

```
# Case Study - Image Classification using Deep CNN in Keras.
```

```
In [ ]: !pip install opencv-python
        #OpenCV is a Python Library that allows you to perform image processing and
        #It provides a wide range of features, including object detection, face reco
```

```
In [1]: # Import necessary modules.
```

```
import cv2
import numpy as np
import matplotlib.pyplot as plt

from tensorflow.keras import datasets, models, layers, optimizers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
```

```
WARNING:tensorflow:From C:\Users\SIMRAN\anaconda3\lib\site-packages\keras
\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is de
recated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy inst
ead.
```

```
In [2]: # Set the batch size, number of epochs.
```

```
batch_size = 32
num_classes = 10
epochs = 40
num_predictions = 20
#this can be set at the later stage after trying different iterations, this
```

```
In [3]: #Lets import data sets from kears
```

```
from tensorflow.keras.datasets import cifar10
```

```
In [4]:
```

```
#if in case data set doesnt run you can use this:
import requests
import ssl

# Bypass SSL verification
ssl._create_default_https_context = ssl._create_unverified_context

# Download CIFAR-10 dataset
url = "https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz"
response = requests.get(url)
```

```
In [5]: # The data, split between train and test sets:
```

```
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
In [6]: # Print the shape of dataset.  
print('x_train shape:', x_train.shape)  
print(x_train.shape[0], 'train samples')  
print(x_test.shape[0], 'test samples')
```

```
x_train shape: (50000, 32, 32, 3)  
50000 train samples  
10000 test samples
```

```
In [7]: # Print the shape of dataset.  
print('y_train shape:', y_train.shape)  
print(y_train.shape[0], 'train samples')  
print(y_test.shape[0], 'test samples')
```

```
y_train shape: (50000, 1)  
50000 train samples  
10000 test samples
```

- The training set contains 50000 images.
- The size of each image is 32x32 pixels.
- Each image has 3 color channels.

```
In [8]: x_train[0, :, :, :].shape #checking shape of the x_train by index
```

```
Out[8]: (32, 32, 3)
```

Highlights:

- How to select the 10th image?
- How to get the red pixels only?
- What is the shape of resulting array?

```
In [9]: y_train #the output of the training sets
```

```
Out[9]: array([[6],  
               [9],  
               [9],  
               ...,  
               [9],  
               [1],  
               [1]], dtype=uint8)
```

```
In [10]: y_train[2][0] #output of the the 2nd index in the training set
```

```
Out[10]: 9
```

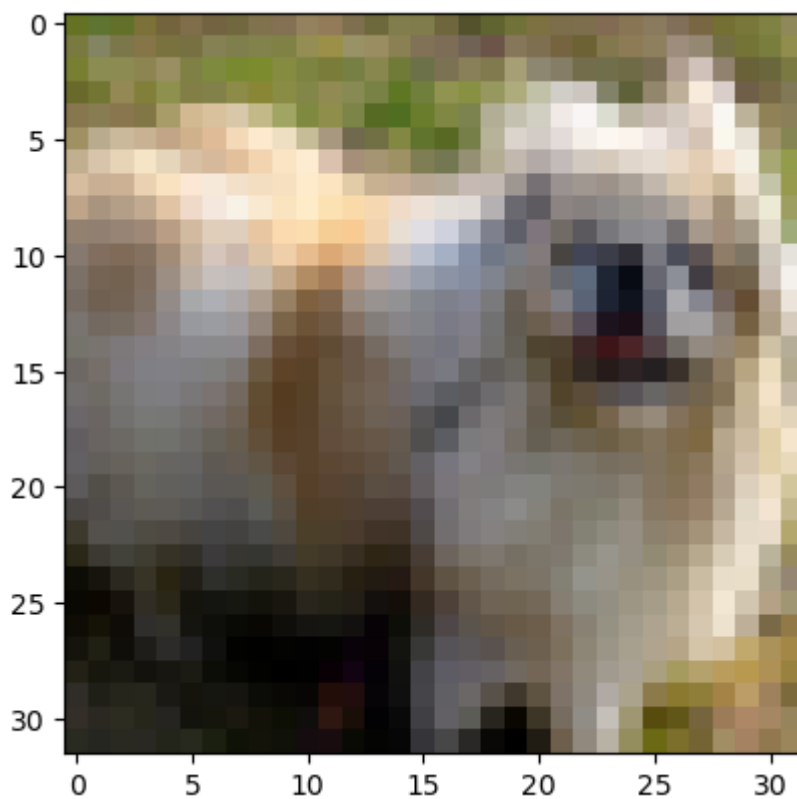
```
In [11]: #lets label the index for better understanding  
label_dict = {0:'airplane', 1:'automobile', 2:'bird', 3:'cat', 4:'deer', 5
```

```
In [12]: #lets check the image and the label for the 40th data from x_train and y_train
i = 40
image = x_train[i]
label = y_train[i][0]
print(f'Label \n Label Id: {label} \n Name: {label_dict[label]}')
plt.imshow(image);
#pixel is less, hence the quality of image seems bad,
#as this code is just for learning purpose, no problem with the the training
```

Label

Label Id: 5

Name: dog



- As the image quality is not good, the edges are not so good. But still we can visualize that there are edges.

```
In [13]: y_test
```

```
Out[13]: array([[3],
                [8],
                [8],
                ...,
                [5],
                [1],
                [7]], dtype=uint8)
```

Please Note:

There are many tools to one-hot encode and they differ in syntax, but the keras one is probably best implemented.

