Practical Artificial Intelligence of Image Recognition, Spring 2023 HW4

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In [ ]:
```
# import modules
from keras.datasets import cifar10
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [ ]:
```
# prepare dataset & labels
from keras.utils import np_utils

(x_img_train,y_label_train),(x_img_test,y_label_test)=cifar10.load_data()
x_img_train_normalize = x_img_train.astype('float32') / 255.0
x_img_test_normalize = x_img_test.astype('float32') / 255.0
y_label_train_OneHot = np_utils.to_categorical(y_label_train)
y_label_test_OneHot = np_utils.to_categorical(y_label_test)
```

Part 1: MLP model

In [ ]:
```
# construct the MLP model with 3 128 node fully connected layers
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10 , activation="softmax")
])
```

In [ ]:
```
# compile the model with loss funcion: categorical crossentropy and optim
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# train the model with epoch:10 batch_size: 128
train_history = history = model.fit(x_img_train_normalize, y_label_train_
                        validation_split=0.2,
                        epochs=10, batch_size=128, verbose=1)
```

```
Epoch 1/10
313/313 [==============================] - 3s 7ms/step - loss: 1.9299 - ac
curacy: 0.2942 - val_loss: 1.8035 - val_accuracy: 0.3497
Epoch 2/10
313/313 [==============================] - 2s 6ms/step - loss: 1.7451 - ac
curacy: 0.3728 - val_loss: 1.7160 - val_accuracy: 0.3885
Epoch 3/10
