Cursive Handwritten Text Segmentation & Recognition

Introduction
Handwriting recognition is one of the very challenging and difficult problems. In recent years, a number of papers have been published with research detailing new techniques for the classification of handwritten numerals and words. In most of the research text recognition carried out by passing each small part of segmented text to neural network. This technique relies on the confidence values for verification of correctness which is very slow & difficult to implement.
In this experiment we proposed very simple and unique algorithms for text recognition which mainly focus on the word segmentation. The algorithm involves the preprocessing, segmentation and recognition steps.

Slant Correction
To make the letter recognition more efficient we corrected the slant angle of image. For slant correction we first calculate the angle for maximum lines with respect to vertical line using 'Hough Lines method'. After finding the angle, image is rotated with same angle in opposite direction around the baseline of text.

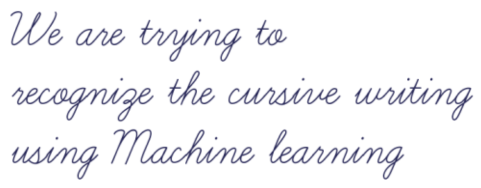
We are trying to
recognize the cursive writing
using Machine learning

Fig. Slant Image

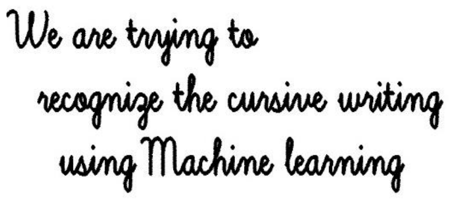
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Fig. De-slant Image

Line Segmentation
Considering the text lines are horizontal in position, the text lines are separated out by extracting the row wise consecutive black pixel existence.

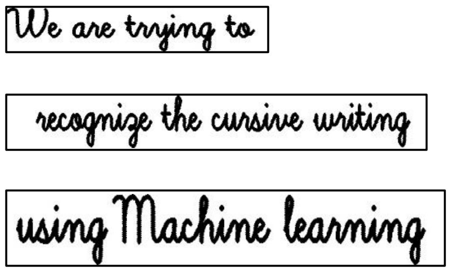
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Fig: Text Lines

Word Segmentation

After extracting the text lines, the image is dilated to join the distant neighboring pixel or to remove the small space between two letters. After that we tried to use contour tracing to accurately segment the intersecting components. Then bounding box is applied on contours to extract words. These word images are then further sent for preprocessing.

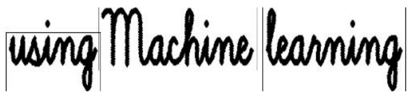

using Machine learning

Fig: Word Separation using contour

Preprocessing

The first step to any document analysis is pre-processing. First the sample image is converted to gray scale image. A binary image is generated out of this grey scale image and one bit binary noise is removed by using erosion. The subsequent steps are all for normalizing the data to common axis. In normalization the various sized images are resized to fixed size image keeping aspect ratio intact.

Top Contour Point Extraction

The top contour points are extracted by taking first black pixel of each column from top.

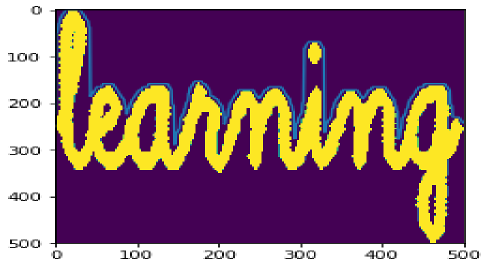


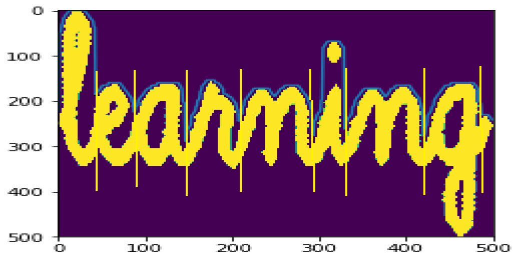
Fig: Graph plot in blue over the top contour points

Character segmentation

We have proposed two approaches for the character segmentation

1. **Local maxima & Minima Technique**

   In this we traverse through each top contour points from left to right. Then the vertical distance of each contour point with its next contour point is measured. If this distance is more than certain threshold value, then we consider this region as possible segment line.



