

Build a CNN Based Classifier for Classifying the Common objects using CIFAR10 Datasets.**Requirements:**

- Five Number of Convolutional 2D Layers starting with 1024 filters.
- Kernel size 3 x 3
- Two Average Pooling Layers, Each after two Convolutional 2D layers.
- Stride 2
- Padding 'valid'
- Optimizer Adam
- Loss function categorical_crossentropy

```
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.layers import Conv2D, AveragePooling2D, Flatten, Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
# Load CIFAR-10 dataset (normalized for better training)
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0
```

```
# Convert class labels to one-hot encoded vectors
num_classes = 10
y_train = tf.keras.utils.to_categorical(y_train, num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)
```

```
print(x_train.shape[1:])
```

↗ (32, 32, 3)

```
# Define the CNN model
model = Sequential()

# First convolutional layer
model.add(Conv2D(1024, kernel_size=(3, 3), activation='relu', padding='valid', input_shape=(32, 32, 3)))

# Second convolutional layer
model.add(Conv2D(512, kernel_size=(3, 3), activation='relu', padding='valid'))

#First Average Pooling Layer
model.add(AveragePooling2D(pool_size=(2, 2),strides=(2, 2)))

# Third convolutional layer
model.add(Conv2D(256, kernel_size=(3, 3), activation='relu', padding='valid'))

# Fourth convolutional layer
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu', padding='valid'))

#Second Average Pooling
model.add(AveragePooling2D(pool_size=(2, 2),strides=(2, 2)))

# Fifth convolutional layer
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', padding='valid'))

# Flatten the output for feeding into the dense layers
model.add(Flatten())

# Dense layer with 10 units (number of classes) for classification
model.add(Dense(num_classes, activation='softmax'))
```

```
# Compile the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
# Train the model
history=model.fit(x_train, y_train, epochs=5, batch_size=32, validation_data=(x_test, y_test))
```

↗ Epoch 1/5
1563/1563 [=====] - 121s 77ms/step - loss: 1.7141 - accuracy: 0.3750 - val_loss: 1.3935 - val_accuracy: 0.4
Epoch 2/5
1563/1563 [=====] - 122s 78ms/step - loss: 1.2816 - accuracy: 0.5371 - val_loss: 1.3590 - val_accuracy: 0.5
Epoch 3/5

05/06/2024, 15:24

CNN Based Classifier using CIFAR10.ipynb - Colab

1563/1563 [=====] - 122s 78ms/step - loss: 1.0761 - accuracy: 0.6157 - val_loss: 1.0378 - val_accuracy: 0.6157
Epoch 4/5
1563/1563 [=====] - 118s 76ms/step - loss: 0.9224 - accuracy: 0.6768 - val_loss: 0.9283 - val_accuracy: 0.6768
Epoch 5/5
1563/1563 [=====] - 122s 78ms/step - loss: 0.8096 - accuracy: 0.7177 - val_loss: 0.9082 - val_accuracy: 0.6825

```
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(x_test, y_test)
print('Test accuracy:', test_acc)
```

↻

313/313 [=====] - 7s 23ms/step - loss: 0.9082 - accuracy: 0.6825
Test accuracy: 0.6825000047683716

```
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt
```

```
# Make predictions on the test set
predictions = model.predict(x_test)
```

↻

313/313 [=====] - 7s 22ms/step

```
# Calculate confusion matrix
cm = confusion_matrix(y_test.argmax(axis=1), predictions.argmax(axis=1))
print('Confusion Matrix:\n', cm)
```

↻

Confusion Matrix:
[[738 23 125 15 12 8 7 1 30 41]
[23 832 20 8 4 16 14 0 12 71]
[56 4 695 32 44 88 54 15 6 6]
[18 7 119 414 54 312 51 15 2 8]
[20 4 152 52 572 86 60 44 4 6]
[4 5 74 78 41 752 16 27 1 2]
[6 4 87 52 27 59 760 1 1 3]
[10 1 83 27 95 159 4 604 1 16]
[130 51 63 17 7 16 5 1 673 37]
[29 106 12 18 7 21 7 5 10 785]]

```
# Generate classification report
print('Classification Report:\n', classification_report(y_test.argmax(axis=1), predictions.argmax(axis=1)))
```

↻

Classification Report:
precision recall f1-score support

0 0.71 0.74 0.73 1000
1 0.80 0.83 0.82 1000
2 0.49 0.69 0.57 1000
3 0.58 0.41 0.48 1000
4 0.66 0.57 0.61 1000
5 0.50 0.75 0.60 1000
6 0.78 0.76 0.77 1000
7 0.85 0.60 0.71 1000
8 0.91 0.67 0.77 1000
9 0.81 0.79 0.79 1000

accuracy 0.68 10000
macro avg 0.71 0.68 0.69 10000
weighted avg 0.71 0.68 0.69 10000

```
# Plot accuracy and loss curves
plt.plot(history.history['accuracy'], label='Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()

plt.plot(history.history['loss'], label='Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```

