

▼ Homework 2 - Implementing a CNN for CIFAR-10 dataset

Part1 - implementation of a basic convolutional neural network

▼ Importing needed libraries

```
import tensorflow as tf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

▼ loading dataset

```
(X_trainData, Y_trainData), (X_testData, Y_testData) = tf.keras.datasets.cifar10.load_data
```

▼ Reshape dataset

convert labels to one-hot encoding

```
from tensorflow.keras.utils import to_categorical

cat_y_trainData = to_categorical(Y_trainData, num_classes=10)
cat_y_testData = to_categorical(Y_testData, num_classes=10)
```

▼ Normalization

between 0 , 1 and float32

```
X_trainData = X_trainData.astype(np.float32) / 255.0
X_testData = X_testData.astype(np.float32) / 255.0
```

▼ Creat our basic CNN model with stacking convelution and pooling layer

importing layers and models

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Dropout, MaxPool2D, Conv2D, Flatten, Glo
```

▼ creating the model

```
input = Input(shape=(32, 32, 3))

x = Conv2D(32, (3, 3), activation='relu', padding='same')(input)
x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = MaxPool2D((2, 2))(x)

x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = MaxPool2D((2, 2))(x)

x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)
x = MaxPool2D((2, 2))(x)

x = Flatten()(x)
x = Dropout(0.2)(x)

x = Dense(units=128)(x)
x = ReLU()(x)

x = Dense(units=10)(x)
predictions = Activation(activation='softmax')(x)

our_CNN_model = Model(input, predictions)
```

▼ print summary

```
our_CNN_model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	[(None, 32, 32, 3)]	0
conv2d (Conv2D)	(None, 32, 32, 32)	896
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496

conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
max_pooling2d_1 (MaxPooling 2D)	(None, 8, 8, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
max_pooling2d_2 (MaxPooling 2D)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
dense (Dense)	(None, 128)	262272
re_lu (ReLU)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1290
activation (Activation)	(None, 10)	0

=====

Total params: 550,570
 Trainable params: 550,570
 Non-trainable params: 0

▼ Compile the model with optimizer and loss function

```
our_CNN_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

▼ Train the model

```
our_CNN_model.fit(x=X_trainData, y=cat_y_trainData, epochs=35, batch_size=32,
                  validation_data=(X_testData, cat_y_testData))
```

```
Epoch 8/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.2925 - accuracy: 0.7500
Epoch 9/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.2715 - accuracy: 0.7692
Epoch 10/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2578 - accuracy: 0.7879
Epoch 11/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2487 - accuracy: 0.8000
Epoch 12/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2357 - accuracy: 0.8125
Epoch 13/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2270 - accuracy: 0.8250
Epoch 14/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.2138 - accuracy: 0.8375
```

```

Epoch 15/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2141 - accuracy
Epoch 16/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2057 - accuracy
Epoch 17/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.2045 - accuracy
Epoch 18/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1984 - accuracy
Epoch 19/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1869 - accuracy
Epoch 20/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1946 - accuracy
Epoch 21/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1823 - accuracy
Epoch 22/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1845 - accuracy
Epoch 23/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1778 - accuracy
Epoch 24/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1749 - accuracy
Epoch 25/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1734 - accuracy
Epoch 26/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1721 - accuracy
Epoch 27/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1679 - accuracy
Epoch 28/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1664 - accuracy
Epoch 29/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1682 - accuracy
Epoch 30/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1640 - accuracy
Epoch 31/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1655 - accuracy
Epoch 32/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1633 - accuracy
Epoch 33/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1571 - accuracy
Epoch 34/35
1563/1563 [=====] - 9s 6ms/step - loss: 0.1617 - accuracy
Epoch 35/35
1563/1563 [=====] - 10s 6ms/step - loss: 0.1545 - accuracy
<keras.callbacks.History at 0x7f478e337b50>

