CS 570

Assignment 3

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a) These are the steps need to be completed for this part.

1.

Load keras.datasets.fashion_mnist data into train_images train_labels test_images test_labels

2.

Implement an MLP architecture that can be trained on the fashion dataset. Select the number of layers and number of nodes in each layer according to your consideration. The input and output layers' nodes need to be determined based on the dataset. Please make sure that your network architecture is DIFFERENT from the architecture used in the sample code provided with this assignment.

3.

Train the network on the training samples. Your program should print the training accuracy for each epoch. Remember 'accuracy' on a data set is defined by the percentage of correct detection out of total number of samples.

4.

Validate the trained model using the test data. Report the final test accuracy. No marks will be deducted if your test accuracy is slightly lower than the best test accuracy, but it should be at least 70%. Please remember that the sample code provided does not calculate the accuracy on the test data set. This part is left for the students to implement.

```
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
2.14.0
```

```
# Check if a GPU is available
if tf.test.is_gpu_available():
    print("GPU is available.")
    print("GPU name:", tf.test.gpu_device_name())
    print("GPU device:", tf.test.gpu_device_name())
else:
    print("No GPU is available.")
```

```
WARNING:tensorflow:From <ipython-input-7-942a1e81d75f>:2: is_gpu_available (from
Instructions for updating:
Use `tf.config.list_physical_devices('GPU')` instead.
GPU is available.
GPU name: /device:GPU:0
GPU device: /device:GPU:0
```

Part a)

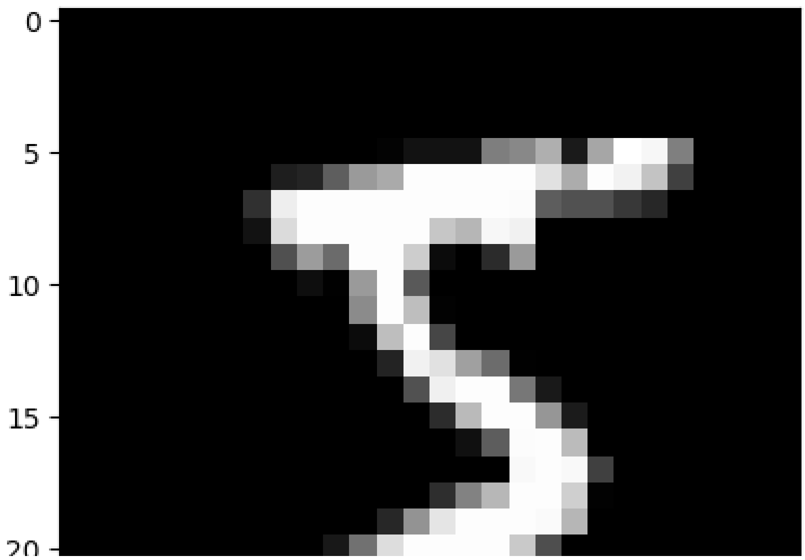
```
# load digit dataset
(train_images, train_labels), (test_images, test_labels) = keras.datasets.mnist.load_

# load CIFAR10 dataset
#(train_images, train_labels), (test_images, test_labels) = datasets.cifar10.load_dat
# Normalize pixel values to be between 0 and 1
#train_images, test_images = train_images / 255.0, test_images / 255.0
```

```
print("Shape of the training dataset, number of images and resolution:", train_images
print("All distinct training labels:", np.unique(train_labels))
```

```
Shape of the training dataset, number of images and resolution: (60000, 28, 28)
All distinct training labels: [0 1 2 3 4 5 6 7 8 9]
```

```
plt.figure()
plt.imshow(train_images[0], cmap='gray')
#plt.colorbar()
plt.grid(False)
plt.suptitle('First Training Image', fontsize=16)
plt.show()
print("First training label: ", train_labels[0])
```

