Handwritten Characters Recognition

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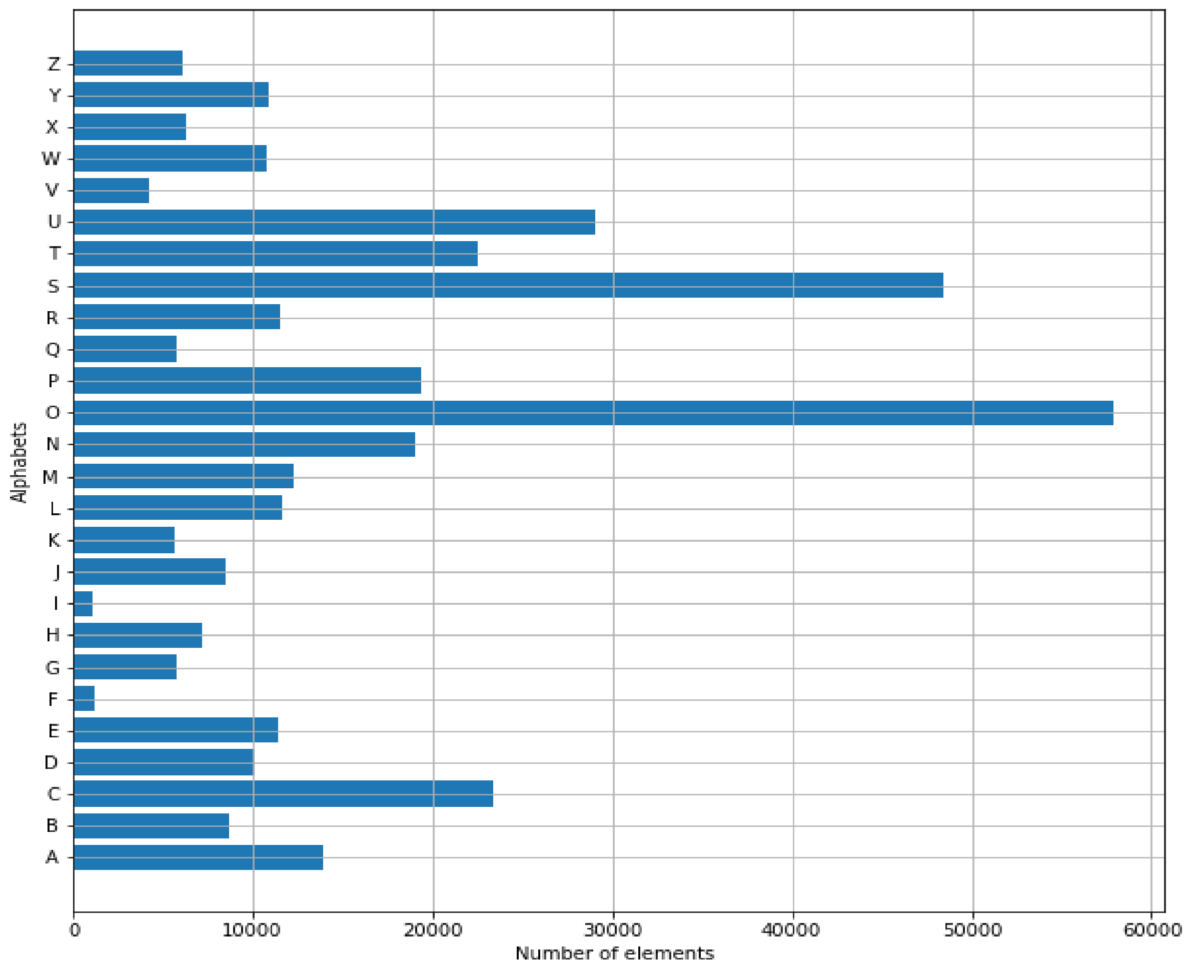
Abstract
This is a Neural Network based model that classifies the english handwritten characters. I used python libraries like Pandas, NumPy, Matplotlib, OpenCV, Sci-kit learn and TensorFlow. You will get data used in this code from here. I recommend you all to use google colab which is a free jupyter like notebook for python coding.

