Experiment_7

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Course Name:	Deep Learning Lab
Course Code:	PMDS603P
Experiment:	7
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0.1 Question 1: First try to fit a simple ANN model with atleast 2 hidden layers and get the accuracy of your model. So that you can compare how the CNN models you are going to fit next will work. Include early stopping in your model as well

0.1.1 Importing necessary libraries

[1]:
```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense, Flatten, Dropout
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
from sklearn.metrics import accuracy_score
import numpy as np

import warnings
warnings.filterwarnings('ignore')
```

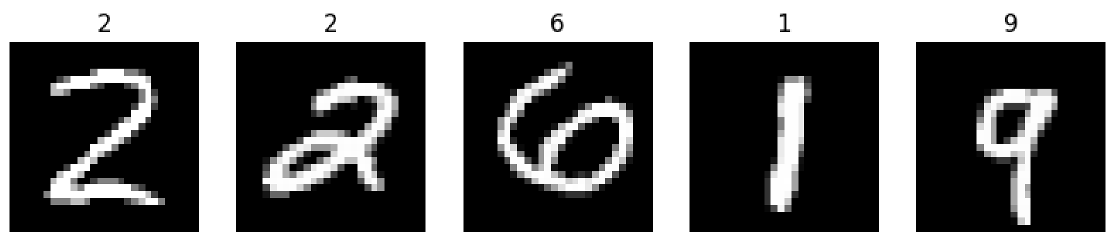
0.1.2 Loading the MNIST dataset

[2]:
```
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train = x_train/255.0
x_test = x_test/255.0
```

0.1.3 Displaying random images

[3]:
```
class_names = [str(i) for i in range(10)]
indices = np.random.choice(len(x_train), size = 5 , replace = False)

plt.figure(figsize = (2*5,3))
for i, idx in enumerate(indices):
    ax = plt.subplot(1,5,i+1)
    img = x_train[idx]
    plt.imshow(img, cmap = 'gray')
    label = class_names[y_train[idx]]
    plt.title(label)
    plt.axis('off')
plt.show()
```



0.1.4 Making the ANN

[5]:
```
model = Sequential()
model.add(Flatten(input_shape = (28,28)))
model.add(Dense(256, activation = 'relu'))
model.add(Dropout(0.3))
model.add(Dense(128, activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(10, activation = 'softmax'))
model.summary()
```

```
Model: "sequential"


 Layer (type)                    Output Shape                  Param #

 flatten (Flatten)               (None, 784)                         0

 dense (Dense)                   (None, 256)                   200,960

 dropout (Dropout)               (None, 256)                         0
```

```
 dense_1 (Dense)                 (None, 128)                 32,896

 dropout_1 (Dropout)             (None, 128)                      0

 dense_2 (Dense)                 (None, 10)                   1,290
```

```
 Total params: 235,146 (918.54 KB)

 Trainable params: 235,146 (918.54 KB)

 Non-trainable params: 0 (0.00 B)
```

[ ]:
```
estop = EarlyStopping(monitor = 'val_loss', min_delta= 1e-4, patience= 5,␣
 ↪verbose = 1, restore_best_weights=True)
model.compile(loss = 'sparse_categorical_crossentropy', optimizer = 'adam',␣
 ↪metrics = ['accuracy'])
```