First Training Image

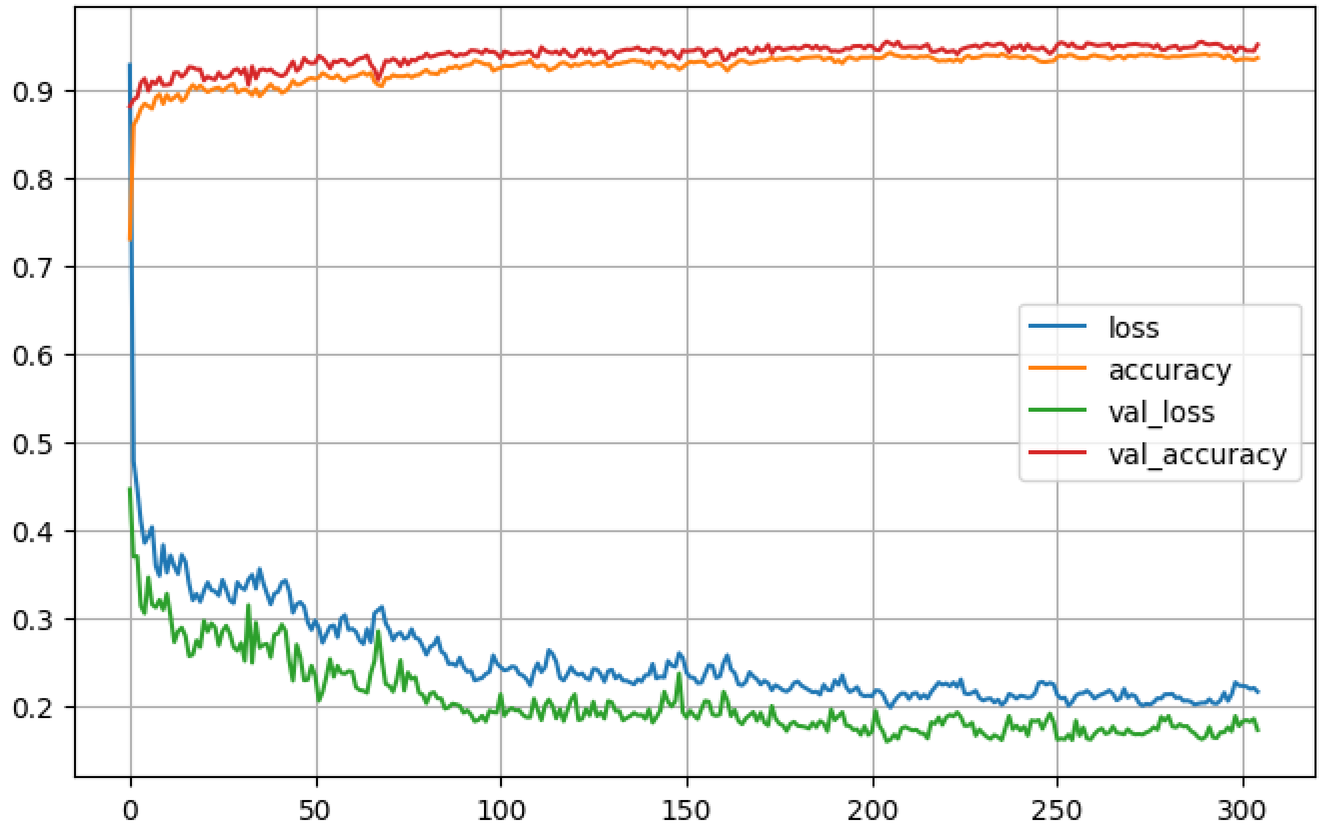



```
#Model old
with tf.device("/GPU:0"):
  model = keras.Sequential([
      keras.layers.Flatten(input_shape=(28, 28)),       #input_shape=(28, 28) for dig
      keras.layers.Dense(512, activation='relu'),
      keras.layers.Dense(64, activation='sigmoid'),
      keras.layers.Dense(10),

  ])

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

  early_stopping_cb = keras.callbacks.EarlyStopping(patience=100,restore_best_weights

  history = model.fit(train_images, train_labels,
                      epochs=1000,
                      validation_split=0.1,
                      callbacks=[early_stopping_cb]
                      )
```

```
Epoch 1/1000
1688/1688 [==============================] - 9s 5ms/step - loss: 0.9285 - accura
Epoch 2/1000
1688/1688 [==============================] - 10s 6ms/step - loss: 0.4784 - accur
Epoch 3/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.4467 - accura
Epoch 4/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.4096 - accura
Epoch 5/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3850 - accura
Epoch 6/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3924 - accura
```

```
Epoch 7/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.4031 - accura
Epoch 8/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3585 - accura
Epoch 9/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3475 - accura
Epoch 10/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3826 - accura
Epoch 11/1000
1688/1688 [==============================] - 8s 5ms/step - loss: 0.3512 - accura
Epoch 12/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3708 - accura
Epoch 13/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3585 - accura
Epoch 14/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3497 - accura
Epoch 15/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3714 - accura
Epoch 16/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3634 - accura
Epoch 17/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3381 - accura
Epoch 18/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3197 - accura
Epoch 19/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3270 - accura
Epoch 20/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3180 - accura
Epoch 21/1000
1688/1688 [==============================] - 6s 4ms/step - loss: 0.3305 - accura
Epoch 22/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3400 - accura
Epoch 23/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3313 - accura
Epoch 24/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3299 - accura
Epoch 25/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3251 - accura
Epoch 26/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3429 - accura
Epoch 27/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3319 - accura
Epoch 28/1000
1688/1688 [==============================] - 6s 3ms/step - loss: 0.3195 - accura
Epoch 29/1000
1688/1688 [==============================] - 5s 3ms/step - loss: 0.3164 - accura
```

```
import pandas as pd
import matplotlib.pyplot as plt

#learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca() # set the vertical range to [0-1]
plt.show()
```




```
# Validate the trained model using the test data

score = model.evaluate(test_images, test_labels, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

    Test loss: 0.20328281819820404
    Test accuracy: 0.9422000050544739
```

