Spring 2024:CS5720 Neural Networks & Deep Learning-

ICP-8 Assignment-7

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GitHub Link: https://github.com/SaiSushmaSriBireddy/Assignment7

Video Link: https://drive.google.com/file/d/1FnBy-2V56rWuKXlGAM6N3odnPeX3-CHu/view?usp=sharing

Use Case Description:

LeNet5, AlexNet, Vgg16,

1. Training the model

2. Evaluating the model

Programming elements:

1. About CNN

2. Hyperparameters of CNN

3. Image classification with CNN

In class programming:

1. Tune hyperparameter and make necessary addition to the baseline model to improve validation accuracy and reduce validation loss.

2. Provide logical description of which steps lead to improved response and what was its impact on architecture behavior.

3. Create at least two more visualizations using matplotlib (Other than provided in the source file)

4. Use dataset of your own choice and implement baseline models provided.

5. Apply modified architecture to your own selected dataset and train it.

6. Evaluate your model on testing set.

7. Save the improved model and use it for prediction on testing data

8. Provide plot of confusion matric

9. Provide Training and testing Loss and accuracy plots in one plot using subplot command and history object.

10. Provide at least two more visualizations reflecting your solution.

11. Provide logical description of which steps lead to improved response for new dataset when compared with baseline model and enhance architecture and what was its impact on architecture behavior.

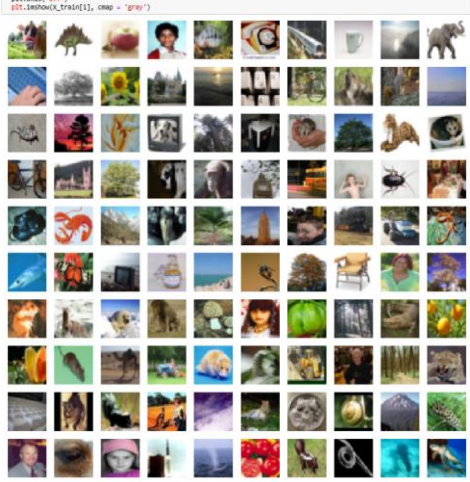
```
In [1]:
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow.keras.datasets import cifar100

from tensorflow.keras.optimizers import RMSprop
from keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout, BatchNormalization

%matplotlib inline
```

```
In [2]:
#Extracting training and testing the dataset
#cifar100 = tf.keras.datasets.cifar100
(X_train,Y_train) , (X_test,Y_test) = cifar100.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-100-python.tar.gz
169001437/169001437 [==============================] - 6s 0us/step
```

```
In [27]:
classes = ['apple', 'aquarium_fish', 'baby', 'bear', 'beaver', 'bed', 'bee', 'beetle', 'bicycle', 'bottle',
```

```
In [3]:
plt.figure(figsize = (16,16))
for i in range(100):
  plt.subplot(10,10,1+i)
  plt.axis('off')
  plt.imshow(X_train[i], cmap = 'gray')
```



```
In [4]:
#Training , Validating and Splitting trained and tested data
from sklearn.model_selection import train_test_split
x_train, x_val, y_train, y_val = train_test_split(X_train,Y_train,test_size=0.2)
```

```
In [6]:
from keras.utils.np_utils import to_categorical
y_train = to_categorical(y_train, num_classes = 100)
```

In [6]:
```python
from keras.utils.np_utils import to_categorical
y_train = to_categorical(y_train, num_classes = 100)
y_val = to_categorical(y_val, num_classes = 100)
```

In [7]:
```python
print(x_train.shape)
print(y_train.shape)
print(x_val.shape)
print(y_val.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(40000, 32, 32, 3)
(40000, 100)
(10000, 32, 32, 3)
(10000, 100)
(10000, 32, 32, 3)
(10000, 1)
```

In [8]:
```python
train_datagen = ImageDataGenerator(
    preprocessing_function = tf.keras.applications.vgg19.preprocess_input,
    rotation_range=10,
    zoom_range = 0.1,
    width_shift_range = 0.1,
    height_shift_range = 0.1,
    shear_range = 0.1,
    horizontal_flip = True
)
train_datagen.fit(x_train)

val_datagen = ImageDataGenerator(preprocessing_function = tf.keras.applications.vgg19.preprocess_input)
val_datagen.fit(x_val)
```

In [9]:
```python
from keras.callbacks import ReduceLROnPlateau
learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy',
                                            patience=3,
                                            verbose=1,
                                            factor=0.5,
                                            min_lr=0.00001)
```

We have used only 16 layers out of 19 layers in the CNN

min_lr=0.00001)

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In [10]:
```python
vgg_model = tf.keras.applications.VGG19(
    include_top=False,
    weights=None,
    input_shape=(32,32,3),
)

vgg_model.summary()
```

Model: "vgg19"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 32, 32, 3)]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv4 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv4 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv4 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0

```
Total params: 20,024,384
Trainable params: 20,024,384
Non-trainable params: 0
```

In [14]:
```python
model = tf.keras.Sequential()
model.add(vgg_model)
model.add(Flatten())
model.add(Dense(1024, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dense(1024, activation = 'relu'))
```