[7]:
```
history = model.fit(x_train,y_train,batch_size=128, epochs = 200, verbose = 1,␣
 ↪validation_data=(x_test,y_test), callbacks=[estop])
```

```
Epoch 1/200
469/469              3s 5ms/step -
accuracy: 0.8054 - loss: 0.6438 - val_accuracy: 0.9578 - val_loss: 0.1405
Epoch 2/200
469/469              2s 4ms/step -
accuracy: 0.9514 - loss: 0.1642 - val_accuracy: 0.9717 - val_loss: 0.0967
Epoch 3/200
469/469              2s 4ms/step -
accuracy: 0.9643 - loss: 0.1163 - val_accuracy: 0.9759 - val_loss: 0.0787
Epoch 4/200
469/469              2s 4ms/step -
accuracy: 0.9721 - loss: 0.0927 - val_accuracy: 0.9751 - val_loss: 0.0779
Epoch 5/200
469/469              2s 4ms/step -
accuracy: 0.9742 - loss: 0.0807 - val_accuracy: 0.9778 - val_loss: 0.0725
Epoch 6/200
469/469              2s 4ms/step -
accuracy: 0.9792 - loss: 0.0688 - val_accuracy: 0.9811 - val_loss: 0.0663
Epoch 7/200
469/469              2s 4ms/step -
accuracy: 0.9808 - loss: 0.0611 - val_accuracy: 0.9800 - val_loss: 0.0658
Epoch 8/200
469/469              2s 4ms/step -
accuracy: 0.9809 - loss: 0.0588 - val_accuracy: 0.9809 - val_loss: 0.0625
Epoch 9/200
```

```
469/469              2s 4ms/step -
accuracy: 0.9841 - loss: 0.0523 - val_accuracy: 0.9819 - val_loss: 0.0596
Epoch 10/200
469/469              2s 4ms/step -
accuracy: 0.9859 - loss: 0.0445 - val_accuracy: 0.9808 - val_loss: 0.0645
Epoch 11/200
469/469              2s 5ms/step -
accuracy: 0.9848 - loss: 0.0456 - val_accuracy: 0.9824 - val_loss: 0.0612
Epoch 12/200
469/469              2s 5ms/step -
accuracy: 0.9873 - loss: 0.0391 - val_accuracy: 0.9814 - val_loss: 0.0635
Epoch 13/200
469/469              2s 5ms/step -
accuracy: 0.9873 - loss: 0.0367 - val_accuracy: 0.9833 - val_loss: 0.0586
Epoch 14/200
469/469              2s 5ms/step -
accuracy: 0.9888 - loss: 0.0346 - val_accuracy: 0.9809 - val_loss: 0.0692
Epoch 15/200
469/469              2s 5ms/step -
accuracy: 0.9895 - loss: 0.0305 - val_accuracy: 0.9825 - val_loss: 0.0679
Epoch 16/200
469/469              2s 5ms/step -
accuracy: 0.9885 - loss: 0.0333 - val_accuracy: 0.9833 - val_loss: 0.0580
Epoch 17/200
469/469              2s 5ms/step -
accuracy: 0.9902 - loss: 0.0292 - val_accuracy: 0.9823 - val_loss: 0.0631
Epoch 18/200
469/469              2s 5ms/step -
accuracy: 0.9897 - loss: 0.0293 - val_accuracy: 0.9818 - val_loss: 0.0616
Epoch 19/200
469/469              2s 5ms/step -
accuracy: 0.9908 - loss: 0.0274 - val_accuracy: 0.9826 - val_loss: 0.0674
Epoch 20/200
469/469              2s 5ms/step -
accuracy: 0.9900 - loss: 0.0296 - val_accuracy: 0.9817 - val_loss: 0.0649
Epoch 21/200
469/469              2s 5ms/step -
accuracy: 0.9912 - loss: 0.0246 - val_accuracy: 0.9821 - val_loss: 0.0705
Epoch 21: early stopping
Restoring model weights from the end of the best epoch: 16.
```

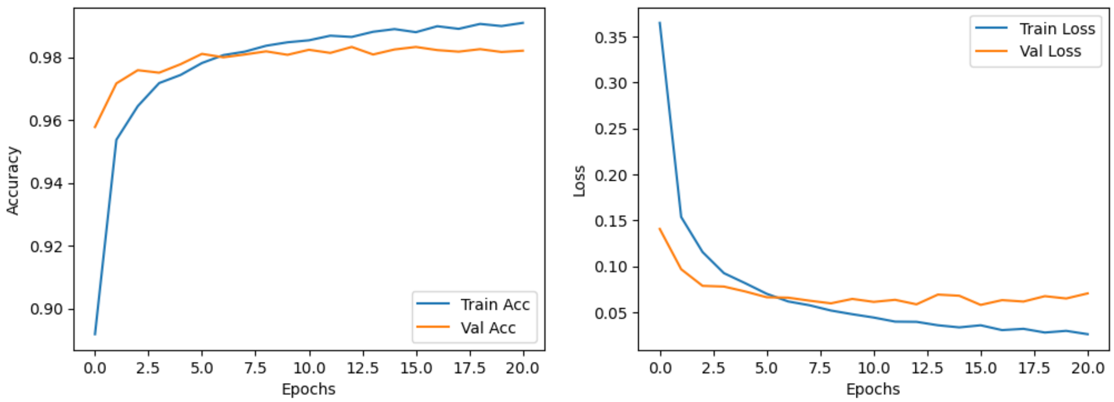
[8]:
```python
loss, val_accuracy = model.evaluate(x_test,y_test)
```

```
313/313              1s 2ms/step -
accuracy: 0.9795 - loss: 0.0711
```