About Data
Data used in this code is in microsoft excel comma separated value. First column of this data is a range of values from 0 to 25. Which refers to 26 English letters A to Z. And the rest of 784 columns are pixel values ranging from 0 to 256. Here is the distribution of letters.



Well, obviously this data is not perfect because all the letters should be in roughly equal amounts.

About imported libraries

1) Pandas - for reading csv files
2) Numpy - for array related work
3) Matplotlib - for plotting images
4) cv2 - for working with images
5) Sklearn - for dividing data into training and testing
6) Tensorflow - for neural network
7) Random - for generating a random number

About data preprocessing

First of all, I created an array “X” which includes all the image arrays from the csv file. The second one is “y” which is numbers from 0 to 25 represents A to Z. I shrunk the array X ranging from 0 to 1 which previously was 0 to 255 for simplicity. Then I divided the dataset into training and testing. Now our 80% of data is for training and 20% for testing.

Build the model

Building the neural network requires configuring the layers of the model, then compiling the model.

Set up the layers : The basic building block of a neural network is the layer. Layers extract representations from the data fed into them. Hopefully, these representations are meaningful for the problem at hand. Most of deep learning consists of chaining together simple layers. Most layers, such as tf.keras.layers.Dense, have parameters that are learned during training.

```
model = tf.keras.Sequential([

   tf.keras.layers.Flatten(input_shape=(784,)),

   tf.keras.layers.Dense(128, activation='relu'),

   tf.keras.layers.Dense(64, activation='relu'),

   tf.keras.layers.Dense(26)

])
```

The first layer in this network, tf.keras.layers.Flatten, transforms the format of the images from a two-dimensional array (of 784 × 1 pixels) to a one-dimensional array (of 784 pixels). Think of this layer as unstacking rows of pixels in the image and lining them up. This layer has no parameters to learn; it only reformats the data. **You can also use input size as (28 × 28 pixels)**.

After the pixels are flattened, the network consists of a sequence of three tf.keras.layers.Dense layers. These are densely connected, or fully connected, neural layers. The first Dense layer has 128 nodes (or neurons). The second Dense layer has 64 nodes (or neurons) The third (and last) layer returns a logits array with length of 26. Each node contains a score that indicates the current image belongs to one of the 26 classes.

Compile the model : Before the model is ready for training, it needs a few more settings. These are added during the model's *compile* step,

- *Loss function* —This measures how accurate the model is during training. You want to minimize this function to "steer" the model in the right direction.
- *Optimizer* —This is how the model is updated based on the data it sees and its loss function.
- *Metrics* —Used to monitor the training and testing steps. The following example uses *accuracy*, the fraction of the images that are correctly classified.

```
model.compile(optimizer='adam',

loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Train the model : Training the neural network model requires the following steps:

1. Feed the training data to the model. In this example, the training data is in the train_X and train_y arrays.
2. The model learns to associate images and labels.
3. You ask the model to make predictions about a test set—in this example, the test_X array.

4. Verify that the predictions match the labels from the test_y array.

Feed the model : To start training, call the model.fit method—so called because it "fits" the model to the training data.

As the model trains, the loss and accuracy metrics are displayed. This model reaches an accuracy of about 0.9871 (or 98.71%) on the training data.

Evaluate accuracy : Next, compare how the model performs on the test dataset.

```
test_loss, test_acc = model.evaluate(test_X,  test_y, verbose=2)

print('Test accuracy:', test_acc)
```

Our model accuracy on test data is 98.03 %. It turns out that the accuracy on the test dataset is a little less than the accuracy on the training dataset. This gap between training accuracy and test accuracy represents *overfitting*. Overfitting happens when a machine learning model performs worse on new, previously unseen inputs than it does on the training data. An overfitted model "memorizes" the noise and details in the training dataset to a point where it negatively impacts the performance of the model on the new data. For more information, see the following:

- Demonstrate overfitting
- Strategies to prevent overfitting

Predicting Results
Now, we have trained our model. I made a function which will preprocess the image data and predict the result.

Saving our model
Save the trained model in .h5 format.

Loading pretrained model
Open another notebook or existing notebook and load libraries. Load model using load_model(“ path of your `Handwritten_Character_Recognition.h5` file”). I also wrote the A to Z alphabets in paint and verified all images in model. Which pretty well works. You can also draw images of A to Z characters and verify on this model.