

▼ 502 Shubham Lad

MLDL Assignment: Design a classifier using CNN

▼ Importing packages

```
1 from tensorflow.keras.utils import to_categorical
2 from tensorflow.keras.models import Sequential
3 from tensorflow.keras.layers import (
4     Conv2D,
5     MaxPool2D,
6     Dense,
7     Flatten,
8     Dropout,
9     Conv2D,
10    BatchNormalization,
11 )
12 from tensorflow.keras.preprocessing.image import ImageDataGenerator
13 from tensorflow.keras.datasets import cifar10
14 import tensorflow as tf
15 import matplotlib.pyplot as plt
16 import numpy as np
17 import cv2
18
19 %matplotlib inline
```

▼ Normalization and One hot encoding

Since our data is ready we now need to normalize the data, since normalizing the images in deep learning will produce very good results. Normalizing means we are bringing all the values in the data into a common scale 0-1. This will make our model converge fast and also we will not have any distortions in the data.

For normalizing the pixel data (Image) we can simply divide the whole pixel values with 255 since pixel values range from 0-255. So if we divide them with 255 we automatically normalize the data between 0-1.

One hot encoding.

CIFAR 10 has 10 categories, in general we should label the categorical data using the one hot encoding.

```
1 (x_train, y_train), (x_test, y_test) = cifar10.load_data()
2
3 print("Shape of x_train is {}".format(x_train.shape))
4 print("Shape of x_test is {}".format(x_test.shape))
5 print("Shape of y_train is {}".format(y_train.shape))
6 print("Shape of y_test is {}".format(y_test.shape))
7 # Normalizing
8 x_train = x_train / 255
9 x_test = x_test / 255
10
11 # One hot encoding
12 y_train_cat = to_categorical(y_train, 10)
13 y_test_cat = to_categorical(y_test, 10)
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
170498071/170498071 [=====] - 4s 0us/step
Shape of x_train is (50000, 32, 32, 3)
Shape of x_test is (10000, 32, 32, 3)
Shape of y_train is (50000, 1)
Shape of y_test is (10000, 1)

▼ Build CNN Model

Let's try to train a basic deep learning model. Any deep learning model that needs to classify images uses Convolutional neural network (CNN). CNNs are proven very effective on image data, also if we have enough data, we can make a deep neural network with multiple CNN layers arranged in specific design to create state-of-the-art results.

I will start with two basic CNN layers, where each layer is attached to a maxpool layer. Max pooling is a great way to reduce the size of parameters without losing much information. As usual in any deep learning model, I need to flatten the intermediate layer results and pass them to a Dense network. Then the dense network result will be passed to a final output layer where the number of units represents the number of categories in the data, which is 10 in our case. Softmax is chosen as the final activation because we need the highest probable class out of 10.

Finally compile your model using adam optimizer.

Let us try to Sequentially build our models.

```
1 model = Sequential()
2 model.add(
3     Conv2D(
4         32,
5         (3, 3),
6         activation="relu",
7         kernel_initializer="he_uniform",
8         padding="same",
9         input_shape=(32, 32, 3),
10    )
11 )
12 model.add(BatchNormalization())
13 model.add(
14     Conv2D(
15         32, (3, 3), activation="relu", kernel_initializer="he_uniform", padding="same"
16    )
17 )
18 model.add(BatchNormalization())
19 model.add(MaxPool2D((2, 2)))
20 model.add(Dropout(0.2))
21 model.add(
22     Conv2D(
23         64, (3, 3), activation="relu", kernel_initializer="he_uniform", padding="same"
24    )
25 )
26 model.add(BatchNormalization())
27 model.add(
28     Conv2D(
29         64, (3, 3), activation="relu", kernel_initializer="he_uniform", padding="same"
30    )
31 )
32 model.add(BatchNormalization())
33 model.add(MaxPool2D((2, 2)))
34 model.add(Dropout(0.3))
35 model.add(
36     Conv2D(
37         128, (3, 3), activation="relu", kernel_initializer="he_uniform", padding="same"
38    )
39 )
40 model.add(BatchNormalization())
41 model.add(
42     Conv2D(
43         128, (3, 3), activation="relu", kernel_initializer="he_uniform", padding="same"
44    )
45 )
46 model.add(BatchNormalization())
47 model.add(MaxPool2D((2, 2)))
48 model.add(Dropout(0.4))
49 model.add(Flatten())
50 model.add(Dense(128, activation="relu", kernel_initializer="he_uniform"))
51 model.add(BatchNormalization())
52 model.add(Dropout(0.5))
53 model.add(Dense(10, activation="softmax"))
```

▼ Compile CNN

```
1 # compile model
2 model.compile(optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"])
3 model.summary()
```