```

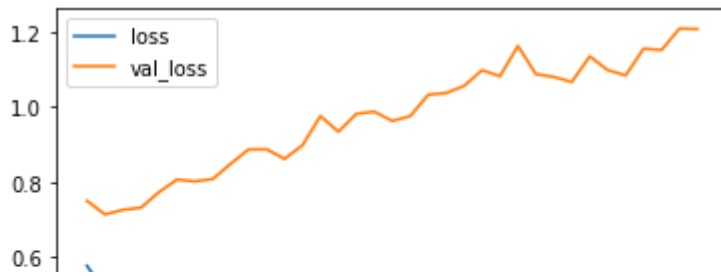
▼ plot model loss history

```

plot_history = pd.DataFrame(our_CNN_model.history.history)
plot_history[['loss', 'val_loss']].plot()

```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f478e331c50>
```



▼ min of loss history

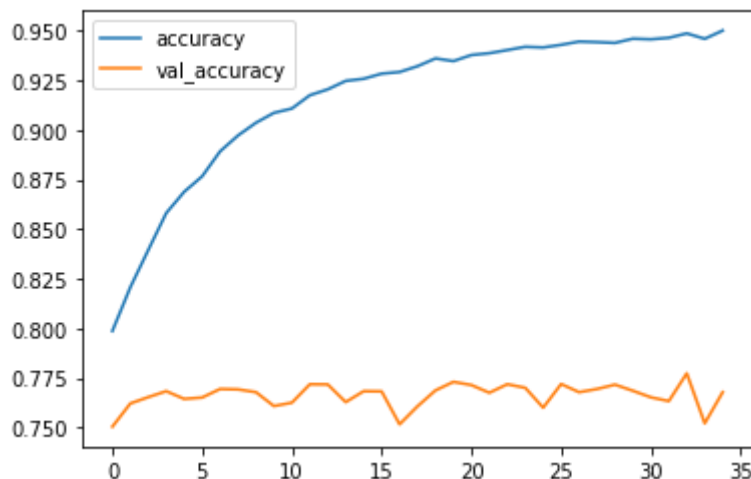
```
np.min(our_CNN_model.history.history['loss'])
```

0.15448826551437378

▼ plot model accuracy

```
plot_history = pd.DataFrame(our_CNN_model.history.history)
plot_history[['accuracy', 'val_accuracy']].plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f478e1cd8d0>
```



▼ max of validation accuracy

```
np.max(our_CNN_model.history.history['val_accuracy'])
```

0.7773000001907349

▼ Evalute the model

```
our_CNN_model.evaluate(X_testData, cat_y_testData)
```

313/313 [=====] - 1s 4ms/step - loss: 1.2077 - accuracy: 0.7

[1.2077003717422485, 0.767799973487854]



▼ Part2 - check the effect of layer's depth on the resalut

▼ We use more hidden layers and GlobalArrangePooling

```
input = Input(shape=(32, 32, 3))

x = Conv2D(filters=32, kernel_size=(3, 3), strides=1, padding='same')(input)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=64, kernel_size=(3, 3), strides=1, padding='same')(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=128, kernel_size=(3, 3), strides=1, padding='same')(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=256, kernel_size=(3, 3), strides=1, padding='same')(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=512, kernel_size=(3, 3), strides=1, padding='same')(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

#globalaveragepooling
x = GlobalAveragePooling2D()(x)

x = Dense(units=128)(x)
x = ReLU()(x)

x = Dense(units=32)(x)
x = ReLU()(x)
x = Dense(units=10)(x)
predictions = Activation(activation='softmax')(x)

our_CNN_model2 = Model(input, predictions)
```

▼ Getting a summary

```
our_CNN_model2.summary()
```

input_5 (InputLayer)	[(None, 32, 32, 3)]	0
conv2d_8 (Conv2D)	(None, 32, 32, 32)	896
re_lu_1 (ReLU)	(None, 32, 32, 32)	0
max_pooling2d_3 (MaxPooling 2D)	(None, 16, 16, 32)	0
conv2d_9 (Conv2D)	(None, 16, 16, 64)	18496
re_lu_2 (ReLU)	(None, 16, 16, 64)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 8, 8, 64)	0
conv2d_10 (Conv2D)	(None, 8, 8, 128)	73856
re_lu_3 (ReLU)	(None, 8, 8, 128)	0
max_pooling2d_5 (MaxPooling 2D)	(None, 4, 4, 128)	0
conv2d_11 (Conv2D)	(None, 4, 4, 256)	295168
re_lu_4 (ReLU)	(None, 4, 4, 256)	0
max_pooling2d_6 (MaxPooling 2D)	(None, 2, 2, 256)	0
conv2d_12 (Conv2D)	(None, 2, 2, 512)	1180160
re_lu_5 (ReLU)	(None, 2, 2, 512)	0
max_pooling2d_7 (MaxPooling 2D)	(None, 1, 1, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense_2 (Dense)	(None, 128)	65664
re_lu_6 (ReLU)	(None, 128)	0
dense_3 (Dense)	(None, 32)	4128
re_lu_7 (ReLU)	(None, 32)	0
dense_4 (Dense)	(None, 10)	330
activation_1 (Activation)	(None, 10)	0

=====

Total params: 1,638,698
Trainable params: 1,638,698

Non-trainable params: 0

▼ compile and training the model