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In [14]:
```python
model = tf.keras.Sequential()
model.add(vgg_model)
model.add(Flatten())
model.add(Dense(1024, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dense(1024, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dense(256, activation = 'relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(100, activation = 'softmax'))

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg19 (Functional)          (None, 1, 1, 512)         20024384

 flatten_1 (Flatten)         (None, 512)               0

 dense_4 (Dense)             (None, 1024)              525312

 batch_normalization_3 (Batc  (None, 1024)             4096
 hNormalization)

 dense_5 (Dense)             (None, 1024)              1049600

 batch_normalization_4 (Batc  (None, 1024)             4096
 hNormalization)

 dense_6 (Dense)             (None, 256)               262400

 batch_normalization_5 (Batc  (None, 256)              1024
 hNormalization)

 dropout_1 (Dropout)         (None, 256)               0

 dense_7 (Dense)             (None, 100)               25700

=================================================================
Total params: 21,896,612
Trainable params: 21,892,004
Non-trainable params: 4,608
_________________________________________________________________
```

In [15]:
```python
optimizer = tf.keras.optimizers.SGD(learning_rate = 0.001, momentum = 0.9)
model.compile(optimizer= optimizer,
          loss='categorical_crossentropy',
          metrics=['accuracy'])
```

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In [16]:
```python
history = model.fit(
    train_datagen.flow(x_train, y_train, batch_size = 128),
    validation_data = val_datagen.flow(x_val,y_val, batch_size = 128),
    epochs = 10,
    verbose = 1,
    callbacks = [learning_rate_reduction]
)
```

```
Epoch 1/10
313/313 [==============================] - 44s 124ms/step - loss: 5.2395 - accuracy: 0.0140 - val_loss: 4.5463 - val_accurac
y: 0.0205 - lr: 0.0010
Epoch 2/10
313/313 [==============================] - 38s 121ms/step - loss: 5.0465 - accuracy: 0.0181 - val_loss: 4.5047 - val_accurac
y: 0.0240 - lr: 0.0010
Epoch 3/10
313/313 [==============================] - 36s 116ms/step - loss: 4.9621 - accuracy: 0.0179 - val_loss: 4.7844 - val_accurac
y: 0.0117 - lr: 0.0010
Epoch 4/10
313/313 [==============================] - 36s 115ms/step - loss: 4.8896 - accuracy: 0.0191 - val_loss: 4.5794 - val_accurac
y: 0.0206 - lr: 0.0010
Epoch 5/10
313/313 [==============================] - 36s 116ms/step - loss: 4.7757 - accuracy: 0.0202 - val_loss: 4.4016 - val_accurac
y: 0.0302 - lr: 0.0010
Epoch 6/10
313/313 [==============================] - 36s 116ms/step - loss: 4.6797 - accuracy: 0.0253 - val_loss: 4.3797 - val_accurac
y: 0.0325 - lr: 0.0010
Epoch 7/10
313/313 [==============================] - 35s 113ms/step - loss: 4.6021 - accuracy: 0.0245 - val_loss: 4.3531 - val_accurac
y: 0.0295 - lr: 0.0010
Epoch 8/10
313/313 [==============================] - 36s 115ms/step - loss: 4.5665 - accuracy: 0.0258 - val_loss: 4.3573 - val_accurac
y: 0.0308 - lr: 0.0010
Epoch 9/10
313/313 [==============================] - 36s 116ms/step - loss: 4.5199 - accuracy: 0.0262 - val_loss: 4.3059 - val_accurac
y: 0.0348 - lr: 0.0010
Epoch 10/10
313/313 [==============================] - 36s 113ms/step - loss: 4.4793 - accuracy: 0.0281 - val_loss: 4.3472 - val_accurac
y: 0.0322 - lr: 0.0010
```

In [17]:
```python
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

plt.figure()
plt.plot(acc,color = 'purple',label = 'Training Acuracy')
plt.plot(val_acc,color = 'blue',label = 'Validation Accuracy')
plt.legend()
```

Out[17]: `<matplotlib.legend.Legend at 0x7f82e645a190>`

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```

Out[17]: <matplotlib.legend.Legend at 0x7f82e645a190>

In [18]:
```
loss = history.history['loss']
val_loss = history.history['val_loss']

plt.figure()
plt.plot(loss,color = 'green',label = 'Training Loss')
plt.plot(val_loss,color = 'red',label = 'Validation Loss')
plt.legend()
```

Out[18]: <matplotlib.legend.Legend at 0x7f82e61622e0>

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```
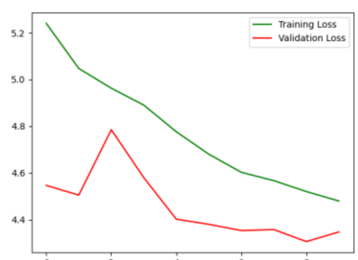

Out[18]: <matplotlib.legend.Legend at 0x7f82e61622e0>



In [19]:
```
X_test = tf.keras.applications.vgg19.preprocess_input(X_test)
y_pred = np.argmax(model.predict(X_test), axis=-1)

y_pred[:10]
```

```
313/313 [==============================] - 3s 9ms/step
```