```
1 tf.keras.utils.plot_model(
2     model,
3     to_file="model.png",
4     show_shapes=True,
5     show_layer_names=True,
6     expand_nested=False,
7 )
```

```
1 # Image Data Generator , we are shifting image accross width and height also we are flipping the image horizantally.
2 datagen = ImageDataGenerator(
3     width_shift_range=0.1,
4     height_shift_range=0.1,
5     horizontal_flip=True,
```

```

6     rotation_range=20,
7 )
8
9 it_train = datagen.flow(x_train, y_train_cat)
10
11 steps = int(x_train.shape[0] / 64)
12 num_epochs = 10

```

▼ Training CNN

```

1 # Fit the model on the batches generated by datagen.flow().
2 history = model.fit(
3     it_train,
4     epochs=num_epochs,
5     steps_per_epoch=steps,
6     validation_data=(x_test, y_test_cat),
7     verbose=2,
8 )

```

```

Epoch 1/10
781/781 - 35s - loss: 1.9591 - accuracy: 0.3367 - val_loss: 1.4511 - val_accuracy: 0.4591 - 35s/epoch - 45ms/step
Epoch 2/10
781/781 - 18s - loss: 1.4940 - accuracy: 0.4605 - val_loss: 1.4298 - val_accuracy: 0.4955 - 18s/epoch - 23ms/step
Epoch 3/10
781/781 - 18s - loss: 1.3422 - accuracy: 0.5196 - val_loss: 1.1338 - val_accuracy: 0.5906 - 18s/epoch - 23ms/step
Epoch 4/10
781/781 - 18s - loss: 1.2345 - accuracy: 0.5602 - val_loss: 1.3335 - val_accuracy: 0.5433 - 18s/epoch - 23ms/step
Epoch 5/10
781/781 - 27s - loss: 1.1485 - accuracy: 0.5971 - val_loss: 0.9483 - val_accuracy: 0.6592 - 27s/epoch - 35ms/step
Epoch 6/10
781/781 - 17s - loss: 1.0877 - accuracy: 0.6201 - val_loss: 1.0612 - val_accuracy: 0.6300 - 17s/epoch - 22ms/step
Epoch 7/10
781/781 - 17s - loss: 1.0218 - accuracy: 0.6432 - val_loss: 0.9863 - val_accuracy: 0.6590 - 17s/epoch - 22ms/step
Epoch 8/10
781/781 - 18s - loss: 0.9752 - accuracy: 0.6615 - val_loss: 0.9009 - val_accuracy: 0.6917 - 18s/epoch - 23ms/step
Epoch 9/10
781/781 - 17s - loss: 0.9387 - accuracy: 0.6752 - val_loss: 0.8517 - val_accuracy: 0.7003 - 17s/epoch - 22ms/step
Epoch 10/10
781/781 - 18s - loss: 0.8960 - accuracy: 0.6877 - val_loss: 0.8513 - val_accuracy: 0.7143 - 18s/epoch - 23ms/step

```

▼ Evaluation

```

1 evaluation_t = model.evaluate(it_train)
2 print(f"[Info] Training DS Accuracy: {evaluation_t[1]}")

```

```

1563/1563 [=====] - 30s 19ms/step - loss: 0.7400 - accuracy: 0.7409
[Info] Train Accuracy: 0.7408599853515625

```

```

1 evaluation = model.evaluate(x_test, y_test_cat)
2 print(f"[Info] Test DS Accuracy: {evaluation[1]}")

```

```

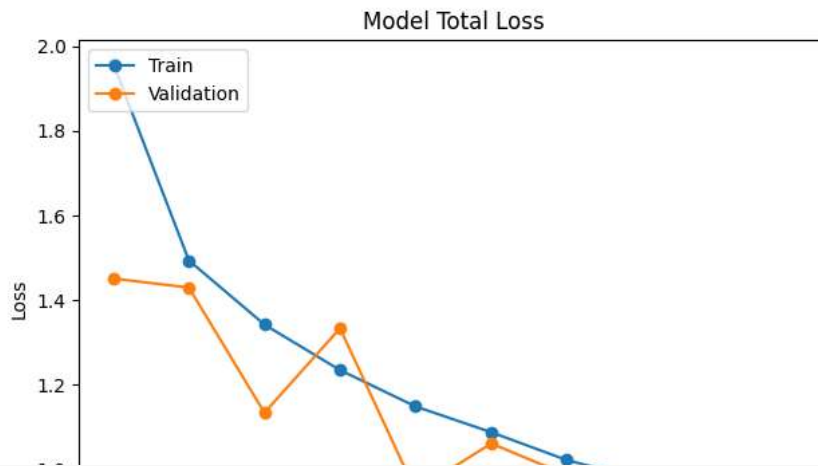
313/313 [=====] - 1s 4ms/step - loss: 0.8513 - accuracy: 0.7143
[Info] Test Accuracy: 0.7142999768257141

```