[9]:
```python
print(f"Validation Accuracy with ANN model: {val_accuracy*100:.4f}%")
```

```
Validation Accuracy with ANN model: 98.3300%
```

[10]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.xlabel("Epochs")
plt.ylabel('Loss')
plt.legend()
plt.show()
```



0.2 Question 2: Now let us try to fit a CNN model to accomplish the same task and look at the improvements. Import necessary modules and functions first. Here you can see we are including the Conv2D and MaxPool2d layers from keras.layers.

[12]:
```
from tensorflow import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Flatten, Conv2D, MaxPool2D
from keras.optimizers import Adam, RMSprop
from keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
```

[ ]:
```
(x_train,y_train),(x_test,y_test) = mnist.load_data()
x_train = x_train/255.0
x_test = x_test/255.0
x_train = x_train.reshape(-1,28,28,1)
```

```
x_test = x_test.reshape(-1,28,28,1)
```

0.2.1 Creating the CNN model

[15]:
```
model = Sequential()
model.add(Conv2D(26,5, strides = (1,1), activation = 'relu', padding='valid',␣
 ↪input_shape = (28,28,1)))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2), padding='valid'))
model.add(Conv2D(20,3, strides = (1,1), activation = 'relu', padding='valid'))
model.add(MaxPool2D(pool_size=(2,2), strides=(1,1), padding='valid'))
model.add(Conv2D(10,3, strides = (1,1), activation = 'relu', padding='valid'))
model.add(MaxPool2D(pool_size=(2,2), strides=(1,1), padding='valid'))
model.add(Flatten())
model.add(Dense(100, activation = 'relu'))
model.add(Dense(10, activation='softmax'))
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 24, 24, 26)	676
max_pooling2d (MaxPooling2D)	(None, 12, 12, 26)	0
conv2d_1 (Conv2D)	(None, 10, 10, 20)	4,700
max_pooling2d_1 (MaxPooling2D)	(None, 9, 9, 20)	0
conv2d_2 (Conv2D)	(None, 7, 7, 10)	1,810
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 10)	0
flatten_1 (Flatten)	(None, 360)	0
dense_3 (Dense)	(None, 100)	36,100
dense_4 (Dense)	(None, 10)	1,010

Total params: 44,296 (173.03 KB)

Trainable params: 44,296 (173.03 KB)

Non-trainable params: 0 (0.00 B)

[16]:
```
estop = EarlyStopping(monitor = 'val_loss', min_delta= 1e-4, patience= 5,␣
↪verbose = 1, restore_best_weights=True)
model.compile(loss = 'sparse_categorical_crossentropy', optimizer = 'rmsprop',␣
↪metrics = ['accuracy'])
```