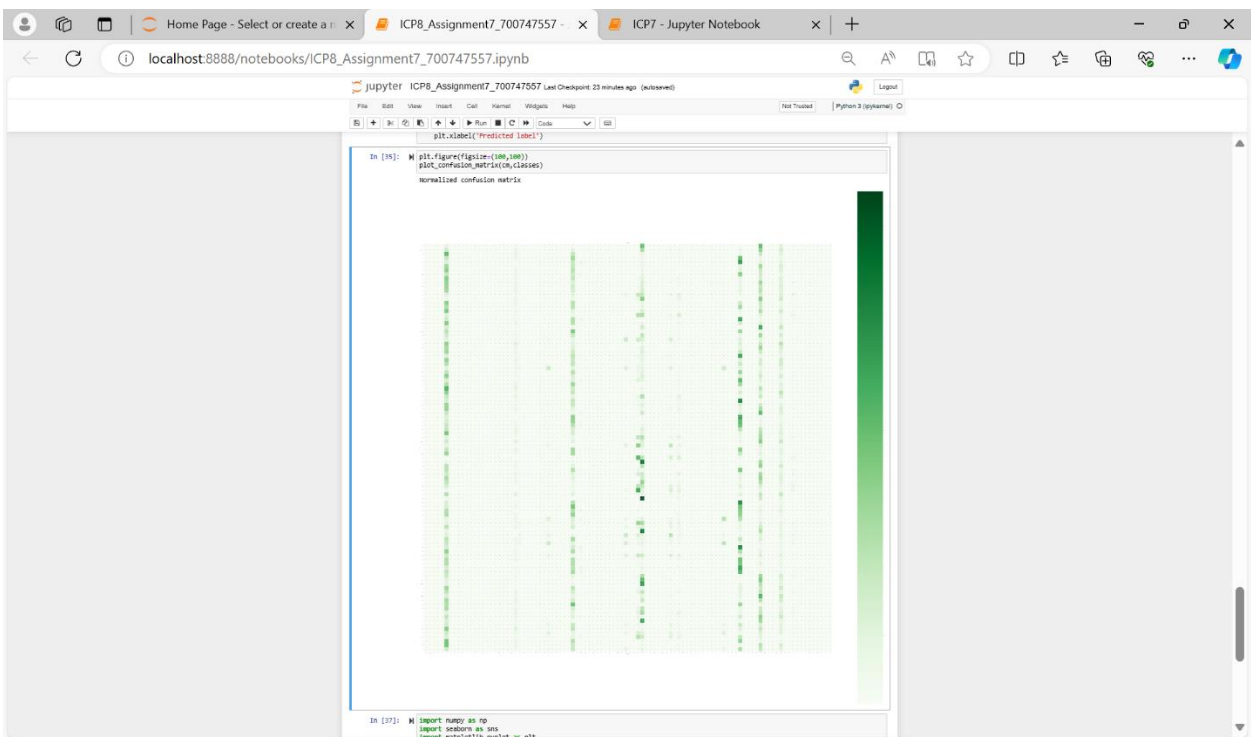
Out[19]: array([53, 77, 36, 5, 87, 77, 77, 77, 52, 82])

In [20]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
print('Testing Accuarcy : ', accuracy_score(Y_test, y_pred))
```

```
Testing Accuarcy :  0.0303
```

```
In [21]:  cm = confusion_matrix(Y_test, y_pred)
          cm

Out[21]:  array([[0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 ...,
                 [0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0]])
```

```
In [30]:  import itertools
          def plot_confusion_matrix(cm, classes,
                                    normalize=True,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Greens):
              """
              This function prints and plots the confusion matrix.
              Normalization can be applied by setting `normalize=True`.
              """
              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              plt.colorbar()
              tick_marks = np.arange(len(classes))
              plt.xticks(tick_marks, classes, rotation=30)
              plt.yticks(tick_marks, classes)

              if normalize:
                  cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                  print("Normalized confusion matrix")
              else:
                  print('Confusion matrix, without normalization')

              #print(cm)

              thresh = cm.max() / 2.
              for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  plt.text(j, i, cm[i, j],
                      horizontalalignment="center",
                      color="white" if cm[i, j] > thresh else "black")

              plt.tight_layout()
              plt.ylabel('True label')
              plt.xlabel('Predicted label')
```



In [37]:

```python
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# assume y_true and y_pred are the true and predicted labels, respectively
# you can obtain them from your model's predictions on a validation set

# calculate the confusion matrix
confusion_matrix = np.zeros((100, 100))
for i in range(len(Y_test)):
    confusion_matrix[Y_test[i], y_pred[i]] += 1

# normalize the confusion matrix
confusion_matrix = confusion_matrix / confusion_matrix.sum(axis=1, keepdims=False)

# create a heatmap using seaborn
sns.set(font_scale=0.5)  # adjust font size to fit more labels
sns.heatmap(confusion_matrix, cmap='Blues', annot=False, xticklabels=False, yticklabels=False)

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```