313/313 [==============================] - 2s 6ms/step - loss: 1.6610 - ac
curacy: 0.4045 - val_loss: 1.6403 - val_accuracy: 0.4213
Epoch 4/10
313/313 [==============================] - 2s 6ms/step - loss: 1.6057 - ac
curacy: 0.4252 - val_loss: 1.5778 - val_accuracy: 0.4393
Epoch 5/10
313/313 [==============================] - 2s 6ms/step - loss: 1.5617 - ac
curacy: 0.4401 - val_loss: 1.5542 - val_accuracy: 0.4437
Epoch 6/10
313/313 [==============================] - 1s 5ms/step - loss: 1.5365 - ac
curacy: 0.4473 - val_loss: 1.5658 - val_accuracy: 0.4380
Epoch 7/10
313/313 [==============================] - 1s 4ms/step - loss: 1.5148 - ac
curacy: 0.4578 - val_loss: 1.5317 - val_accuracy: 0.4571
Epoch 8/10
313/313 [==============================] - 2s 6ms/step - loss: 1.4848 - ac
curacy: 0.4699 - val_loss: 1.6246 - val_accuracy: 0.4293
Epoch 9/10
313/313 [==============================] - 2s 6ms/step - loss: 1.4688 - ac
curacy: 0.4735 - val_loss: 1.5838 - val_accuracy: 0.4344
Epoch 10/10
313/313 [==============================] - 2s 6ms/step - loss: 1.4516 - ac
curacy: 0.4799 - val_loss: 1.5271 - val_accuracy: 0.4574
```

In [ ]:

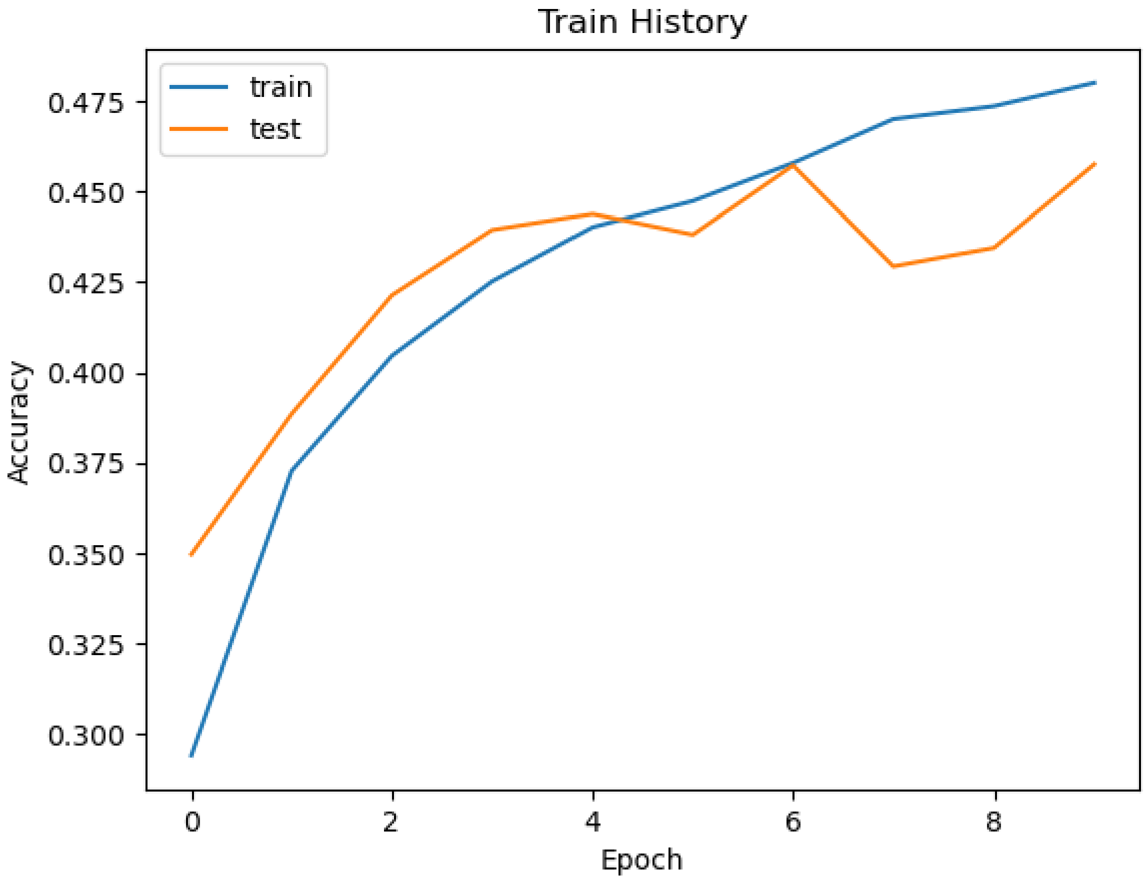
```
import matplotlib.pyplot as plt
# functions for data visualization
def show_acc_train_history(train_acc,test_acc):
    plt.plot(train_history.history[train_acc])
    plt.plot(train_history.history[test_acc])
    plt.title('Train History')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```