[17]:
```
history = model.fit(x_train,y_train,batch_size=128, epochs = 200, verbose = 1,␣
↪validation_data=(x_test,y_test), callbacks=[estop])
```

```
Epoch 1/200
469/469              6s 12ms/step -
accuracy: 0.8025 - loss: 0.6023 - val_accuracy: 0.9761 - val_loss: 0.0748
Epoch 2/200
469/469              6s 13ms/step -
accuracy: 0.9697 - loss: 0.0947 - val_accuracy: 0.9678 - val_loss: 0.0981
Epoch 3/200
469/469              6s 14ms/step -
accuracy: 0.9818 - loss: 0.0587 - val_accuracy: 0.9877 - val_loss: 0.0358
Epoch 4/200
469/469              7s 15ms/step -
accuracy: 0.9856 - loss: 0.0443 - val_accuracy: 0.9886 - val_loss: 0.0380
Epoch 5/200
469/469              7s 15ms/step -
accuracy: 0.9883 - loss: 0.0376 - val_accuracy: 0.9828 - val_loss: 0.0541
Epoch 6/200
469/469              6s 14ms/step -
accuracy: 0.9904 - loss: 0.0305 - val_accuracy: 0.9905 - val_loss: 0.0334
Epoch 7/200
469/469              6s 14ms/step -
accuracy: 0.9905 - loss: 0.0292 - val_accuracy: 0.9907 - val_loss: 0.0310
Epoch 8/200
469/469              7s 14ms/step -
accuracy: 0.9932 - loss: 0.0233 - val_accuracy: 0.9863 - val_loss: 0.0450
Epoch 9/200
469/469              6s 13ms/step -
accuracy: 0.9933 - loss: 0.0216 - val_accuracy: 0.9922 - val_loss: 0.0277
Epoch 10/200
469/469              6s 14ms/step -
accuracy: 0.9936 - loss: 0.0203 - val_accuracy: 0.9916 - val_loss: 0.0297
Epoch 11/200
469/469              6s 13ms/step -
accuracy: 0.9941 - loss: 0.0177 - val_accuracy: 0.9917 - val_loss: 0.0261
Epoch 12/200
469/469              7s 14ms/step -
accuracy: 0.9956 - loss: 0.0141 - val_accuracy: 0.9920 - val_loss: 0.0287
Epoch 13/200
```

```
469/469              6s 13ms/step -
accuracy: 0.9955 - loss: 0.0146 - val_accuracy: 0.9925 - val_loss: 0.0309
Epoch 14/200
469/469              6s 13ms/step -
accuracy: 0.9964 - loss: 0.0120 - val_accuracy: 0.9908 - val_loss: 0.0356
Epoch 15/200
469/469              7s 15ms/step -
accuracy: 0.9963 - loss: 0.0122 - val_accuracy: 0.9893 - val_loss: 0.0424
Epoch 16/200
469/469              6s 13ms/step -
accuracy: 0.9970 - loss: 0.0097 - val_accuracy: 0.9916 - val_loss: 0.0351
Epoch 16: early stopping
Restoring model weights from the end of the best epoch: 11.
```

[18]:

```
loss, val_accuracy = model.evaluate(x_test,y_test)
```

```
313/313              1s 3ms/step -
accuracy: 0.9898 - loss: 0.0320
```

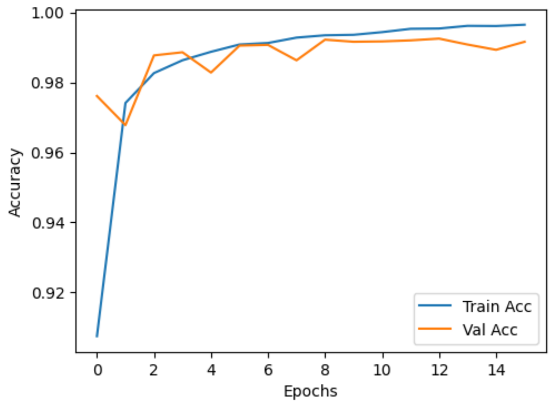
[19]:

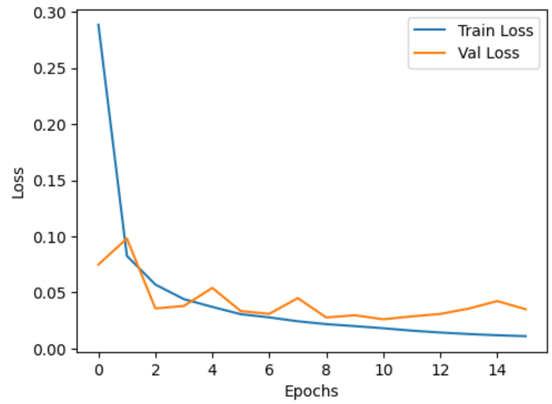
```
print(f"Validation Accuracy with CNN model: {val_accuracy*100:.4f}%")
```

```
Validation Accuracy with CNN model: 99.1700%
```

[20]:

```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.xlabel("Epochs")
plt.ylabel('Loss')
plt.legend()
plt.show()
```





0.3 Question 3: Now you can try to fit a CNN model with CIFAR10 dataset we have seen in the previous lab with an appropriate model. See whether you get an improved accuracy for the model when you are using CNN models

[21]:
```
(x_train,y_train),(x_test,y_test) = keras.datasets.cifar10.load_data()
x_train = x_train/255.0
x_test = x_test/255.0
```

0.3.1 Displaying random images from the dataset

[22]:
```
class_names = ["Airplane","Automobile","Bird","Cat","Deer",
"Dog","Frog","Horse","Ship","Truck"]
indices = np.random.choice(len(x_train), size = 5 , replace = False)
plt.figure(figsize = (2*5,3))
for i, idx in enumerate(indices):
    ax = plt.subplot(1,5,i+1)
    img = x_train[idx]
    plt.imshow(img)
    label = class_names[y_train[idx][0]]
    plt.title(label)
    plt.axis('off')
plt.show()
```

0.3.2 Building the CNN model

[24]:
```
model = Sequential()
model.add(Conv2D(32,5, strides = (1,1), activation = 'relu', padding='same',␣
 ↪input_shape = x_train.shape[1:]))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2), padding='valid'))
model.add(Dropout(0.5))
model.add(Conv2D(32,3, strides = (1,1), activation = 'relu', padding='same'))
model.add(MaxPool2D(pool_size=(2,2), strides=(1,1), padding='same'))
model.add(Dropout(0.3))
model.add(Conv2D(64,3, strides = (1,1), activation = 'relu', padding='same'))
model.add(MaxPool2D(pool_size=(2,2), strides=(1,1), padding='valid'))
model.add(Dropout(0.2))
model.add(Flatten())
model.add(Dense(256, activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(128, activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 32, 32, 32)	2,432
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 32)	0
dropout_2 (Dropout)	(None, 16, 16, 32)	0
conv2d_4 (Conv2D)	(None, 16, 16, 32)	9,248
max_pooling2d_4 (MaxPooling2D)	(None, 16, 16, 32)	0
dropout_3 (Dropout)	(None, 16, 16, 32)	0
conv2d_5 (Conv2D)	(None, 16, 16, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 15, 15, 64)	0
dropout_4 (Dropout)	(None, 15, 15, 64)	0
flatten_2 (Flatten)	(None, 14400)	0
dense_5 (Dense)	(None, 256)	3,686,656

```
dropout_5 (Dropout)            (None, 256)                     0

dense_6 (Dense)                (None, 128)                32,896

dropout_6 (Dropout)            (None, 128)                     0

dense_7 (Dense)                (None, 10)                  1,290
```

Total params: 3,751,018 (14.31 MB)

Trainable params: 3,751,018 (14.31 MB)

Non-trainable params: 0 (0.00 B)

[25]:
```
estop = EarlyStopping(monitor = 'val_loss', min_delta= 1e-4, patience= 5,␣
 ↪verbose = 1, restore_best_weights=True)
model.compile(loss = 'sparse_categorical_crossentropy', optimizer = 'adam',␣
 ↪metrics = ['accuracy'])
```

[26]:
```
history = model.fit(x_train,y_train,batch_size=128, epochs = 200, verbose = 1,␣
 ↪validation_data=(x_test,y_test), callbacks=[estop])
```

```
Epoch 1/200
391/391              42s 102ms/step -
accuracy: 0.2432 - loss: 2.0091 - val_accuracy: 0.4601 - val_loss: 1.5177
Epoch 2/200
391/391              43s 110ms/step -
accuracy: 0.4584 - loss: 1.4745 - val_accuracy: 0.5367 - val_loss: 1.2985
Epoch 3/200
391/391              36s 93ms/step -
accuracy: 0.5290 - loss: 1.3127 - val_accuracy: 0.5738 - val_loss: 1.1988
Epoch 4/200
391/391              36s 92ms/step -
accuracy: 0.5711 - loss: 1.2005 - val_accuracy: 0.5973 - val_loss: 1.1224
Epoch 5/200
391/391              62s 158ms/step -
accuracy: 0.6028 - loss: 1.1177 - val_accuracy: 0.5804 - val_loss: 1.1996
Epoch 6/200
391/391              70s 179ms/step -
accuracy: 0.6270 - loss: 1.0588 - val_accuracy: 0.6431 - val_loss: 1.0033
Epoch 7/200
391/391              61s 155ms/step -
accuracy: 0.6525 - loss: 0.9932 - val_accuracy: 0.6644 - val_loss: 0.9693
Epoch 8/200
```