2. **Middle Cut Line method**

   In this method, the upper contour points and lower contours points are extracted. And then mean value is calculated for both upper & lower contour points. This mean value gives us the approximate upper base line & lower base line. Considering these two lines we find the mid line and cut the word image from this mid line.

   After cutting the image from mid line we traverse through this line and find the complete blank spaces. This region can be considered as segment point. The segment points are then applied to original word image for segmentation.

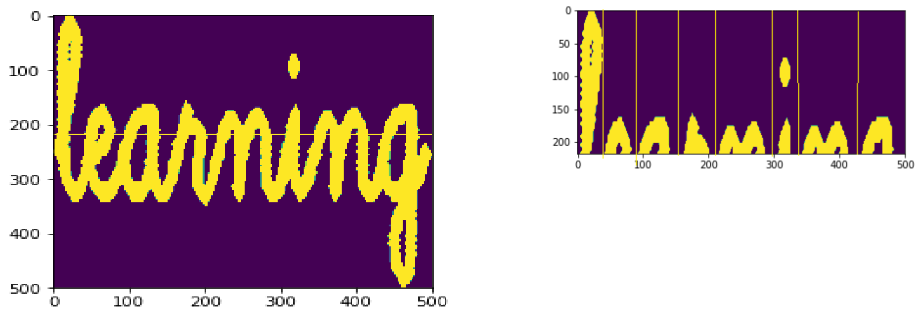


Fig: Cut Image from middle of Upper & lower baseline and segmented

Over Segmentation removal

In the segmentation process, due to bad quality images, words are getting over segmented. We tried to minimize the over segmentation problem by setting some threshold. If the distance between two segment lines are less than the threshold value, then that segment line will be rolled out and consider its next segment line. The threshold was set by trial and error method initially, can be changed to a much concrete formula later.

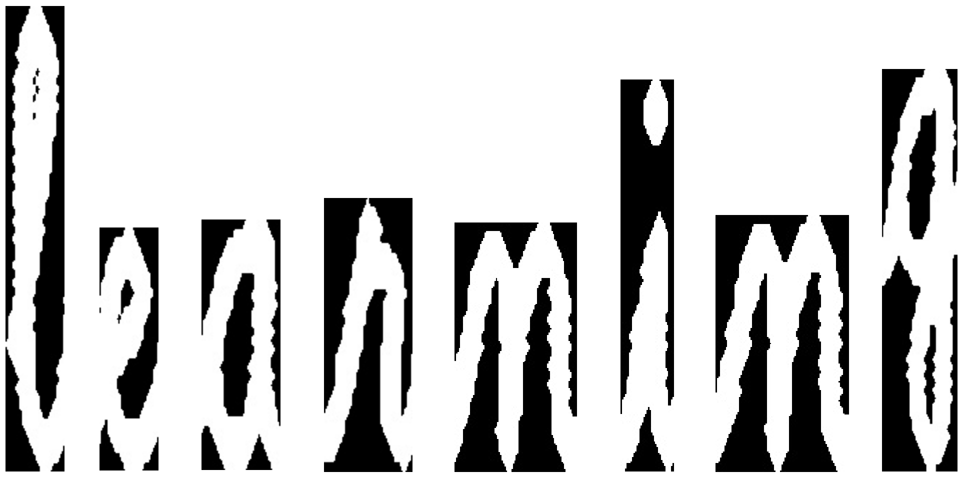


Fig. Segmented letters

Image Standardization

As we are going to evaluate the segmented letter images on standardize trained image model which is of fixed size 28*28 pixel, we resize the images with same size including padding of 4 pixels on each side. We cropped the various sized input images to cut the extra padding on each side and then resized them to 20*20 pixel.