In [ ]:

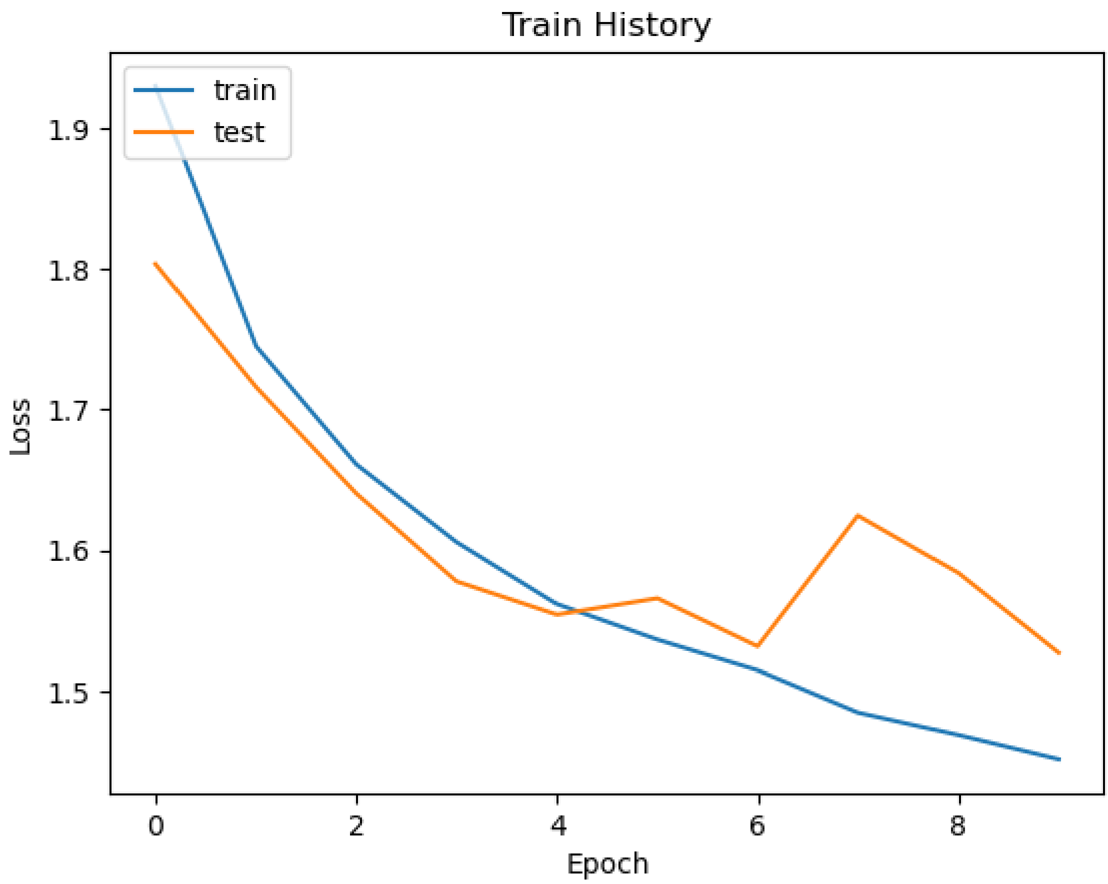
```
def show_loss_train_history(train_loss,test_loss):
    plt.plot(train_history.history[train_loss])
    plt.plot(train_history.history[test_loss])
    plt.title('Train History')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```

In [ ]:

```
show_acc_train_history('accuracy','val_accuracy')
```



In [ ]:
```
show_loss_train_history('loss','val_loss')
```



Part 2: CNN model

In [ ]:
```
data_augmentation = tf.keras.Sequential([
  tf.keras.layers.RandomFlip("horizontal_and_vertical"),
  tf.keras.layers.RandomRotation(0.1),
])
# construct the CNN model with data_augmentation
model = tf.keras.models.Sequential([
  data_augmentation,
  tf.keras.layers.Conv2D(filters=32,kernel_size=(3,3),
                 input_shape=(32, 32,3),
                 activation='relu',
                 padding='same'),
  tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
  tf.keras.layers.Conv2D(filters=64, kernel_size=(3, 3),
                 activation='relu', padding='same'),
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(2048, activation='relu'),
  tf.keras.layers.Dense(1024, activation='relu'),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10 , activation="softmax")
])
```

In [ ]:
```
# compile the model with loss funcion: categorical crossentropy and optim
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# train the model with epoch:10 batch_size: 64
train_history = model.fit(x_img_train_normalize, y_label_train_OneHot,
                        validation_split=0.2,
                        epochs=10, batch_size=64, verbose=1)
```

```
Epoch 1/10
625/625 [==============================] - 12s 15ms/step - loss: 1.7878 -
accuracy: 0.3409 - val_loss: 1.5190 - val_accuracy: 0.4411
Epoch 2/10
625/625 [==============================] - 9s 15ms/step - loss: 1.5063 - a
ccuracy: 0.4514 - val_loss: 1.3935 - val_accuracy: 0.4939
Epoch 3/10
625/625 [==============================] - 9s 15ms/step - loss: 1.4001 - a
ccuracy: 0.4981 - val_loss: 1.3142 - val_accuracy: 0.5297
Epoch 4/10
625/625 [==============================] - 9s 15ms/step - loss: 1.3166 - a
ccuracy: 0.5293 - val_loss: 1.2838 - val_accuracy: 0.5464
Epoch 5/10
625/625 [==============================] - 9s 15ms/step - loss: 1.2551 - a
ccuracy: 0.5510 - val_loss: 1.1902 - val_accuracy: 0.5847
Epoch 6/10
625/625 [==============================] - 9s 15ms/step - loss: 1.2067 - a
ccuracy: 0.5685 - val_loss: 1.2346 - val_accuracy: 0.5654
Epoch 7/10
625/625 [==============================] - 9s 15ms/step - loss: 1.1527 - a
ccuracy: 0.5893 - val_loss: 1.1490 - val_accuracy: 0.5996
Epoch 8/10
625/625 [==============================] - 9s 15ms/step - loss: 1.1216 - a
ccuracy: 0.6015 - val_loss: 1.1350 - val_accuracy: 0.6029
Epoch 9/10
625/625 [==============================] - 9s 15ms/step - loss: 1.0802 - a
ccuracy: 0.6183 - val_loss: 1.0909 - val_accuracy: 0.6229
Epoch 10/10
625/625 [==============================] - 9s 15ms/step - loss: 1.0479 - a
ccuracy: 0.6281 - val_loss: 1.1610 - val_accuracy: 0.6092
```

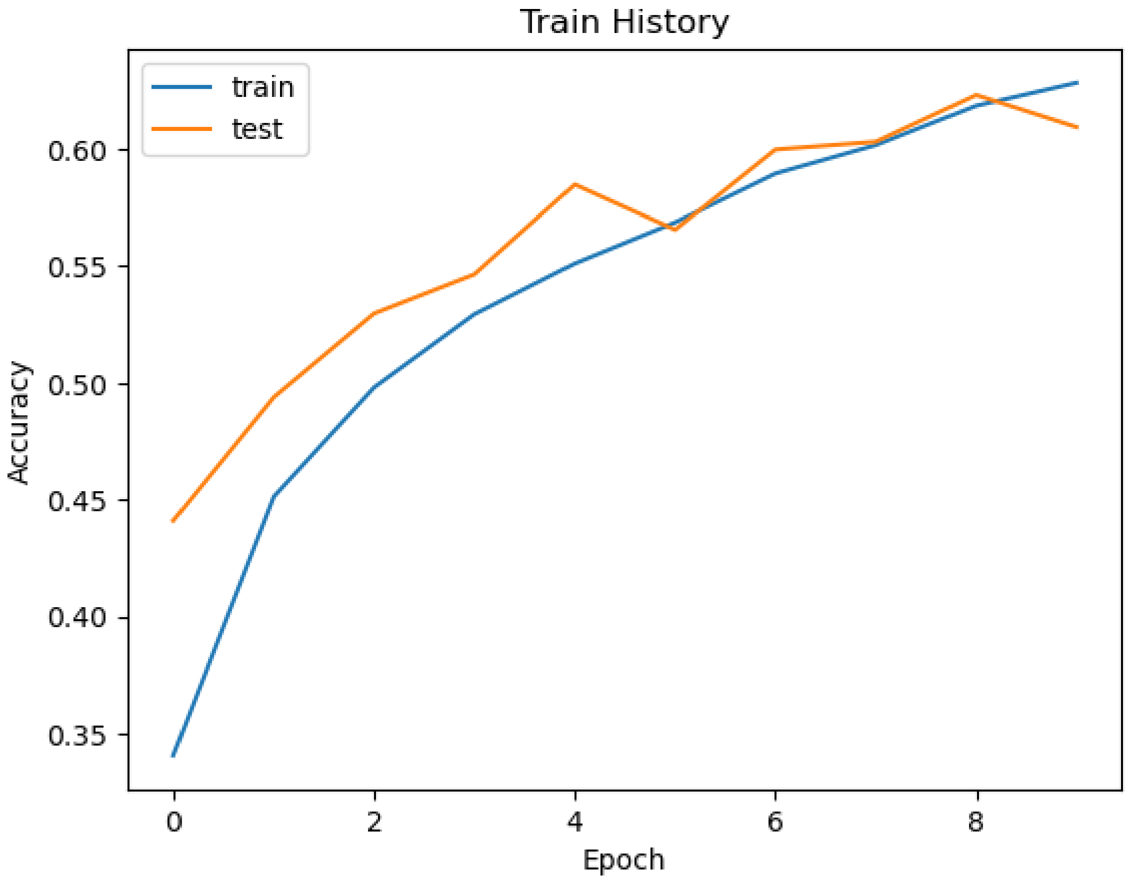
In [ ]:

```
model.summary()
```

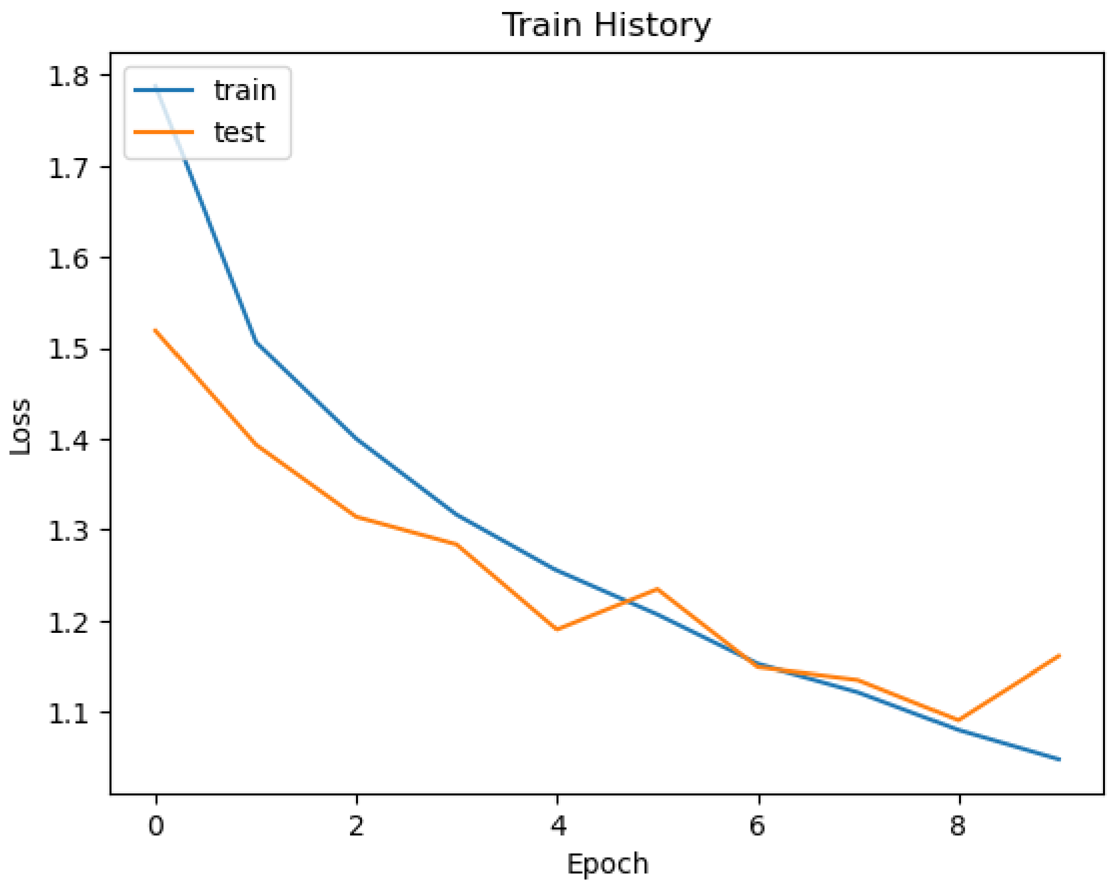
```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 sequential_7 (Sequential)   (None, 32, 32, 3)         0         
                                                                 
 conv2d_4 (Conv2D)           (None, 32, 32, 32)        896       
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 16, 16, 32)       0         
 2D)                                                             
                                                                 
 conv2d_5 (Conv2D)           (None, 16, 16, 64)        18496     
                                                                 
 flatten_5 (Flatten)         (None, 16384)             0         
                                                                 

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 sequential_7 (Sequential)   (None, 32, 32, 3)         0         
                                                                 
 conv2d_4 (Conv2D)           (None, 32, 32, 32)        896       
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 16, 16, 32)       0         
 2D)                                                             
                                                                 
 conv2d_5 (Conv2D)           (None, 16, 16, 64)        18496     
                                                                 
 flatten_5 (Flatten)         (None, 16384)             0         
                                                                 
 dense_20 (Dense)            (None, 2048)              33556480  
                                                                 
 dense_21 (Dense)            (None, 1024)              2098176   
                                                                 
 dense_22 (Dense)            (None, 512)               524800    
                                                                 
 dropout_5 (Dropout)         (None, 512)               0         
                                                                 
 dense_23 (Dense)            (None, 10)                5130      
                                                                 
=================================================================
Total params: 36,203,978
Trainable params: 36,203,978
Non-trainable params: 0
_________________________________________________________________
```

This is the architecture of our model.

In [ ]:
```
show_acc_train_history('accuracy','val_accuracy')
```



In [ ]:
```
show_loss_train_history('loss','val_loss')
```



We can see that our CNN model outperform the MLP model (62% v.s. 48%), and from the accuracy graph, we can see that data augmentation makes our model less prone to overfitting.