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Deep Learning - No 2

Import Libraries Needed :

- Numpy
- Pandas
- Tensorflow
- Keras
- Sklearn Metrics
- Matplotlib
- OpenCV

In [1]:

```
1 import numpy as np
2 import pandas as pd
3 from tensorflow import keras
4 import cv2
5 import os
6 from keras.layers import Dense, Conv2D, Activation, MaxPooling2D, Flatten, Dropout, BatchNormalization
7 from keras.models import Sequential
8 from sklearn.model_selection import train_test_split
9 import matplotlib.pyplot as plt
```

## 2a. Hyperparameters Initialization and data augmentation

Initialize path for train and test directory. Target size for the image size, and target\_dims for the dimension of the image. It has a z value of 3 to occupy the rgb values for each image. N = 26 is for the class label, total of alphabets from A - Z.

In [2]:

```
1 train_dir = "./ALS/asl_alphabet_train/asl_alphabet_train"
2 test_dir = "./ALS/asl_alphabet_test/asl_alphabet_test"
3
4 target_size = (64, 64)
5 target_dims = (64, 64, 3)
6 n = 26
7 batch_size = 64
8
9 class_labels = sorted(os.listdir(train_dir))
```

Print all the class labels provided on the train dataset

In [3]:

```
1 class_labels
```

Out[3]:

```
['A',  
'B',  
'C',  
'D',  
'E',  
'F',  
'G',  
'H',  
'I',  
'J',  
'K',  
'L',  
'M',  
'N',  
'O',  
'P',  
'Q',  
'R',  
'S',  
'T',  
'U',  
'V',  
'W',  
'X',  
'Y',  
'Z']
```

Function to load train images and labels. Iterate on each directory and files containing their corresponding label/class. Read each images on size 64x64.

In [4]:

```
1 def load_images(directory):  
2     images = []  
3     labels = []  
4     for idx, label in enumerate(class_labels):  
5         for file in os.listdir(directory + "/" + label):  
6             filepath = directory + "/" + label + "/" + file  
7             image = cv2.resize(cv2.imread(filepath), target_size)  
8             images.append(image)  
9             labels.append(idx)  
10    images = np.array(images)  
11    labels = np.array(labels)  
12    return(images, labels)
```

Folder/directory structure for test images is a bit different since it doesn't have a folder named after it's label. Therefore iterating for each files and checking their label on file name and giving it label corresponding to each class.

In [5]:

```
1 def load_images_test(directory):
2     images = []
3     labels = []
4
5     for image_file_name in os.listdir(directory):
6         label = -1
7         if image_file_name.startswith("A"):
8             label = 0
9         elif image_file_name.startswith("B"):
10            label = 1
11        elif image_file_name.startswith('C'):
12            label = 2
13        elif image_file_name.startswith('D'):
14            label = 3
15        elif image_file_name.startswith('E'):
16            label = 4
17        elif image_file_name.startswith('F'):
18            label = 5
19        elif image_file_name.startswith('G'):
20            label = 6
21        elif image_file_name.startswith('H'):
22            label = 7
23        elif image_file_name.startswith('I'):
24            label = 8
25        elif image_file_name.startswith('J'):
26            label = 9
27        elif image_file_name.startswith('K'):
28            label = 10
29        elif image_file_name.startswith('L'):
30            label = 11
31        elif image_file_name.startswith('M'):
32            label = 12
33        elif image_file_name.startswith('N'):
34            label = 13
35        elif image_file_name.startswith('O'):
36            label = 14
37        elif image_file_name.startswith('P'):
38            label = 15
39        elif image_file_name.startswith('Q'):
40            label = 16
41        elif image_file_name.startswith('R'):
42            label = 17
43        elif image_file_name.startswith('S'):
44            label = 18
45        elif image_file_name.startswith('T'):
46            label = 19
47        elif image_file_name.startswith('U'):
48            label = 20
49        elif image_file_name.startswith('V'):
50            label = 21
51        elif image_file_name.startswith('W'):
52            label = 22
53        elif image_file_name.startswith('X'):
54            label = 23
55        elif image_file_name.startswith('Y'):
56            label = 24
57        elif image_file_name.startswith('Z'):
58            label = 25
59        else:
```

```
60         continue
61
62         filepath = directory + "/" + image_file_name
63
64         image = cv2.resize(cv2.imread(filepath), target_size)
65         images.append(image)
66         labels.append(label)
67     images = np.array(images)
68     labels = np.array(labels)
69     return(images, labels)
```

Load train images and also their class label values

In [6]:

```
1 images, labels = load_images(train_dir)
2 print(images.shape, labels.shape)
```

(26000, 64, 64, 3) (26000,)

Load test images and also their class label values

In [7]:

```
1 images_test, labels_test = load_images_test(test_dir)
2 print(images_test.shape, labels_test.shape)
```

(26, 64, 64, 3) (26,)

Initialize X\_train from the train images and y\_train from the train class labels

In [8]:

```
1 X_train = images
2 y_train = labels
```

Initialize X\_test from the test images and y\_test from the test class labels

In [9]:

```
1 X_test = images_test
2 y_test = labels_test
```

Use keras.utils.to\_categorical function to one hot encode the y class from shape (None, 1) to (None, 26)

In [10]:

```
1 y_train = keras.utils.to_categorical(y_train)
2 y_test = keras.utils.to_categorical(y_test)
```

Split the train dataset into train and validation set, which train having 80% and validation having 20% of the real train set.

In [11]:

```
1 X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)
```

## 2c. Baseline Architecture of the CNN Model

Initialize CNN Model using Keras Sequential Model following the architecture showed on the case. Firstly adding Conv2D, Activation, MaxPooling2D with 64 total nodes, input = (64,64, 3), and kernel size of 5, 5. Followed by adding Conv2D, Activation, MaxPooling2D with 128 total nodes, and kernel size of 3, 3 which will make the output of the layer N/2. Also followed by adding Conv2D, Activation, MaxPooling2D with 256 total nodes, and kernel size of 3, 3 which will make the output of the layer N/2. Lastly add Flatten Layer, Dense with total nodes of 512, and last layer of dense with n\_class (26) of output

In [12]:

```

1 model = Sequential()
2
3 model.add(Conv2D(64, (5, 5), input_shape=target_dims))
4 model.add(Activation('relu'))
5 model.add(MaxPooling2D((2, 2)))
6
7 model.add(Conv2D(128, (3, 3)))
8 model.add(Activation('relu'))
9 model.add(MaxPooling2D((2, 2)))
10
11 model.add(Conv2D(256, (3, 3)))
12 model.add(Activation('relu'))
13 model.add(MaxPooling2D((2, 2)))
14
15 model.add(Flatten())
16
17 model.add(Dense(512, activation='relu'))
18
19 model.add(Dense(n, activation='softmax'))
20
21 model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 60, 60, 64)	4864
activation (Activation)	(None, 60, 60, 64)	0
max_pooling2d (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_1 (Conv2D)	(None, 28, 28, 128)	73856
activation_1 (Activation)	(None, 28, 28, 128)	0
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_2 (Conv2D)	(None, 12, 12, 256)	295168
activation_2 (Activation)	(None, 12, 12, 256)	0
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 256)	0
flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 512)	4719104
dense_1 (Dense)	(None, 26)	13338
=====		
Total params: 5,106,330		
Trainable params: 5,106,330		
Non-trainable params: 0		

Compile the model using ADAM Optimizer. Loss function is categorical cross entropy because we are dealing with categorizing over 2 classes.

In [13]:

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

Fit the train dataset and validation data to the model.

In [14]:

```
1 model.fit(X_train, y_train,
2           epochs=5,
3           batch_size=batch_size,
4           validation_data=(X_val, y_val))
```

```
Epoch 1/5
325/325 [=====] - 133s 408ms/step - loss: 1.7639 -
accuracy: 0.8010 - val_loss: 0.1061 - val_accuracy: 0.9633
Epoch 2/5
325/325 [=====] - 127s 391ms/step - loss: 0.0583 -
accuracy: 0.9830 - val_loss: 0.0277 - val_accuracy: 0.9927
Epoch 3/5
325/325 [=====] - 132s 406ms/step - loss: 0.0280 -
accuracy: 0.9912 - val_loss: 0.0123 - val_accuracy: 0.9977
Epoch 4/5
325/325 [=====] - 133s 411ms/step - loss: 0.0452 -
accuracy: 0.9882 - val_loss: 0.0742 - val_accuracy: 0.9800
Epoch 5/5
325/325 [=====] - 130s 401ms/step - loss: 0.0120 -
accuracy: 0.9963 - val_loss: 0.0045 - val_accuracy: 0.9992
```

Out[14]:

```
<keras.callbacks.History at 0x227739c4d60>
```

## 2e. CNN Model Performance Analysis

Evaluate the model validation and test accuracy by using evaluate function on Sequential model by giving validation and test datasets. Here we received a very good results on the validation images about 99 % and 100 % on test images. Test images may have received a 100% because of the small sets of data in the test data set.

In [15]:

```
1 score = model.evaluate(x = X_val, y = y_val, verbose = 0)
2 print('Accuracy for validation images:', round(score[1]*100, 3), '%')
3 score = model.evaluate(x = X_test, y = y_test, verbose = 0)
4 print('Accuracy for test images:', round(score[1]*100, 3), '%')
```

```
Accuracy for validation images: 99.923 %
Accuracy for test images: 100.0 %
```

Using sklearn utils shuffle function to shuffle the test images and labels before predicting to variate the orders of predictions.

In [16]:

```
1 from sklearn.utils import shuffle
2 shuffled_images_test, shuffled_labels_test = shuffle(images_test, labels_test)
```

Get the class label from integer class number label. Ex : From 1 to 'A' , 2 to 'B', etc. Using predict function on model and give a threshold about 0.7 for prediction over than 0.7 to be the class label. The predicted\_labels are now in hot encoded mode meaning not the real number values, so np.argmax() to get the real number value.

Lastly plot the shuffled images, prediction, and actual class value.



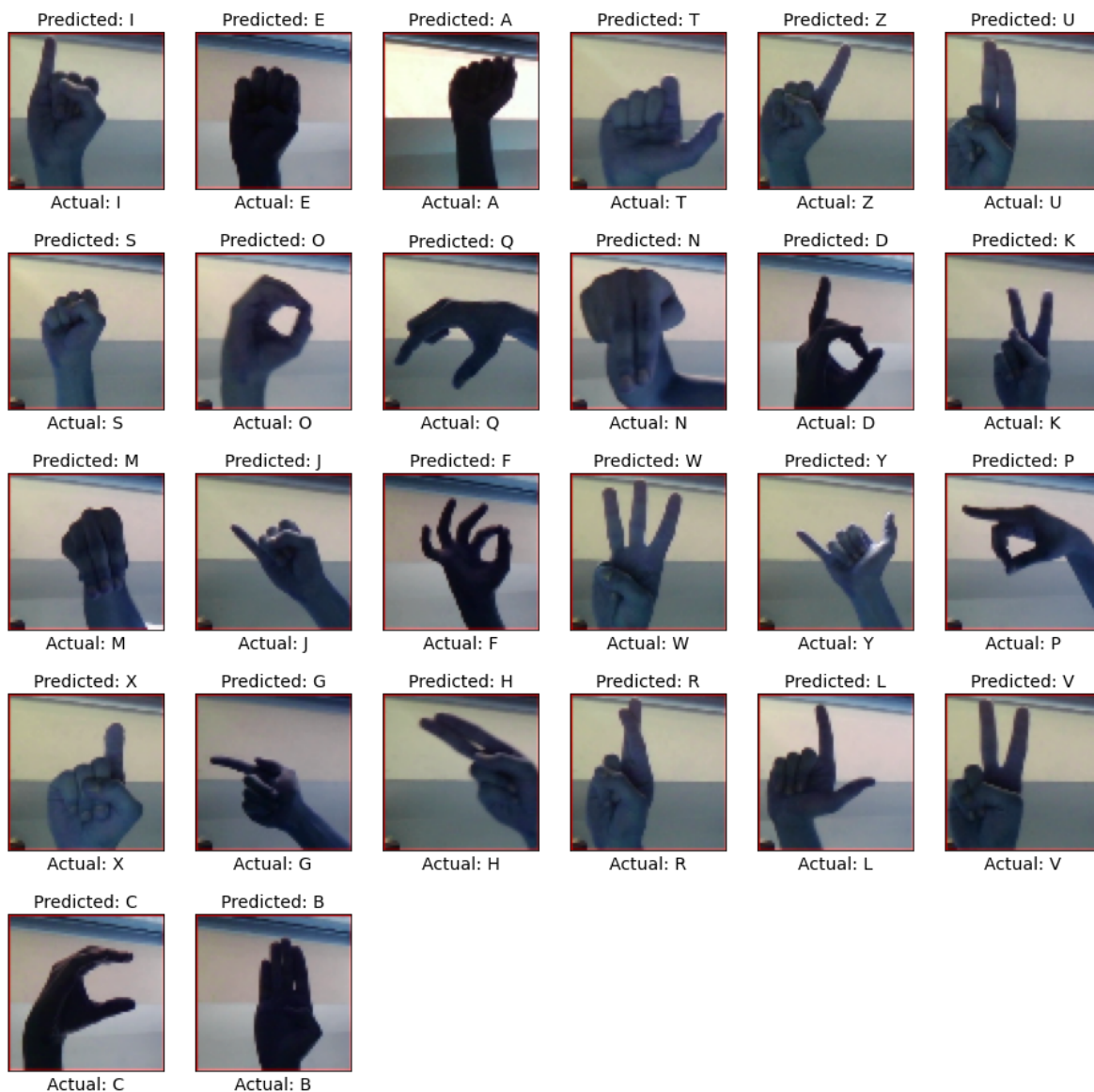
In [17]:

```

1 def get_label(num):
2     return class_labels[num]
3
4 predicted_labels = (model.predict(shuffled_images_test) >= 0.7).astype('int64')
5 predicted_labels = np.argmax(predicted_labels, axis=1)
6
7 row = 5
8 col = 6
9 fig, axes = plt.subplots(row, col, figsize=(16, 16))
10 c = 0
11
12 for i in range(row):
13     for j in range(col):
14         if(c >= 26):
15             axes[i][j].set_axis_off()
16         else:
17             axes[i][j].set_xticks([])
18             axes[i][j].set_yticks([])
19             axes[i][j].imshow(shuffled_images_test[c])
20             axes[i][j].set_title(f'Predicted: {get_label(predicted_labels[c])}', fontst
21             axes[i][j].set_xlabel(f'Actual: {get_label(shuffled_labels_test[c])}', font
22             c += 1

```

1/1 [=====] - 0s 130ms/step



## 2d. Architecture Tuning and hyperparameter tuning

To tune the model architecture, we will add a BatchNormalization layer on the last MaxPooling layer. Instead of doing the normalizing in the raw data, batch normalization is done between the layers of a neural network. Instead of using the entire data set, it is done in mini-batches. It facilitates learning by accelerating training and utilizing higher learning rates. Also adding a Dropout layer to reduce overfitting and improve generalization error in the CNN model.

In [18]:

```

1 model_2 = Sequential()
2
3 model_2.add(Conv2D(64, (5, 5), input_shape=target_dims))
4 model_2.add(Activation('relu'))
5 model_2.add(MaxPooling2D((2, 2)))
6
7 model_2.add(Conv2D(128, (3, 3)))
8 model_2.add(Activation('relu'))
9 model_2.add(MaxPooling2D((2, 2)))
10
11 model_2.add(Conv2D(256, (3, 3)))
12 model_2.add(Activation('relu'))
13 model_2.add(MaxPooling2D((2, 2)))
14
15 model.add(BatchNormalization())
16
17 model_2.add(Flatten())
18
19 model.add(Dropout(0.5))
20
21 model_2.add(Dense(512, activation='relu'))
22 model_2.add(Dense(n, activation='softmax'))
23
24 model_2.summary()

```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_3 (Conv2D)	(None, 60, 60, 64)	4864
activation_3 (Activation)	(None, 60, 60, 64)	0
max_pooling2d_3 (MaxPooling 2D)	(None, 30, 30, 64)	0
conv2d_4 (Conv2D)	(None, 28, 28, 128)	73856
activation_4 (Activation)	(None, 28, 28, 128)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 14, 14, 128)	0
conv2d_5 (Conv2D)	(None, 12, 12, 256)	295168
activation_5 (Activation)	(None, 12, 12, 256)	0
max_pooling2d_5 (MaxPooling 2D)	(None, 6, 6, 256)	0
flatten_1 (Flatten)	(None, 9216)	0
dense_2 (Dense)	(None, 512)	4719104
dense_3 (Dense)	(None, 26)	13338
=====		
Total params: 5,106,330		
Trainable params: 5,106,330		

Non-trainable params: 0

Compile the model using ADAM Optimizer. Loss function is categorical cross entropy because we are dealing with categorizing over 2 classes.

In [19]:

```
1 model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=["accuracy"])
```

Fit the train dataset and validation data to the model.

In [20]:

```
1 model_2.fit(X_train, y_train,
2             epochs=5,
3             batch_size=batch_size,
4             validation_data=(X_val, y_val))
```

Epoch 1/5

325/325 [=====] - 125s 384ms/step - loss: 1.7476 - accuracy: 0.7986 - val\_loss: 0.0792 - val\_accuracy: 0.9688

Epoch 2/5

325/325 [=====] - 135s 416ms/step - loss: 0.0651 - accuracy: 0.9798 - val\_loss: 0.0527 - val\_accuracy: 0.9840

Epoch 3/5

325/325 [=====] - 136s 420ms/step - loss: 0.0284 - accuracy: 0.9924 - val\_loss: 0.0107 - val\_accuracy: 0.9969

Epoch 4/5

325/325 [=====] - 132s 405ms/step - loss: 0.0413 - accuracy: 0.9894 - val\_loss: 0.0276 - val\_accuracy: 0.9913

Epoch 5/5

325/325 [=====] - 126s 386ms/step - loss: 0.0162 - accuracy: 0.9963 - val\_loss: 0.0094 - val\_accuracy: 0.9983

Out[20]:

<keras.callbacks.History at 0x227298c8850>

## 2e. Tuned CNN Model Performance Analysis

Evaluate the tuned model

In [21]:

```
1 score = model_2.evaluate(x = X_val, y = y_val, verbose = 0)
2 print('Accuracy for validation images:', round(score[1]*100, 3), '%')
3 score = model_2.evaluate(x = X_test, y = y_test, verbose = 0)
4 print('Accuracy for test images:', round(score[1]*100, 3), '%')
```

Accuracy for validation images: 99.827 %

Accuracy for test images: 100.0 %

Using sklearn utils shuffle function to shuffle the test images and labels before predicting to variate the orders of predictions.

In [22]:

```
1 shuffled_images_test, shuffled_labels_test = shuffle(images_test, labels_test)
```

Get the class label from integer class number label. Ex : From 1 to 'A' , 2 to 'B', etc. Using predict function on model and give a threshold about 0.7 for prediction over than 0.7 to be the class label. The predicted\_labels are now in hot encoded mode meaning not the real number values, so np.argmax() to get the real number value. Lastly plot the shuffled images, prediction, and actual class value.

In [24]:

```

1 def get_label(num):
2     return class_labels[num]
3
4 predicted_labels = (model_2.predict(shuffled_images_test) >= 0.7).astype('int64')
5 predicted_labels = np.argmax(predicted_labels, axis=1)
6
7 row = 5
8 col = 6
9 fig, axes = plt.subplots(row, col, figsize=(16, 16))
10 c = 0
11
12 for i in range(row):
13     for j in range(col):
14         if(c >= 26):
15             axes[i][j].set_axis_off()
16         else:
17             axes[i][j].set_xticks([])
18             axes[i][j].set_yticks([])
19             axes[i][j].imshow(shuffled_images_test[c])
20             axes[i][j].set_title(f'Predicted: {get_label(predicted_labels[c])}', fontst
21             axes[i][j].set_xlabel(f'Actual: {get_label(shuffled_labels_test[c])}', font
22             c += 1

```

1/1 [=====] - 0s 52ms/step