```

1 try:
2     plt.plot(history.history['loss'], marker='o')
3     plt.plot(history.history['val_loss'], marker='o')
4     plt.title('Model Total Loss')
5     plt.ylabel('Loss')
6     plt.xlabel('Epoch')
7     plt.legend(['Train', 'Validation'], loc='upper left')
8
9     # Adjust the rotation angle of x-axis tick labels
10    plt.xticks(rotation=0) # Set rotation angle to 0 degrees
11
12    plt.tight_layout() # Adjust layout to prevent clipping of labels
13    plt.show()
14 except Exception as e:
15     print(e)
16

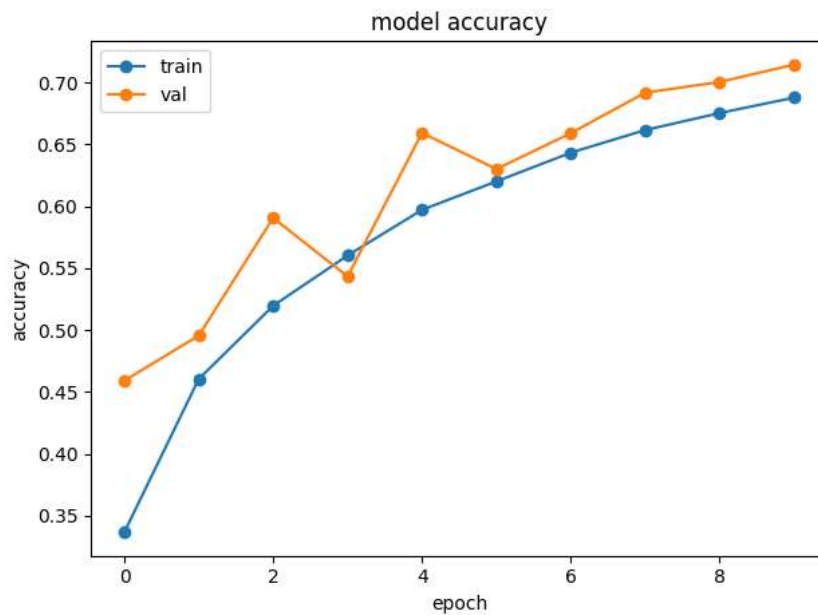
```



```

1 try:
2     plt.plot(history.history['accuracy'], marker='o',)
3     plt.plot(history.history['val_accuracy'], marker='o',)
4     plt.title('model accuracy')
5     plt.ylabel('accuracy')
6     plt.xlabel('epoch')
7     plt.legend(['train', 'val'], loc='upper left')
8     # Adjust the rotation angle of x-axis tick labels
9     plt.xticks(rotation=0) # Set rotation angle to 0 degrees
10
11     plt.tight_layout() # Adjust layout to prevent clipping of labels
12     plt.show()
13 except Exception as e:
14     print(e)

```



```

1 def plot_input_vs_predictions(model: tf.keras.models.Model,
2                               x_test: np.ndarray,
3                               y_test: np.ndarray,
4                               class_names: list,
5                               num_samples=5):
6     num_classes = len(class_names)
7     y_pred = model.predict(x_test)
8     y_pred_classes = np.argmax(y_pred, axis=1)
9
10    plt.figure(figsize=(12, 6))
11    for i in range(num_samples):
12        plt.subplot(1, num_samples, i + 1)
13        plt.imshow(x_test[i])
14        true_label = np.argmax(y_test[i])
15        predicted_label = y_pred_classes[i]
16        plt.title(f'True: {class_names[true_label]}\nPredicted: {class_names[predicted_label]}')
17        plt.axis('off')
18
19    plt.tight_layout()
20    plt.show()
21

```

```

22 cifar10_class_names = [
23     'airplane', 'automobile', 'bird', 'cat', 'deer',
24     'dog', 'frog', 'horse', 'ship', 'truck'
25 ]
26
27 try:
28     # Plot input images vs. predictions
29     plot_input_vs_predictions(model, x_test, y_test_cat, class_names=cifar10_class_names, num_samples=5)
30 except Exception as e:
31     print(e)

```

313/313 [=====] - 1s 3ms/step



