os.environ['OMP_NUM_THREADS'] = '1'
# os.environ['CUDA_VISIBLE_DEVICES'] = '0'
tf.__version__
```

Out[1]: '2.4.1'

In [2]:
```
tf.config.list_physical_devices()
```

Out[2]:
```
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU'),
 PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```



For task 1, running on local CPU takes around 16seconds per epoch and 2s/step totaling up to 748 seconds. However, when running on the SCC using 1 GPU, the time for each epoch decreased to 3seconds and approx. 300ms/step, decreasing total run time to 127seconds.

Similarly, for task 2, running on local CPU takes around 10seconds per epoch and 1s/step totaling up to 1060 seconds. However, when running on the SCC using 1 GPU, the time for each epoch decreased to 3seconds and approx. 300ms/step, decreasing total run time to 296seconds.

This proves that running on a GPU drastically improves the training time of neural network models.