```
391/391             46s 117ms/step -
accuracy: 0.6660 - loss: 0.9487 - val_accuracy: 0.6826 - val_loss: 0.8955
Epoch 9/200
391/391             47s 121ms/step -
accuracy: 0.6765 - loss: 0.9172 - val_accuracy: 0.6811 - val_loss: 0.9246
Epoch 10/200
391/391             41s 105ms/step -
accuracy: 0.6872 - loss: 0.8855 - val_accuracy: 0.6827 - val_loss: 0.9187
Epoch 11/200
391/391             45s 114ms/step -
accuracy: 0.6980 - loss: 0.8572 - val_accuracy: 0.6887 - val_loss: 0.8899
Epoch 12/200
391/391             60s 154ms/step -
accuracy: 0.7095 - loss: 0.8182 - val_accuracy: 0.6826 - val_loss: 0.9365
Epoch 13/200
391/391             58s 149ms/step -
accuracy: 0.7153 - loss: 0.8114 - val_accuracy: 0.7134 - val_loss: 0.8171
Epoch 14/200
391/391             55s 141ms/step -
accuracy: 0.7240 - loss: 0.7793 - val_accuracy: 0.6892 - val_loss: 0.9158
Epoch 15/200
391/391             47s 121ms/step -
accuracy: 0.7265 - loss: 0.7747 - val_accuracy: 0.6833 - val_loss: 0.9396
Epoch 16/200
391/391             43s 110ms/step -
accuracy: 0.7339 - loss: 0.7522 - val_accuracy: 0.7189 - val_loss: 0.8089
Epoch 17/200
391/391             43s 109ms/step -
accuracy: 0.7401 - loss: 0.7380 - val_accuracy: 0.7099 - val_loss: 0.8359
Epoch 18/200
391/391             43s 111ms/step -
accuracy: 0.7448 - loss: 0.7270 - val_accuracy: 0.7197 - val_loss: 0.8131
Epoch 19/200
391/391             45s 116ms/step -
accuracy: 0.7515 - loss: 0.6976 - val_accuracy: 0.7342 - val_loss: 0.7767
Epoch 20/200
391/391             52s 133ms/step -
accuracy: 0.7533 - loss: 0.7006 - val_accuracy: 0.6721 - val_loss: 1.0006
Epoch 21/200
391/391             45s 116ms/step -
accuracy: 0.7540 - loss: 0.6898 - val_accuracy: 0.7278 - val_loss: 0.7985
Epoch 22/200
391/391             51s 129ms/step -
accuracy: 0.7617 - loss: 0.6690 - val_accuracy: 0.7322 - val_loss: 0.7815
Epoch 23/200
391/391             46s 119ms/step -
accuracy: 0.7739 - loss: 0.6405 - val_accuracy: 0.7308 - val_loss: 0.7874
Epoch 24/200
```

```
391/391                   52s 133ms/step -
accuracy: 0.7718 - loss: 0.6396 - val_accuracy: 0.7250 - val_loss: 0.8232
Epoch 24: early stopping
Restoring model weights from the end of the best epoch: 19.
```

[27]:
```python
loss, val_accuracy = model.evaluate(x_test,y_test)
```

```
313/313                   4s 13ms/step -
accuracy: 0.7305 - loss: 0.7857
```

[28]:
```python
print(f"Validation Accuracy of Cifar10 dataset with CNN model:␣
  ↪{val_accuracy*100:.4f}%")
```

```
Validation Accuracy of Cifar10 dataset with CNN model: 73.4200%
```

[29]:
```python
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.xlabel("Epochs")
plt.ylabel('Loss')
plt.legend()
plt.show()
```