- `keras.utils.to_categorical`

- sklearn.preprocessing.OneHotEncoder
- pandas get_dummies

In [14]: `y_train.shape` *#Lets reshape it using onehot encoder, below shown are two ways*

Out[14]: (50000, 1)

In [15]: *# Convert Labels to one hot vectors.*

```
from sklearn.preprocessing import LabelBinarizer
enc = LabelBinarizer()
y_train = enc.fit_transform(y_train)
y_test = enc.fit_transform(y_test)
```

In [16]: `print(y_train.shape)`
`print(y_test.shape)`

(50000, 10)
(10000, 10)

In [21]: *#y_train, it can be seen now as, 1 where it is positive with the image*
`y_train[0]`

Out[21]: array([0, 0, 0, 0, 0, 0, 1, 0, 0, 0])

In []: *#second method for the same*
`import pandas as pd`
`from sklearn.preprocessing import OneHotEncoder`

`pd.get_dummies(y)`

Create the Model:

- Convolutional input layer, 32 feature maps with a size of 5x5 and a rectifier activation function.
- Batch Normalization Layer.
- Convolutional layer, 32 feature maps with a size of 5x5 and a rectifier activation function.
- Batch Normalization layer.
- Max Pool layer with size 2x2.
- Dropout layer at 25%.
-
- Convolutional layer, 64 feature maps with a size of 3x3 and a rectifier activation function.
- Batch Normalization layer.
- Dropout layer at 25%.
- Convolutional layer, 64 feature maps with a size of 3x3 and a rectifier activation function.
- Batch Normalization layer.
- Max Pool layer with size 2x2.
- Dropout layer at 25%.
-
- GlobalMaxPooling2D layer.
- Fully connected layer with 256 units and a rectifier activation function.
- Dropout layer at 50%.
- Fully connected output layer with 10 units and a softmax activation function.

In [18]: *# Set the CNN model*

```
batch_size = None

model = models.Sequential()
model.add(layers.Conv2D(32, (5, 5), padding='same', activation="relu", input_shape=(1, 28, 28)))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.2))

model.add(layers.Conv2D(64, (5, 5), padding='same', activation="relu"))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.3))

model.add(layers.Conv2D(64, (3, 3), padding='same', activation="relu"))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.4))

model.add(layers.Conv2D(64, (3, 3), padding='same', activation="relu"))
model.add(layers.BatchNormalization())
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.5))

model.add(layers.Flatten())
model.add(layers.Dense(256, activation="relu")) #one hidden layer with 256 units
model.add(layers.Dropout(0.5))

# softmax
model.add(layers.Dense(10, activation="softmax"))

model.summary()
```

WARNING:tensorflow:From C:\Users\SIMRAN\anaconda3\lib\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\SIMRAN\anaconda3\lib\site-packages\keras\src\layers\normalization\batch_normalization.py:979: The name tf.nn.fused_batch_norm is deprecated. Please use tf.compat.v1.nn.fused_batch_norm instead.

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 32, 32, 32)	2432
batch_normalization (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0
conv2d_1 (Conv2D)	(None, 16, 16, 64)	51264
batch_normalization_1 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0
conv2d_2 (Conv2D)	(None, 8, 8, 64)	36928
batch_normalization_2 (Batch Normalization)	(None, 8, 8, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 64)	0
dropout_2 (Dropout)	(None, 4, 4, 64)	0
conv2d_3 (Conv2D)	(None, 4, 4, 64)	36928
batch_normalization_3 (Batch Normalization)	(None, 4, 4, 64)	256
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 64)	0
dropout_3 (Dropout)	(None, 2, 2, 64)	0
flatten (Flatten)	(None, 256)	0
dense (Dense)	(None, 256)	65792
dropout_4 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 10)	2570

```
=====
Total params: 196810 (768.79 KB)
Trainable params: 196362 (767.04 KB)
Non-trainable params: 448 (1.75 KB)
=====
```

When training the network, what you want is minimize the cost by applying a algorithm of your choice. It could be SGD, AdamOptimizer, AdagradOptimizer, or something. You have to study how each algorithm works to choose what to use, but AdamOptimizer works find for most cases in general.

```
In [19]: # initiate Adam optimizer
opt = optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=0.000001)
```

```
In [20]: # Let's train the model
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])
```