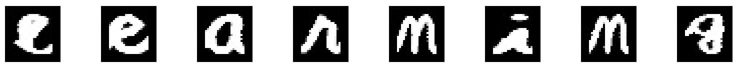
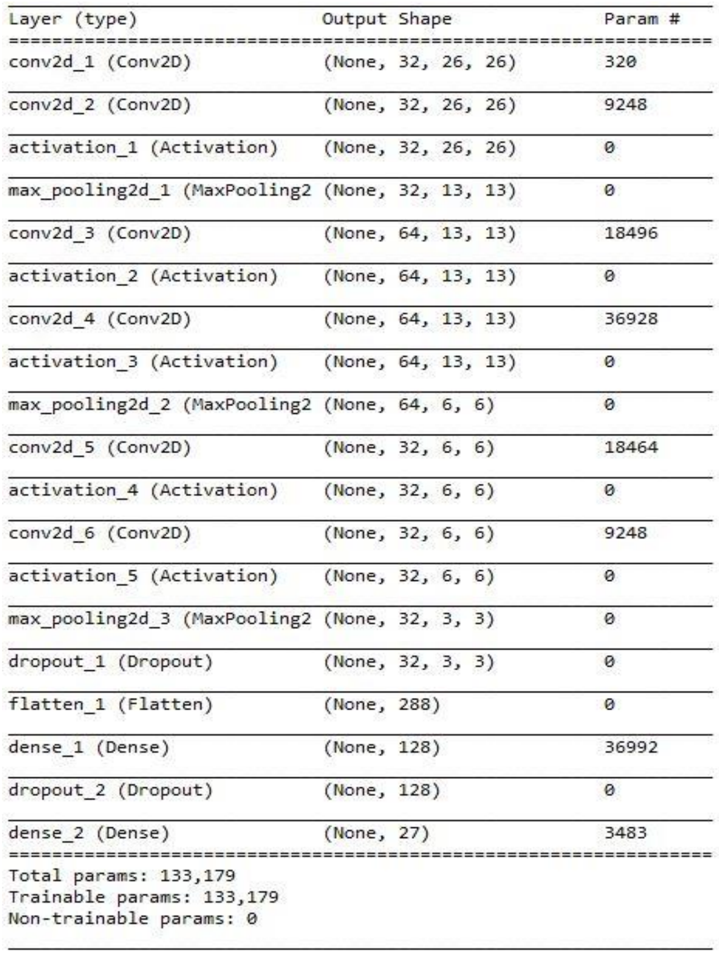


Fig: Segmented letters in 28*28-pixel size

Character Recognition

In this application we propose the use of Convolution Neural Networks for recognition of characters which utilizes the unsupervised learning technique for training. We have created CNN multilayered model using KERAS backed by Tensorflow. For training purpose, we have used MNIST character dataset. The dataset consists of over 1L labeled images of handwritten letters. The images are in 28*28-pixel format.

We trained the model on 70% of data and tested on 30% of data. The measured accuracy got from the CNN model is around 90%.



```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 26, 26)        320
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 26, 26)        9248
_________________________________________________________________
activation_1 (Activation)    (None, 32, 26, 26)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 13, 13)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 64, 13, 13)        18496
_________________________________________________________________
activation_2 (Activation)    (None, 64, 13, 13)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 64, 13, 13)        36928
_________________________________________________________________
activation_3 (Activation)    (None, 64, 13, 13)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 64, 6, 6)          0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 32, 6, 6)          18464
_________________________________________________________________
activation_4 (Activation)    (None, 32, 6, 6)          0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 32, 6, 6)          9248
_________________________________________________________________
activation_5 (Activation)    (None, 32, 6, 6)          0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 32, 3, 3)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 3, 3)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 288)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               36992
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 27)                3483
=================================================================
Total params: 133,179
Trainable params: 133,179
Non-trainable params: 0
_________________________________________________________________
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Fig: Convolutional Neural Network Model