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HANDWRITING RECOGNITION USING CNN

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Abstract

The recognition and discovery of handwriting has become an important subject in modern times. Human handwriting can be easily hidden in a variety of ways including free handwriting, image tracking and transfer, making real manuscript recognition still a challenging task but recognition of English words lacks simplicity and accuracy. Although it's diagnostic method is well reported, good deception can outperform existing tools. Existing recognition systems have led to many research activities in automated detection and recognition tasks using computer techniques, feature extraction, class comparisons, performance testing and pattern recognition. To simplify, simplify English writing, simplicity and efficiency, we are developing a handwriting acquisition and recognition system based on CNN's in-depth learning model.

1. Introduction

Everyone has a different style of writing as part of their personality; even if the same group of words were written several times by an individual handwriting may not look the same. Different ways the notable features of handwriting are: inclination, basic patterns, prosperity, height, width and size of letters, lifting pens and splitting, connecting strokes, first and last strokes, unusual letter formation, line quality, spaces (spaces and line between character and word), pressure of pen and ornaments and markings. Apart from the fact that some of the author's situations also play an important role in affecting handwriting style such as paper slides, table quality and materials, handwriting systems receive input from touch screen, electric pen, scanner, ink colors, pen type, images and paper documents. It is processed and renders the output as digital text suitable for sequential access

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and deception. Many different methods have been used both online and offline, using mathematical methods, structural methods, neural network, and syntactic methods. The big problem faced by this system is to classify the image of any handwritten word, which might be of the form of tilted, cursive or block writing. The problem can be solved with an automated model that helps the user to solve the problem of converting the handwritten format into a digital format. The most challenging part of the traditional approach is the separation of the recognition pattern. In the division section, the letters are taken from the image for each word. Then separate each letter separately to reproduce the word. To complete this task we use the CNN model to extract features from a given character image and its library of various models designed to identify or understand handwritten characters and will provide digital text output. There is a real world work where a handwriting recognition system is required such as postal address description, analysis, post verification, information technology, education system, research bank check, addresses. The report explores new strategies and various approaches that promise to reduce its processing time while providing the highest accuracy of its recognition.

2. Literature Review

In this literature [1] author proposed method that provides the solution to convert the handwritten text using Multilayer Feed-Forward Neural Network without using feature extraction. It involves series of steps: Image Acquisition, Pre-processing, Segmentation, Classification and Recognition, and Post Processing. This method has a dataset for each character (26 alphabets). They uses fifty different character dataset for training the neural network. The result of this trained network is transformed to the classification and recognition. In this system, each handwritten character of the input was resized into 30×20 pixels, which means each resized character has 600 pixels and the result of this process is considered as a features. These features are taken for training the neural network. The proposed system has the accuracy up to 91.5.

In this paper [2] defines the convolutional neural network based on the methods of Data Pre-processing and Augmentation, Vocabulary Training, fragmentation, text size, Classification Level Character and Segmentation of handwritten recognition system. Long Short Term Memory Networks (LSTMN). The Convolution Neural Network (CNN) process is used to separate each character from a part of a word and create a binding box for each character. Divided characters were then sent to another CNN model in the process of character-class separation. Eventually it converted the handwritten letter into a compatible digital letter format. The literature [3] introduced an English-language comprehension program based on the division of the novel and a hand-drawn dictionary that uses a variety of Pre-Criticizing Processing, Distinguishing, Character Recognition and Voice Recognition. In the separation section, word order is separated by small images of individual letters using the labeling process. This process provides information about the number of characters in an image. The classification method describes the decision-making process of the recognition system that provides a printed text of the identified character in a systematic way by calculating the value of ASCII using the reference index of test models. Convolutional neural networks are widely introduced into the offline algorithm. The experiments were performed using UNIPEN lower case data sets giving 92.20%.