Part b)

Hyperparameter tuning **is a technique to select the (almost) best model architecture for a machine learning problem. In this case, we will try to select the best combination for 3 parameters which are the** **number of hidden layers, the number of nodes in each hidden layer, and the activation function**. For our case, we will select between two different choices for each hyperparameter and try all combinations of hyperparameter values. Finally, we will select the hyperparameter combination that returns the best validation accuracy. You need to complete the below tasks.

1.

Consider that your model has three hyperparameters such as the number of hidden layers, the number of nodes in each hidden layer, and the activation function. Each of the hyperparameters can take two values which are (3, 4), (64, 128), ('sigmoid', 'relu') respectively. Implement the grid search algorithm discussed in the class to select each possible hyperparameter combination at a time, define an MLP model with the selected hyperparameter combination, and train the model. The mentioned steps need to be performed in a loop to iterate over each possible hyperparameter combination (in this case the number of possible combinations is 8). Remember to split the train_images into training and validation sets so that you can compute validation accuracy (no cross validation is needed for this assignment for each iteration of the loop Your program must print each combination of hyperparameters and its validation accuracy. Marks will be deducted if this information is not displayed. Selection of hyperparameter combinations, generating the MLP architecture, training the network, and reporting validation accuracy should be done programmatically using loops. Do not use hardcoded hyperparameter combinations and hardcoded network models.

```
from keras.layers import Dense
from sklearn.model_selection import train_test_split


"""
Here when using the grid search , Since it takes lot of computation
time to get epochs that model coverges,  I fixed the maximum number of epochs to 20.
"""
# grid boundares
layers = [3, 4]
no_nodes = [64, 128]
activation_fns = ['sigmoid', 'relu']

model_accuracies = {}
best_model = None
best_model_no = 0
best_accuracy = 0

i = 0


# Splitting training data into train and valiation sets.
X_train, X_validation, y_train, y_validation = train_test_split(train_images, train_l

# For each hyperparameter set
for nodes in no_nodes:
  for activation in activation_fns:
    for no_of_layers in layers:

      # Creating the model
      model = keras.Sequential([keras.layers.Flatten(input_shape=(28, 28)),       #in
                               ])
      for l in range(no_of_layers):
        model.add(Dense(nodes, activation=activation))
```

```
    model.add(Dense(10))




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

    early_stopping_cb = keras.callbacks.EarlyStopping(patience=100,restore_best_wei

    # traing the model and validate with validation data set
    with tf.device("/GPU:0"):
      history = model.fit(X_train, y_train,
                          epochs=20,
                          validation_data=(X_validation, y_validation),
                          callbacks=[early_stopping_cb],
                          verbose = 0)




    last_epoch = len(history.history['accuracy'])  # Get the number of epochs to co
    model_training_accuracy = history.history['accuracy'][last_epoch - 1]
    model_validation_accuracy = history.history['val_accuracy'][last_epoch - 1]

    #Storing training and validation accuracies for part 3
    model_accuracies[i] = [model_training_accuracy, model_validation_accuracy]

    print(f'Model {i+1} : \n hideen layers - {no_of_layers}, nodes -{nodes}, activa


    # storing best model for part 2
    if model_validation_accuracy > best_accuracy:
      best_accuracy = model_validation_accuracy
      best_model = model
      best_model_no = i+1



    i += 1

print(f'Best model is Model {best_model_no} with validation accuracy : {best_accuracy
```

```
Model 1 :
 hideen layers - 3, nodes -64, activation - sigmoid, Validation acuuracy : 0.929
Model 2 :
 hideen layers - 4, nodes -64, activation - sigmoid, Validation acuuracy : 0.920
Model 3 :
```

```
 hideen layers - 3, nodes -64, activation - relu, Validation acuuracy : 0.965749
Model 4 :
 hideen layers - 4, nodes -64, activation - relu, Validation acuuracy : 0.955833
Model 5 :
 hideen layers - 3, nodes -128, activation - sigmoid, Validation acuuracy : 0.94
Model 6 :
 hideen layers - 4, nodes -128, activation - sigmoid, Validation acuuracy : 0.93
Model 7 :
 hideen layers - 3, nodes -128, activation - relu, Validation acuuracy : 0.96525
Model 8 :
 hideen layers - 4, nodes -128, activation - relu, Validation acuuracy : 0.97458
Best model is Model 8 with validation accuracy : 0.9745833277702332
```