```
our_CNN_model2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
our_CNN_model2.fit(x=X_trainData, y=cat_y_trainData, epochs=50, batch_size=32, validation_data=(X_valData, cat_y_valData))
```

```
1563/1563 [=====] - 10s 6ms/step - loss: 0.0999 - accuracy: 0.8999 ->
Epoch 24/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0966 - accuracy: 0.9034
Epoch 25/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0924 - accuracy: 0.9069
Epoch 26/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0856 - accuracy: 0.9104
Epoch 27/50

1563/1563 [=====] - 10s 6ms/step - loss: 0.0820 - accuracy: 0.9139
Epoch 28/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0797 - accuracy: 0.9174
Epoch 29/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0866 - accuracy: 0.9109
Epoch 30/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0768 - accuracy: 0.9244
Epoch 31/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0855 - accuracy: 0.9179
Epoch 32/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0711 - accuracy: 0.9314
Epoch 33/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0731 - accuracy: 0.9279
Epoch 34/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0684 - accuracy: 0.9344
Epoch 35/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0730 - accuracy: 0.9279
Epoch 36/50
1563/1563 [=====] - 11s 7ms/step - loss: 0.0652 - accuracy: 0.9414
Epoch 37/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0735 - accuracy: 0.9279
Epoch 38/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0696 - accuracy: 0.9344
Epoch 39/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0641 - accuracy: 0.9414
Epoch 40/50
1563/1563 [=====] - 10s 7ms/step - loss: 0.0615 - accuracy: 0.9449
Epoch 41/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0614 - accuracy: 0.9449
Epoch 42/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0636 - accuracy: 0.9414
Epoch 43/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0630 - accuracy: 0.9414
Epoch 44/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0675 - accuracy: 0.9379
Epoch 45/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0565 - accuracy: 0.9514
Epoch 46/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0584 - accuracy: 0.9479
Epoch 47/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0566 - accuracy: 0.9514
Epoch 48/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0530 - accuracy: 0.9549
Epoch 49/50
1563/1563 [=====] - 10s 6ms/step - loss: 0.0546 - accuracy: 0.9514
Epoch 50/50
```

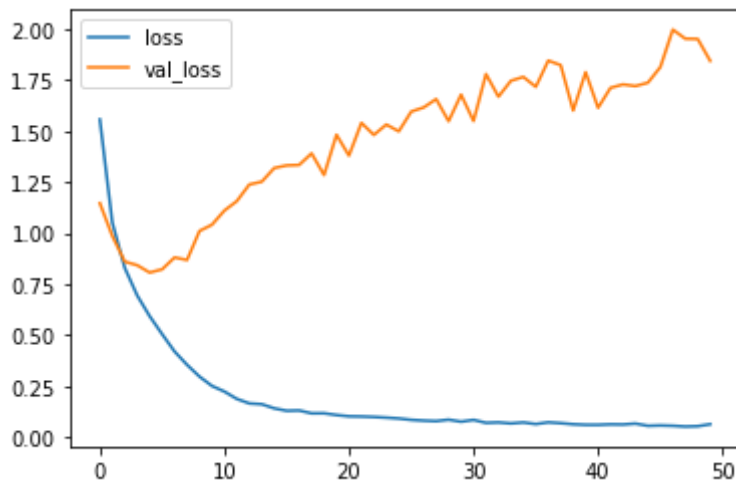


```
epoch 50/50
```

```
1563/1563 [=====] - 10s 6ms/step - loss: 0.0643 - accuracy: 0.9734  
<keras.callbacks.History at 0x7f478e1b1510>
```

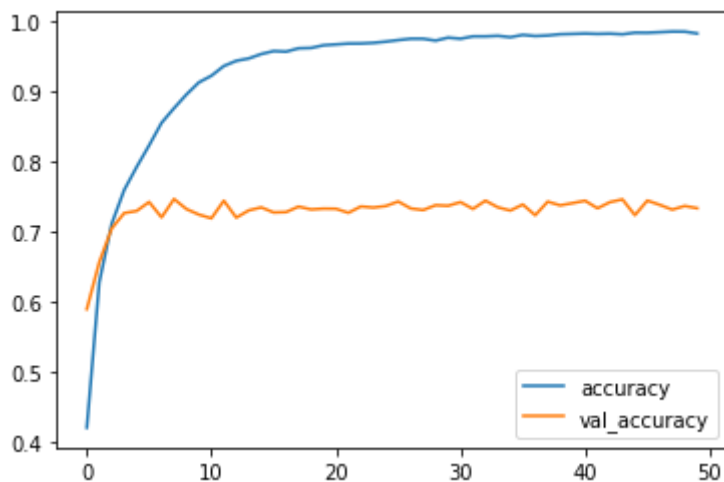
```
plot_history = pd.DataFrame(our_CNN_model2.history.history)  
plot_history[['loss', 'val_loss']].plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f47368e88d0>
```



```
plot_history[['accuracy', 'val_accuracy']].plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f47021e8ed0>
```



▼ Evaluate the model

```
our_CNN_model2.evaluate(X_testData, cat_y_testData)
```

```
313/313 [=====] - 1s 4ms/step - loss: 1.8434 - accuracy: 0.7324  
[1.8434138298034668, 0.7324000000953674]
```

Part3 - check the early-stopping technic to reach an optimum model

use early-stopping in our model

to reach a fewer loss and a better accuracy

```
from tensorflow.keras.callbacks import EarlyStopping
```

```
early_stopping = EarlyStopping(monitor='val_loss', mode='min', patience=10, restore_best_weights=True)
```

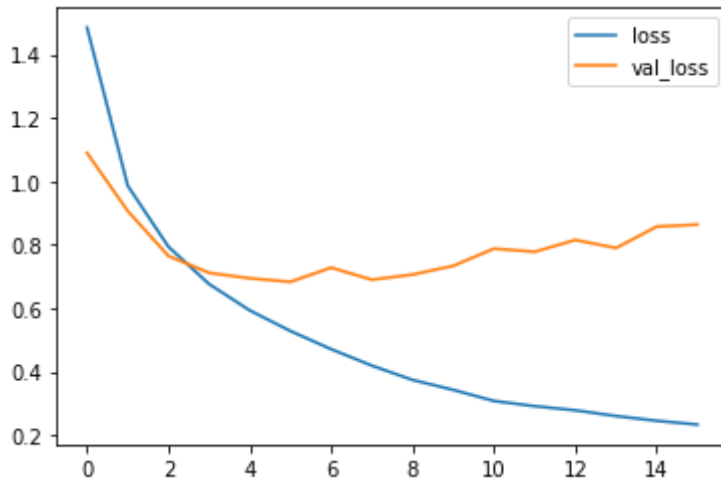
```
our_CNN_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
our_CNN_model.fit(x=X_trainData, y=cat_y_trainData, epochs=40, batch_size=32,
                  validation_data=(X_testData, cat_y_testData), callbacks=[early_stopping])
```