In Paper [4] the author developed an offline digital recognition system using various machine learning techniques such as: Multilayer Perception, Support Vector Machine, Naïve Bayes Net, Random Forest, J48 and Random Tree and used a handwriting recognition system. This paper compares the accuracy and level of machine recognition described above learning strategies. Examination of this paper used the WEKA database and achieved 90.37% accuracy obtained using the multilayer perception method. In the text [5] he introduced the optical character recognition (OCR) system to detect printed or handwritten text. The program categorizes text image images according to their physical properties and appearance. Visual acuity is measured by the use of the strength values of the distribution elements and the shape is determined by the structural features. This approach provided an impressive editorial test using the IAM database of the optical character recognition (OCR) system to distinguish printed or handwritten text at word level. The accuracy achieved by the system was 94.5% and 98.6%. In paper [6] he described how to create a default way to separate a text image using a possible decision-making strategy. The main purpose of the paper was to provide inexpensive computer software and show significant improvements in reducing the amount of time and memory retention compared to the existing algorithm and also improved the accuracy of the sections. Therefore, this new method of separation usually avoids errors. This approach provided a 22% improvement in separation and reduced operating time.

In the text [7] he proposed the Global Supervised Low Rank Exception (GSLRE) method and the Adaptive Drop-Weight (ADW) method. Explains CNN's nine-layer network to see Chinese handwriting text with 3755 sections and algorithms reduce the cost of computation nine times. The paper achieves more than 97% accuracy.

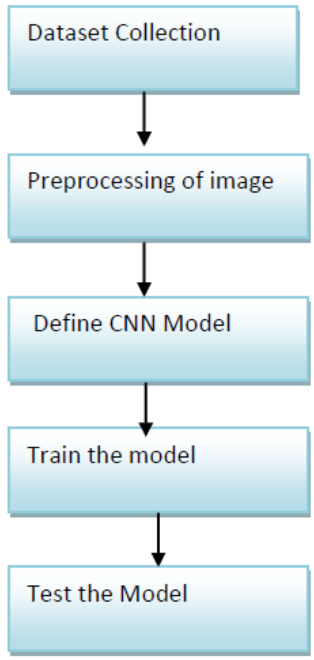
Literature Review Table

S. No.	Article Title	Technique Used	Database Used	Accuracy
1	Neural Network based on Handwritten Awareness System	Image Acquisition Preliminary processing Separation Separation and Recognition	After processing 4840 characters Data collected from 100 authors.	Accuracy: 91.5% Efficiency: 85.5%
2	Manuscript Recognition using Deep Reading	Pre-processing and data addition Vocabulary size Word Level Setting Training Separation Character level classification	IAM Handwriting Dataset, with 1500 types of handwritten text, where the form is handwritten paper, from 600 authors, offering 5500+ sentences and 11500+ words	VGG- 19 28% 22% 20% RESNET - 31% 27% 22% 18 RESNET- 35% 27% 25% 34 Char- 38% 31% level
3	A novel hybrid CNN–SVM classifier for recognizing handwritten digits	SVM classification Hybrid CNN-SVM model	MNIST Digit Database	Recognition rate without rejection : 99.65% Recognition rate %(with 5.60% rejection): 94.40

4	A System for Handwritten and Printed Text Classification	Text localization Feature extraction Classification	IAM Dataset	Accuracy : 94.5% Efficiency : 98.6%
5	Efficient and accurate document image	Soft classification algorithm Feature extraction	Hewlett-Packard(HP)	Development separation rate: 22% Working time is reduced 18% to 50% memory requirements
6	Handwritten Character Recognition by Alternately Trained Relaxation Convolutional Neural Network	R-CNN: Relaxation Convolution ATR-CNN: Alternate Training	MNIST ICDAR	Error rate: 3.94%
7	Building Fast and Compact Convolutional Neural Networks for Offline Handwritten Chinese Character Recognition	Expansion of the International Monitored Standard Adaptive Drop-weight Unnecessary Communication Analysis	CASIA-HWDB1.0 and CASIA-HWDB1.1 (training database)ICDAR-2013 (test data)	Accuracy : above 97%
8	Deep Learning Approach for Devanagari Script Recognition	Preview to remove audio, binary image conversion, resize, and mask performance Boltzmann (RBM) equipment unloaded unattended Distributed	ISI Kolkata, CPAR-201214 and our multi-user database	Supervised learning accuracy: 83.44% and supervised learning accuracy: 91.81%