2.

Select the hyperparameter combination with the best validation accuracy, and train the MLP model (with the best hyperparameters) using the full training dataset (train_images images). Report the test accuracy calculated on the final trained model. Please check the meaning of ‘accuracy’ defined in part a) of the assignment.

```
# Training the full taining set using the best model.
with tf.device("/GPU:0"):
  history = best_model.fit(train_images, train_labels,
                    epochs=1000,
                    validation_split=0.1,
                    callbacks=[early_stopping_cb],
                    verbose = 2
                    )
```

```
Epoch 50/1000
1688/1688 - 5s - loss: 0.0202 - accuracy: 0.9962 - val_loss: 0.1961 - val_accura
Epoch 51/1000
1688/1688 - 6s - loss: 0.0429 - accuracy: 0.9934 - val_loss: 0.2002 - val_accura
Epoch 52/1000
1688/1688 - 5s - loss: 0.0307 - accuracy: 0.9949 - val_loss: 0.3000 - val_accura
Epoch 53/1000
1688/1688 - 5s - loss: 0.0316 - accuracy: 0.9954 - val_loss: 0.3133 - val_accura
Epoch 54/1000
1688/1688 - 5s - loss: 0.0231 - accuracy: 0.9958 - val_loss: 0.2642 - val_accura
Epoch 55/1000
1688/1688 - 5s - loss: 0.0351 - accuracy: 0.9962 - val_loss: 0.2462 - val_accura
Epoch 56/1000
1688/1688 - 6s - loss: 0.0214 - accuracy: 0.9964 - val_loss: 0.2978 - val_accura
Epoch 57/1000
1688/1688 - 5s - loss: 0.0249 - accuracy: 0.9959 - val_loss: 0.1657 - val_accura
Epoch 58/1000
1688/1688 - 6s - loss: 0.0448 - accuracy: 0.9942 - val_loss: 0.2029 - val_accura
Epoch 59/1000
1688/1688 - 5s - loss: 0.0261 - accuracy: 0.9956 - val_loss: 0.2618 - val_accura
Epoch 60/1000
1688/1688 - 5s - loss: 0.0257 - accuracy: 0.9964 - val_loss: 0.3934 - val_accura
Epoch 61/1000
1688/1688 - 5s - loss: 0.0308 - accuracy: 0.9941 - val_loss: 0.3734 - val_accura
Epoch 62/1000
1688/1688 - 5s - loss: 0.0349 - accuracy: 0.9947 - val_loss: 0.3559 - val_accura
Epoch 63/1000
1688/1688 - 6s - loss: 0.0253 - accuracy: 0.9964 - val_loss: 0.2849 - val_accura
Epoch 64/1000
1688/1688 - 5s - loss: 0.0375 - accuracy: 0.9941 - val_loss: 0.1732 - val_accura
Epoch 65/1000
1688/1688 - 6s - loss: 0.0314 - accuracy: 0.9954 - val_loss: 0.2257 - val_accura
Epoch 66/1000
1688/1688 - 5s - loss: 0.0387 - accuracy: 0.9932 - val_loss: 0.2602 - val_accura
Epoch 67/1000
1688/1688 - 6s - loss: 0.0398 - accuracy: 0.9952 - val_loss: 0.3723 - val_accura
Epoch 68/1000
```

```
# Calculate accuracy of test set using the trained best model over full training data
score = best_model.evaluate(test_images, test_labels, verbose=0)
print('Best model test accuracy:', score[1])
```