```
Epoch 1/40
1563/1563 [=====] - 13s 7ms/step - loss: 1.4843 - accuracy: 0.1500
Epoch 2/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.9856 - accuracy: 0.2500
Epoch 3/40
1563/1563 [=====] - 10s 6ms/step - loss: 0.7936 - accuracy: 0.3500
Epoch 4/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.6757 - accuracy: 0.4000
Epoch 5/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.5926 - accuracy: 0.4500
Epoch 6/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.5276 - accuracy: 0.5000
Epoch 7/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.4705 - accuracy: 0.5500
Epoch 8/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.4186 - accuracy: 0.6000
Epoch 9/40
1563/1563 [=====] - 10s 6ms/step - loss: 0.3735 - accuracy: 0.6500
Epoch 10/40
1563/1563 [=====] - 10s 6ms/step - loss: 0.3422 - accuracy: 0.7000
Epoch 11/40
1563/1563 [=====] - 10s 7ms/step - loss: 0.3072 - accuracy: 0.7500
Epoch 12/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.2908 - accuracy: 0.8000
Epoch 13/40
1563/1563 [=====] - 10s 6ms/step - loss: 0.2778 - accuracy: 0.8500
Epoch 14/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.2598 - accuracy: 0.9000
Epoch 15/40
1563/1563 [=====] - 9s 6ms/step - loss: 0.2447 - accuracy: 0.9500
Epoch 16/40
1563/1563 [=====] - 10s 6ms/step - loss: 0.2329 - accuracy: 0.9500
<keras.callbacks.History at 0x7faf9001df50>
```

▼ plot model loss history

```
plot_history = pd.DataFrame(our_CNN_model.history.history)
plot_history[['loss', 'val_loss']].plot()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7faf420eb050>



▼ min of loss history

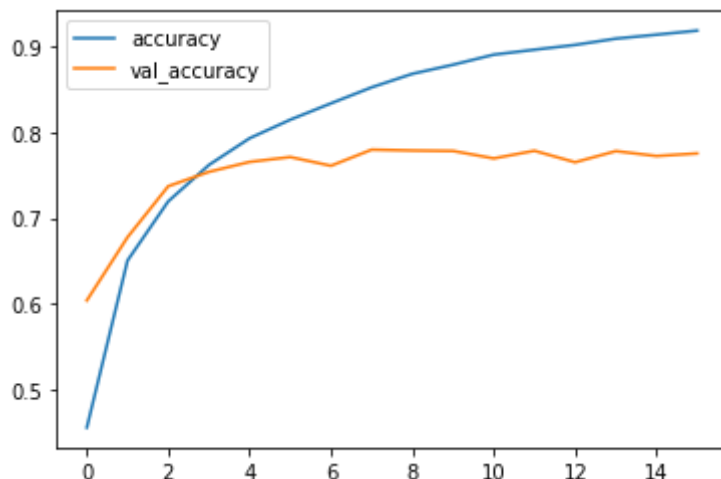
```
np.min(our_CNN_model.history.history['loss'])
```

0.23287376761436462

▼ plot model accuracy

```
plot_history = pd.DataFrame(our_CNN_model.history.history)
plot_history[['accuracy', 'val_accuracy']].plot()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7faf2b701090>



▼ max of validation accuracy

```
np.max(our_CNN_model.history.history['val_accuracy'])

0.779699981212616
```

▼ Evalute the model

```
our_CNN_model.evaluate(X_testData, cat_y_testData)
```

```
313/313 [=====] - 1s 4ms/step - loss: 0.6829 - accuracy: 0.7
[0.682878851890564, 0.7710999846458435]
```



confusion matrix and classification report

▼ should be sparse

```
predictions = our_CNN_model.predict(X_testData)
predictions_sparse = np.argmax(predictions, axis=1)
predictions[0], predictions_sparse[0]
```

```
313/313 [=====] - 1s 2ms/step
(array([1.4575123e-03, 4.9356726e-04, 4.6526126e-04, 8.7052953e-01,
        2.1654585e-05, 1.1634006e-01, 3.9997026e-03, 1.8319597e-03,
        4.5076455e-03, 3.5320688e-04], dtype=float32), 3)
```

▼ printing classification report

```
from sklearn.metrics import confusion_matrix, classification_report
```

```
print(classification_report(Y_testData, predictions_sparse))
```

	precision	recall	f1-score	support
0	0.75	0.84	0.79	1000
1	0.86	0.91	0.88	1000
2	0.72	0.62	0.67	1000
3	0.60	0.65	0.62	1000
4	0.68	0.80	0.74	1000
5	0.78	0.58	0.67	1000
6	0.86	0.76	0.81	1000
7	0.76	0.85	0.80	1000
8	0.90	0.83	0.87	1000
9	0.84	0.87	0.86	1000

accuracy			0.77	10000
macro avg	0.78	0.77	0.77	10000
weighted avg	0.78	0.77	0.77	10000

▼ use cinfusion matrix

```
confusion_matrix(Y_testData, predictions_sparse)
```

```
array([[843, 20, 27, 14, 19, 0, 0, 13, 38, 26],
       [ 10, 914, 1, 1, 2, 1, 5, 1, 15, 50],
       [ 97, 5, 620, 50, 93, 37, 48, 31, 7, 12],
       [ 25, 9, 49, 650, 77, 76, 34, 56, 7, 17],
       [ 18, 1, 44, 44, 799, 11, 20, 54, 3, 6],
       [ 14, 4, 46, 199, 54, 579, 10, 89, 3, 2],
       [ 11, 4, 38, 83, 74, 16, 756, 8, 5, 5],
       [ 15, 4, 22, 28, 46, 16, 1, 849, 2, 17],
       [ 68, 40, 11, 11, 4, 1, 1, 5, 835, 24],
       [ 27, 66, 4, 9, 5, 4, 1, 8, 10, 866]])
```

▼ Part4 - using dropout layer and batch normalization to report its effect

▼ Import dropout layer

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Dropout, MaxPool2D
from tensorflow.keras.layers import Conv2D, Flatten, GlobalAveragePooling2D, ReLU, Activation
```

▼ Create the model using dropout layer

```
input = Input(shape=(32, 32, 3))

x = Conv2D(filters=32, kernel_size=(5, 5), strides=1, padding='same')(input)
x = BatchNormalization()(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=64, kernel_size=(3, 3), strides=1, padding='same')(x)
x = BatchNormalization()(x)
x = ReLU()(x)
x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Conv2D(filters=128, kernel_size=(3, 3), strides=1, padding='same')(x)
x = BatchNormalization()(x)
x = ReLU()(x)
```

```

x = MaxPool2D(pool_size=(2, 2), strides=2, padding='same')(x)

x = Flatten()(x)

x = Dense(units=128)(x)
x = ReLU()(x)
x = Dropout(0.3)(x)
x = Dense(units=10)(x)
predictions = Activation(activation='softmax')(x)

our_CNN_model3 = Model(input, predictions)

```

▼ summary of the model

```
our_CNN_model3.summary()
```

Model: "model_1"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 32, 32, 3)]	0
conv2d_6 (Conv2D)	(None, 32, 32, 32)	2432
batch_normalization (Batch Normalization)	(None, 32, 32, 32)	128
re_lu_1 (ReLU)	(None, 32, 32, 32)	0
max_pooling2d_3 (MaxPooling 2D)	(None, 16, 16, 32)	0
conv2d_7 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_1 (Batch Normalization)	(None, 16, 16, 64)	256
re_lu_2 (ReLU)	(None, 16, 16, 64)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 8, 8, 64)	0
conv2d_8 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_2 (Batch Normalization)	(None, 8, 8, 128)	512
re_lu_3 (ReLU)	(None, 8, 8, 128)	0
max_pooling2d_5 (MaxPooling 2D)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 128)	262272

re_lu_4 (ReLU)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1290
activation_1 (Activation)	(None, 10)	0

```

=====
Total params: 359,242
Trainable params: 358,794
Non-trainable params: 448

```

▼ compile the model with optimizer

```
our_CNN_model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

▼ Train the model using early stopping

```
our_CNN_model3.fit(x=X_trainData, y=cat_y_trainData, epochs=40, batch_size=32,
                  validation_data=(X_testData, cat_y_testData), callbacks=[early_stopping])
```

```

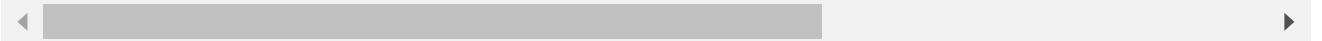
Epoch 1/40
1563/1563 [=====] - 10s 6ms/step - loss: 1.6155 - accuracy: 0.0000
Epoch 2/40
1563/1563 [=====] - 8s 5ms/step - loss: 1.3231 - accuracy: 0.0000
Epoch 3/40
1563/1563 [=====] - 8s 5ms/step - loss: 1.2022 - accuracy: 0.0000
Epoch 4/40
1563/1563 [=====] - 8s 5ms/step - loss: 1.1183 - accuracy: 0.0000
Epoch 5/40
1563/1563 [=====] - 8s 5ms/step - loss: 1.0417 - accuracy: 0.0000
Epoch 6/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.9661 - accuracy: 0.0000
Epoch 7/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.9125 - accuracy: 0.0000
Epoch 8/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.8638 - accuracy: 0.0000
Epoch 9/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.8119 - accuracy: 0.0000
Epoch 10/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.7792 - accuracy: 0.0000
Epoch 11/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.7352 - accuracy: 0.0000
Epoch 12/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.6948 - accuracy: 0.0000
Epoch 13/40
1563/1563 [=====] - 12s 8ms/step - loss: 0.6614 - accuracy: 0.0000
Epoch 14/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.6303 - accuracy: 0.0000
Epoch 15/40

```

```

1563/1563 [=====] - 9s 6ms/step - loss: 0.5987 - accuracy: 0.60
Epoch 16/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.5526 - accuracy: 0.65
Epoch 17/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.5240 - accuracy: 0.68
Epoch 18/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.4905 - accuracy: 0.70
Epoch 19/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.4735 - accuracy: 0.72
Epoch 20/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.4428 - accuracy: 0.75
Epoch 21/40
1563/1563 [=====] - 8s 5ms/step - loss: 0.4120 - accuracy: 0.78
<keras.callbacks.History at 0x7fae35fe2890>

```



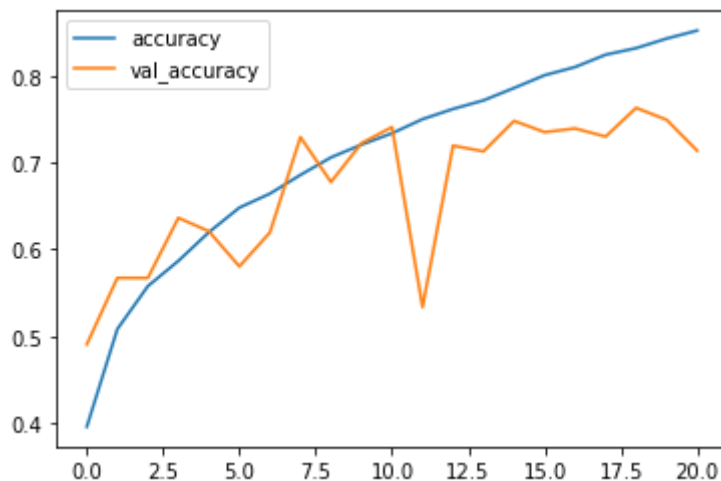
▼ loss function and accuracy metric

```

plot_history3 = pd.DataFrame(our_CNN_model3.history.history)
plot_history3[['accuracy', 'val_accuracy']].plot()

```

<matplotlib.axes._subplots.AxesSubplot at 0x7fae33e51f10>



▼ plot model loss history

```

plot_history3[['loss', 'val_loss']].plot()

```


<matplotlib.axes._subplots.AxesSubplot at 0x7faea0a42d90>



▼ Evaluate the data



```
our_CNN_model3.evaluate(X_testData, cat_y_testData)
```

```
313/313 [=====] - 1s 3ms/step - loss: 0.7697 - accuracy: 0.7
[0.7697134017944336, 0.7407000064849854]
```



▼ Part5 - using some portion of data

```
X_trainData = X_trainData[:40000]
X_trainData.shape
```

```
(10000, 32, 32, 3)
```

```
Y_trainData = Y_trainData[:40000]
Y_trainData.shape
```

```
(10000, 1)
```

```
cat_y_trainData = cat_y_trainData[0:40000]
cat_y_trainData.shape
```

```
(10000, 10)
```

```
our_CNN_model3.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
our_CNN_model3.fit(x=X_trainData, y=cat_y_trainData, epochs=40, batch_size=32,
                    validation_data=(X_testData, cat_y_testData), callbacks=[early_stopping])
```

```
Epoch 1/40
```

```
313/313 [=====] - 3s 8ms/step - loss: 0.4471 - accuracy: 0.8
```

```
Epoch 2/40
```

```
313/313 [=====] - 2s 7ms/step - loss: 0.4158 - accuracy: 0.8
```

```
Epoch 3/40
```

```
313/313 [=====] - 3s 9ms/step - loss: 0.3825 - accuracy: 0.8
```

```
Epoch 4/40
```

```
313/313 [=====] - 2s 7ms/step - loss: 0.3728 - accuracy: 0.8
```

```
Epoch 5/40
```

```
313/313 [=====] - 3s 9ms/step - loss: 0.3307 - accuracy: 0.8
```

```
Epoch 6/40
```

```
313/313 [=====] - 2s 7ms/step - loss: 0.3248 - accuracy: 0.8
```

```
Epoch 7/40
```

```
313/313 [=====] - 2s 7ms/step - loss: 0.3042 - accuracy: 0.8
```

```
Epoch 8/40
```

```

313/313 [=====] - 3s 9ms/step - loss: 0.2952 - accuracy: 0.8
Epoch 9/40
313/313 [=====] - 2s 7ms/step - loss: 0.2991 - accuracy: 0.8
Epoch 10/40
313/313 [=====] - 3s 9ms/step - loss: 0.2801 - accuracy: 0.9
Epoch 11/40
313/313 [=====] - 3s 9ms/step - loss: 0.2614 - accuracy: 0.9
<keras.callbacks.History at 0x7fae34465650>

```

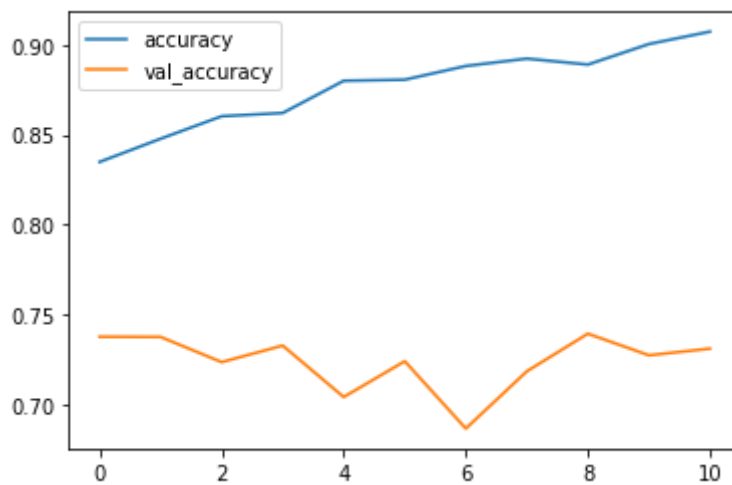
▼ loss function and accuracy metric

```

plot_history3 = pd.DataFrame(our_CNN_model3.history.history)
plot_history3[['accuracy', 'val_accuracy']].plot()

```

↳ <matplotlib.axes._subplots.AxesSubplot at 0x7fae34c2abd0>



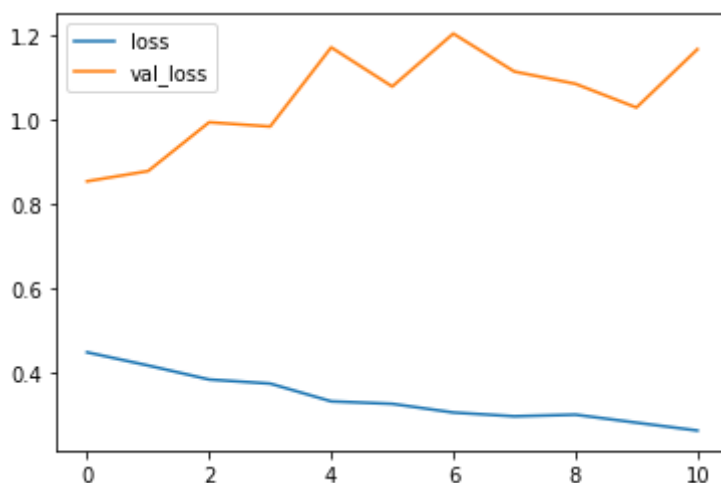
▼ plot model loss history

```

plot_history3[['loss', 'val_loss']].plot()

```

<matplotlib.axes._subplots.AxesSubplot at 0x7fae34bab390>



▼ Evaluate the data

```
our_CNN_model3.evaluate(X_testData, cat_y_testData)
```

```
313/313 [=====] - 1s 3ms/step - loss: 0.8529 - accuracy: 0.7  
[0.8528999090194702, 0.7378000020980835]
```



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