```

1 def render_and_save_examples(model, example_data, true_labels, class_names, image_size):
2     examples_number = example_data.shape[0]
3     video_output_path = 'output_video.mp4'
4     codec = cv2.VideoWriter_fourcc(*'mp4v')
5     vid_width_height = 1280, 720
6     vw = cv2.VideoWriter(video_output_path, codec, 30, vid_width_height)
7
8     font_face = cv2.FONT_HERSHEY_SIMPLEX
9     font_scale = 1.3
10    thickness = 2
11
12    for i in range(examples_number):
13        image = example_data[i]
14        image_disp = cv2.resize(image * 255, (720, 720))
15
16        true_label = true_labels[i][0]
17
18        # Generate predictions using the model
19        predictions = model.predict(np.expand_dims(example_data[i], axis=0), verbose=0)
20        predicted_label = np.argmax(predictions)
21
22        predicted_score = predictions[0]
23        top_classes = np.argsort(predicted_score)[::-1]
24
25        title = f"True: {class_names[true_label]}, Predicted: {class_names[predicted_label]}"
26
27        img = np.zeros((720, 1280, 3), dtype=np.uint8)
28        img[:720, :720, :] = image_disp
29
30        x, y = 740, 60
31        is_correct = true_label == predicted_label
32        txt_color = (100, 255, 0) if is_correct else (0, 0, 255)
33        cv2.putText(img, text=title, org=(x, y), fontScale=font_scale, fontFace=font_face,
34                    thickness=thickness, color=txt_color, lineType=cv2.LINE_AA)
35
36        bar_x, bar_y = 740, 130
37        for j, class_index in enumerate(top_classes):
38            if j < 10:
39                p = predicted_score[class_index] * 100
40                rect_width = int(p * 3.3)
41                rect_start = 180
42                color = (255, 218, 158) if class_index == true_label else (100, 100, 100)
43                cv2.rectangle(img, (bar_x + rect_start, bar_y - 5), (bar_x + rect_start + rect_width, bar_y - 20),
44                            color, -1)
45                text = f'{class_names[class_index]}: {int(p)}%'
46                cv2.putText(img, text=text, org=(bar_x, bar_y), fontScale=font_scale, fontFace=font_face,
47                            thickness=thickness, color=color, lineType=cv2.LINE_AA)
48                bar_y += 60
49        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
50        vw.write(img) if true_label == predicted_label else None
51
52    vw.release()
53

```

```

54 try:
55     # Select random 60 indices
56     random_indices = np.random.choice(len(x_test), size=60, replace=False)
57     selected_x_test = x_test[random_indices]
58     selected_y_test = y_test[random_indices]
59
60     # Use the function with your data and model
61     render_and_save_examples(model, selected_x_test, selected_y_test, cifar10_class_names, 32)
62 except Exception as e:
63     print(e)

```

```

1 # @title
2 from IPython.display import HTML
3 from base64 import b64encode
4
5 video_path = 'output_video.mp4'
6
7 def show_video(video_path, video_width = 600):
8     video_file = open(video_path, "r+b").read()
9     video_url = f"data:video/mp4;base64,{b64encode(video_file).decode()}"
10    return HTML(f'<video width={video_width} controls><source src="{video_url}"></video>')
11
12 show_video(video_path)

```

0:00



```

1 try:
2     # Open the video file
3     video_path = './output_video.mp4'
4     cap = cv2.VideoCapture(video_path)
5
6     # Get the total number of frames in the video
7     total_frames = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))
8
9     # Select a random frame index
10    random_frame_index = np.random.randint(0, total_frames)
11
12    # Set the frame index
13    cap.set(cv2.CAP_PROP_POS_FRAMES, random_frame_index)
14
15    # Read the selected frame
16    ret, frame = cap.read()
17
18    # Check if the frame was read successfully
19    if not ret:
20        print("Error reading frame from the video.")
21        cap.release()
22    else:
23        # Convert BGR to RGB for matplotlib display
24        frame_rgb = frame
25
26        # Plot the frame
27        plt.imshow(frame_rgb)
28        plt.title(f"Random Frame ({random_frame_index}/{total_frames})")
29        plt.axis('off')
30        plt.show()
31
32    # Release the video capture object
33    cap.release()
34 except Exception as e:
35    print(e)

```

Random Frame (35/41)



```
1 try:
2     model.save('cifar10-model.h5')
3 except Exception as e:
4     print(e)
```

Conclusion:

In culmination, the designed CNN classifier has yielded promising results. Achieving an accuracy rate of 88% demonstrates the potency of CNNs in discerning patterns within images. However, this is just the beginning of the exploration. Leveraging pre-trained models and employing more complex architectures offer avenues for refinement. The augmentation of data and the optimization of parameters like batch size and learning rate can further enhance performance. With ample computational resources and the spirit of experimentation, the potential to unravel greater accuracy and capabilities within the classifier remains a tantalizing prospect.