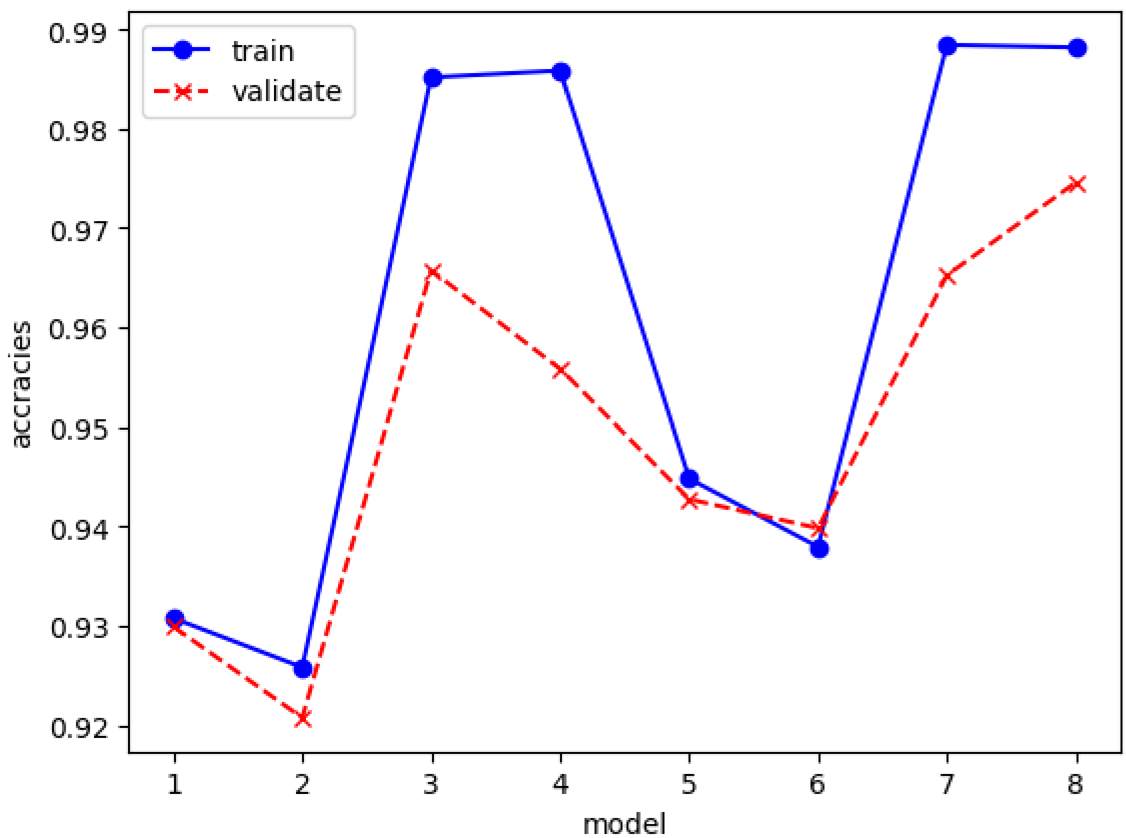
```
Best model test accuracy: 0.9772999882698059
```

3.

Plot the last training and validation accuracies for each hyperparameter combination. This means when you train an MLP corresponding to a hyperparameter combination, save the final training and validation accuracy. Eight different hyperparameter combinations will give you 8 pairs of final training-validation accuracy. Now if you assign indices 1-8 to all hyperparameter combinations (the order of indices doesn't matter here), you can generate a 2D plot such that hyperparameter combination indices can be plotted along the 'x' axis and their corresponding final training accuracy can be plotted along the 'y' axis. Similarly, a plot for hyperparameter combination indices vs.

validation accuracies can be generated. Do you find any similarity in patterns between the two plots? Theoretically, are you supposed to see any similarity between these plots? Please describe in detail.

```
plt.figure()

# Extract model_accuracies dictionary keys and valuess
model = [m +1 for m in list(model_accuracies.keys())]
train_acc = [value[0] for value in model_accuracies.values()]
valid_acc = [value[1] for value in model_accuracies.values()]

# Creat plots
plt.plot(model, train_acc, label='y1', marker='o', linestyle='-', color='blue')
plt.plot(model, valid_acc, label='y2', marker='x', linestyle='--', color='red')


plt.xlabel('model')
plt.ylabel('accracies')
plt.legend(['train', 'validate'])
plt.show()
```



Theoretically, are you supposed to see any similarity between these plots?

By analysing the graph it can see that the model which has the highest train accuracy ,also has the highest validation accuracy regradless the overfitting.

In here its model 3, 4, and 7, 8

the common trait to all these is they all have same activation function. Hence right activation plays a big role in accuracy of the model.