Standarizing the data

- The pixel values are in the range of 0 to 255 for each of the red, green and blue channels.
- It is good practice to work with normalized data. Because the input values are well understood, we can easily normalize to the range 0 to 1 by dividing each value by the maximum observation which is 255.
- Note, the data is loaded as integers, so we must cast it to floating point values in order to perform the division.

```
In [21]: #standarizing the data
x_train = x_train.astype('float32') # Conversion to float type from integer
x_test = x_test.astype('float32')
x_train /= 255.0 # Division by 255
x_test /= 255.0
```

```
In [22]: #Adding Early stopping callback to the fit function is going to stop the training
#if the val_loss is not going to change even '0.001' for more than 10 continuous epochs

from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

early_stopping = EarlyStopping(monitor='val_loss', min_delta=0.001, patience=10)

#Adding Model Checkpoint callback to the fit function is going to save the weights
#Hence saving the best weights occurred during training

model_checkpoint = ModelCheckpoint('cifar_cnn_checkpoint_{epoch:02d}_loss_{val_loss:0.2f}.h5',
                                  monitor='val_loss',
                                  verbose=1,
                                  save_best_only=True,
                                  save_weights_only=True,
                                  mode='auto',
                                  period=1)
```

WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to specify the frequency in number of batches seen.


```
In [23]: x_train.shape[0]
```

```
Out[23]: 50000
```

```
In [24]: x_train = x_train.reshape(x_train.shape[0], 32, 32, 3)
x_test = x_test.reshape(x_test.shape[0], 32, 32, 3)
```

```
print(x_train.shape)
print(x_test.shape)
```

```
(50000, 32, 32, 3)
(10000, 32, 32, 3)
```

```
In [25]: history = model.fit(x_train,
                             y_train,
                             batch_size=batch_size,
                             epochs=100,
                             validation_data=(x_test, y_test),
                             shuffle=True,
                             verbose=1,
                             callbacks=[early_stopping,model_checkpoint])
```

```
# plot training history
```

```
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

```
#for Learning purpose less epochs is choosen, you should tune this hyperparameter
```

```
Epoch 30: val_loss did not improve from 0.66675
1563/1563 [=====] - 104s 66ms/step - loss: 0.7317 - accuracy: 0.7463 - val_loss: 0.8866 - val_accuracy: 0.7029
Epoch 31/100
1563/1563 [=====] - ETA: 0s - loss: 0.7213 - accuracy: 0.7529
Epoch 31: val_loss did not improve from 0.66675
1563/1563 [=====] - 105s 67ms/step - loss: 0.7213 - accuracy: 0.7529 - val_loss: 0.6793 - val_accuracy: 0.7679
Epoch 32/100
1563/1563 [=====] - ETA: 0s - loss: 0.7234 - accuracy: 0.7518
Epoch 32: val_loss improved from 0.66675 to 0.62610, saving model to cifar_cnn_checkpoint_32_loss0.6261.h5
1563/1563 [=====] - 105s 67ms/step - loss: 0.7234 - accuracy: 0.7518 - val_loss: 0.6261 - val_accuracy: 0.7874
Epoch 33/100
1563/1563 [=====] - ETA: 0s - loss: 0.7126 - accuracy: 0.7557
Epoch 33: val_loss did not improve from 0.62610
1563/1563 [=====] - 104s 67ms/step - loss: 0.7126 - accuracy: 0.7557 - val_loss: 0.6261 - val_accuracy: 0.7874
```

```
In [26]: # Score trained model.
scores = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])
# sigmoid
```

```
313/313 [=====] - 7s 22ms/step - loss: 0.6071 - a
ccuracy: 0.7912
Test loss: 0.6071414351463318
Test accuracy: 0.7911999821662903
```

```
#hyperparameter tuning can increase the accuracy also the pixel of the
image is less which can be the reason for the
# low accuracy for now, but the score is good for the prediction
```

```
In [27]: predictions = model.predict(x_test)
```

```
313/313 [=====] - 9s 22ms/step
```

```
In [28]: preds = pd.DataFrame(predictions)
preds
```

Out[28]:

	0	1	2	3	4	5	6	7	
0	1.085919e-04	1.776379e-04	0.000682	0.582963	0.000526	0.314984	0.099586	1.553694e-04	5
1	6.605163e-03	2.580067e-01	0.000073	0.000268	0.000003	0.000003	0.000027	2.000701e-06	7
2	1.644520e-02	1.034624e-02	0.000529	0.003659	0.000160	0.000023	0.000211	9.543000e-05	9
3	9.325504e-01	4.512614e-04	0.011549	0.002303	0.002365	0.000132	0.000329	9.004054e-05	4
4	7.867246e-06	1.356194e-05	0.004512	0.001868	0.001040	0.000052	0.992479	9.727671e-07	2
...
9995	4.390072e-01	9.073644e-04	0.022465	0.112056	0.018362	0.016399	0.006648	2.214676e-03	3
9996	2.422249e-06	2.352338e-07	0.000811	0.529121	0.001928	0.411737	0.056266	1.334896e-04	2
9997	3.970541e-08	8.770414e-09	0.000059	0.004642	0.000003	0.995146	0.000013	1.380672e-04	6
9998	5.757232e-02	8.837342e-01	0.006984	0.009757	0.011011	0.003464	0.016252	4.518481e-04	5
9999	1.212057e-06	1.047841e-08	0.000035	0.000012	0.005108	0.000182	0.000001	9.946608e-01	4

10000 rows × 10 columns



In []:

