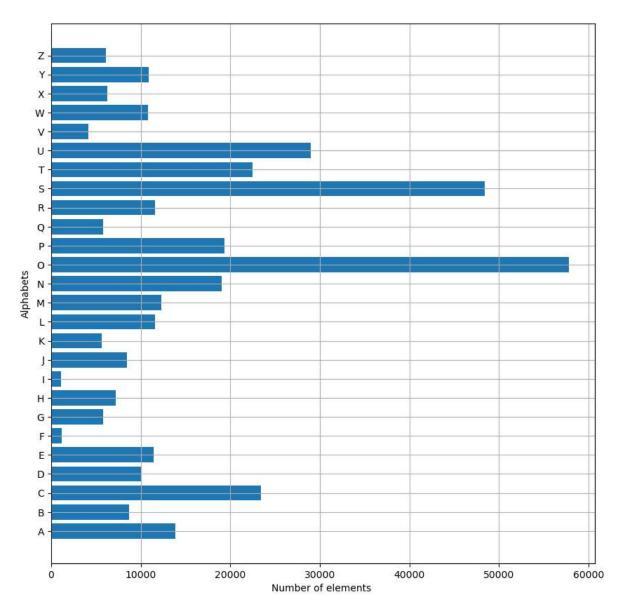
- **matplotlib. pyplot** is a collection of functions that make matplotlib work like MATLAB. Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.
- **OpenCV** is a great tool for image processing and performing computer vision tasks
- **NumPy** is a Python library used for working with arrays
- **Keras** is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used to make the implementation of neural networks easy.
 - It is a tensor flow deep learning library to create a deep learning model for both regression and classification problems.

Sequential model:

• It allows us to create a deep learning model by adding layers to it. Here, every unit in a layer is connected to every unit in the previous layer.

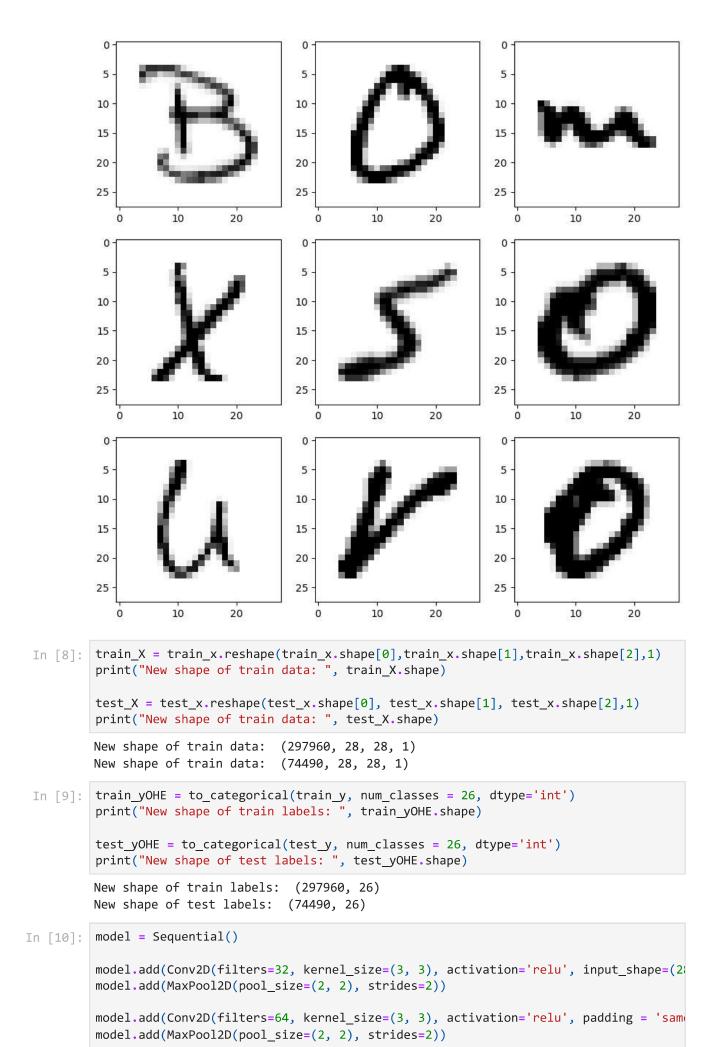
```
In [1]: import matplotlib.pyplot as plt
    import cv2
    import numpy as np
    from keras.models import Sequential
    from keras.layers import Dense, Flatten, Conv2D, MaxPool2D, Dropout
    from tensorflow.keras.optimizers import SGD, Adam
    from keras.callbacks import ReduceLROnPlateau, EarlyStopping
    from tensorflow.keras.utils import to_categorical
    import pandas as pd
    import numpy as np
    from sklearn.model_selection import train_test_split
    from sklearn.utils import shuffle
In [2]: data = pd.read_csv(r"A_Z Handwritten Characters Data.csv").astype('float32')
    print(data.head(10))
```

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        [10 rows x 785 columns]
In [3]: X = data.drop('0',axis = 1)
        y = data['0']
In [4]: |
        train_x, test_x, train_y, test_y = train_test_split(X, y, test_size = 0.2)
        train_x = np.reshape(train_x.values, (train_x.shape[0], 28,28))
        test_x = np.reshape(test_x.values, (test_x.shape[0], 28,28))
        print("Train data shape: ", train_x.shape)
        print("Test data shape: ", test_x.shape)
        Train data shape: (297960, 28, 28)
        Test data shape: (74490, 28, 28)
        word_dict = {0:'A',1:'B',2:'C',3:'D',4:'E',5:'F'
In [5]:
                     6: 'G',7: 'H',8: 'I',9: 'J',10: 'K',11: 'L',
                     12: 'M',13: 'N',14: 'O',15: 'P',16: 'Q',17: 'R',
                      18: 'S',19: 'T',20: 'U',21: 'V',22: 'W',23: 'X',
                      24: 'Y', 25: 'Z'}
In [6]: |
        y_{int} = np.int0(y)
        count = np.zeros(26, dtype='int')
        for i in y_int:
            count[i] +=1
        alphabets = []
        for i in word dict.values():
             alphabets.append(i)
        fig, ax = plt.subplots(1,1, figsize=(10,10))
        ax.barh(alphabets, count)
        plt.xlabel("Number of elements ")
        plt.ylabel("Alphabets")
        plt.grid()
        plt.show()
```



```
In [7]: shuff = shuffle(train_x[:100])
fig, ax = plt.subplots(3,3, figsize = (10,10))
axes = ax.flatten()

for i in range(9):
    _, shu = cv2.threshold(shuff[i], 30, 200, cv2.THRESH_BINARY)
    axes[i].imshow(np.reshape(shuff[i], (28,28)), cmap="Greys")
plt.show()
```

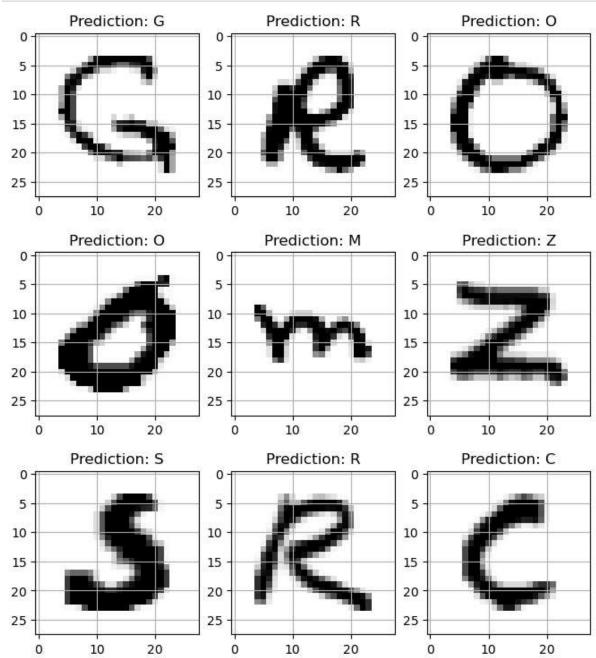


model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding = 'va

```
model.add(MaxPool2D(pool_size=(2, 2), strides=2))
         model.add(Flatten())
         model.add(Dense(64,activation ="relu"))
         model.add(Dense(128,activation ="relu"))
         model.add(Dense(26,activation ="softmax"))
         model.compile(optimizer = Adam(learning rate=0.001), loss='categorical crossentropy
In [11]:
         history = model.fit(train X, train yOHE, epochs=1, validation data = (test X,test
         9312/9312 [=====================] - 222s 24ms/step - loss: 0.1548 - accur
         acy: 0.9581 - val_loss: 0.0691 - val_accuracy: 0.9815
In [12]:
         model.summary()
         model.save(r'model hand.h5')
         Model: "sequential"
          Layer (type)
                                     Output Shape
                                                              Param #
         ______
                                     (None, 26, 26, 32)
          conv2d (Conv2D)
                                                              320
          max_pooling2d (MaxPooling2D (None, 13, 13, 32)
          conv2d_1 (Conv2D)
                                     (None, 13, 13, 64)
                                                              18496
          max_pooling2d_1 (MaxPooling (None, 6, 6, 64)
          2D)
          conv2d 2 (Conv2D)
                                     (None, 4, 4, 128)
                                                              73856
          max_pooling2d_2 (MaxPooling (None, 2, 2, 128)
          2D)
          flatten (Flatten)
                                     (None, 512)
          dense (Dense)
                                     (None, 64)
                                                              32832
          dense 1 (Dense)
                                     (None, 128)
                                                              8320
          dense 2 (Dense)
                                     (None, 26)
                                                              3354
         ______
         Total params: 137,178
         Trainable params: 137,178
         Non-trainable params: 0
         print("The validation accuracy is :", history.history['val_accuracy'])
print("The training accuracy is :", history.history['accuracy'])
In [13]:
         print("The validation loss is :", history.history['val_loss'])
         print("The training loss is :", history.history['loss'])
         The validation accuracy is : [0.9815142750740051]
         The training accuracy is : [0.9580850005149841]
         The validation loss is : [0.06907927989959717]
         The training loss is : [0.15480975806713104]
         fig, axes = plt.subplots(3,3, figsize=(8,9))
In [14]:
         axes = axes.flatten()
```

```
for i,ax in enumerate(axes):
    img = np.reshape(test_X[i], (28,28))
    ax.imshow(img, cmap="Greys")

pred = word_dict[np.argmax(test_yOHE[i])]
    ax.set_title("Prediction: "+pred)
    ax.grid()
```



```
In [15]: img = cv2.imread(r'D:\NIET\YEAR II\SEM IV\Mini Project\Images\img_a.jpg')
    img_copy = img.copy()

img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (450,500))

In [16]: img_copy = cv2.GaussianBlur(img_copy, (7,7), 0)
    img_gray = cv2.cvtColor(img_copy, cv2.COLOR_BGR2GRAY)
    _, img_thresh = cv2.threshold(img_gray, 100, 255, cv2.THRESH_BINARY_INV)

img_final = cv2.resize(img_thresh, (28,28))
    img_final =np.reshape(img_final, (1,28,28,1))
```