		back-up teaching of distribution		
9	Deep Feature Embedding for Accurate Recognition and Retrieval of Handwritten Text	HWNet Architecture Embedding text and image	The IAM Handwriting Database contains 1,539 pages and 1,15,320 words George Washington has 20 pages and 4,894 words Bentham manuscripts have 796 pages and 1,54,470 words	Accuracy: 91.58% Error rate: 6.69%
10	Word spotting and recognition via a joint deep embedding of image and text	Problem construction Word embedding Embedding word text A multi-layer perceptron simulation model	IAM Offline RIMES George Washington (GW) Lord Byron (LB) IFN / ENIT	Operating Outcome: Example query (QBE) detection of words is 97.90% Question-by-string (QBS) word exposure is 92.97% Word recognition is 91.55%. Error rate: less than 11.9%

3. Proposed Approach



3.1 Dataset Collection

The Dataset Recognition Database used for this project is publicly available online. This database contains more than 400,000 handwritten words taken from various projects. Here we convert characters into scanned documents into digital forms for character recognition using image processing technology. It usually works well on typed fonts. However, there are still difficult challenges with machines to identify handwritten characters, due to the huge differences in individual writing styles.

3.2 Preparation and preparation of images

• Images are uploaded as grayscale and rebuilt into 256 widths and 64 lengths.

• Width and length are cut if it is more than 256 and 64 respectively. If small, the image has white pixels. Finally the image is rotated clockwise to bring the image shape to (x, y).

• Image has become standard to wide $[0, 1]$

3.3 Define CNN model

In-depth learning comes under the class of machine learning algorithms that consist of sequential layers. The previous layer output is the next layer input. Different types of its learning process exist unchecked, unsupervised or under surveillance. Representation of different learning algorithms makes it ideal and prepared to find the most efficient way to represent data. In-depth learning process Deep in feature extraction and classification is not important because the model automatically removes the features while training the model. It is widely used in research fields such as image processing, image retrieval, speech recognition, natural language processing and bioinformatics. The CNN model is chosen as an in-depth learning method in this profession. CNN, can easily identify and classify objects by first processing, and successfully analyzes the visuals images and can easily distinguish the necessary features with its multi-layered structure. There are four main layers available: flexible layer, integration layer, working opening layer and fully integrated layer.

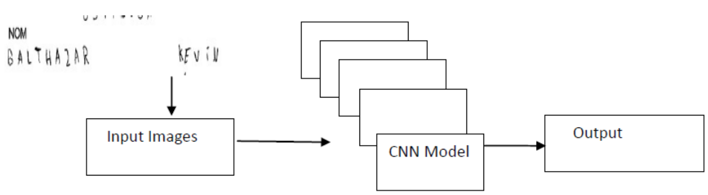


Figure 1. Basic CNN Architecture.

3.4 Train the model

The model is trained on set of approx. 3000 images and divided into set of training and validation set.

4. Experiment Result

4.1 Dataset collection:

3.5 Test the model

The model is tested on some image data to check whether our machine able to correctly predict the output or not.

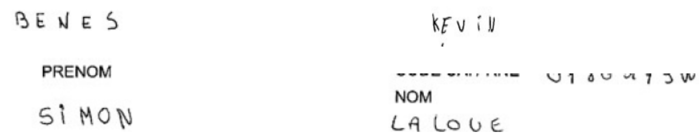


Figure 2. Dataset images.

4.2 CNN Output

The model provides the total number of parameters calculated by CNN

Background (type) Output Status Param
input (InputLayer) [(None, 256, 64, 1)] 0
conv1 (Conv2D) (None, 256, 64, 32) 320
batch_normalization (BatchNo (None, 256, 64, 32) 128
activation (Active) (None, 256, 64, 32) 0
max1 (MaxPooling2D) (None, 128, 32, 32) 0
conv2 (Conv2D) (None, 128, 32, 64) 18496
batch_normalization_1 (Collection (None, 128, 32, 64) 256
activation_1 (Active) (None, 128, 32, 64) 0
max2 (MaxPooling2D) (None, 64, 16, 64) 0
stop (Stop) (None, 64, 16, 64) 0
conv3 (Conv2D) (None, 64, 16, 128) 73856
batch_normalization_2 (Collection (None, 64, 16, 128) 512
activation_2 (Active) (None, 64, 16, 128) 0
max3 (MaxPooling2D) (None, 64, 8, 128) 0
dropout_1 (Dropout) (None, 64, 8, 128) 0
reset (Reshape) (None, 64, 1024) 0
Dense1 (Dense) (None, 64, 64) 65600
Lstm1 (Bidirectional) (None, 64, 512) 657408
lstm2 (Bidirectional) (None, 64, 512) 1574912
cramped2 (Dense) (None, 64, 30) 15390
softmax (Activation) (None, 64, 30) 0

Total parameters: 2,406,878

Training parameters: 2,406,430

Untrained parameters: 448

Figure 3. CNN output.

The model is trained on the training image dataset and epoch value is counted at each step to check the total loss occur at each phase

```
Epoch 1/25
24/24 [==============================] - 136s 6s/step - loss: 21.8414 - val_loss: 23.2205
Epoch 2/25
24/24 [==============================] - 124s 5s/step - loss: 20.6728 - val_loss: 23.7525
Epoch 3/25
24/24 [==============================] - 125s 5s/step - loss: 20.3731 - val_loss: 24.4212
Epoch 4/25
24/24 [==============================] - 125s 5s/step - loss: 20.2109 - val_loss: 23.6268
Epoch 5/25
24/24 [==============================] - 135s 6s/step - loss: 20.1031 - val_loss: 22.8790
Epoch 6/25
24/24 [==============================] - 123s 5s/step - loss: 20.0177 - val_loss: 22.1234
Epoch 7/25
24/24 [==============================] - 124s 5s/step - loss: 19.9304 - val_loss: 21.9210
Epoch 8/25
24/24 [==============================] - 124s 5s/step - loss: 19.8505 - val_loss: 21.3029
Epoch 9/25
24/24 [==============================] - 128s 5s/step - loss: 19.7587 - val_loss: 21.1260
Epoch 10/25
24/24 [==============================] - 135s 6s/step - loss: 19.6810 - val_loss: 21.0101
Epoch 11/25
24/24 [==============================] - 122s 5s/step - loss: 19.5846 - val_loss: 21.0123
Epoch 12/25
24/24 [==============================] - 123s 5s/step - loss: 19.4760 - val_loss: 21.2923
Epoch 13/25
24/24 [==============================] - 123s 5s/step - loss: 19.3568 - val_loss: 20.9356

Epoch 14/25
24/24 [==============================] - 123s 5s/step - loss: 19.1906 - val_loss: 21.3790
Epoch 15/25
24/24 [==============================] - 124s 5s/step - loss: 19.0491 - val_loss: 21.5917
Epoch 16/25
24/24 [==============================] - 124s 5s/step - loss: 18.8709 - val_loss: 21.0720
Epoch 17/25
24/24 [==============================] - 133s 6s/step - loss: 18.7032 - val_loss: 20.6596
Epoch 18/25
24/24 [==============================] - 124s 5s/step - loss: 18.5204 - val_loss: 20.0650
Epoch 19/25
24/24 [==============================] - 124s 5s/step - loss: 18.2910 - val_loss: 20.4801
Epoch 20/25
24/24 [==============================] - 127s 5s/step - loss: 18.0599 - val_loss: 19.5564
Epoch 21/25
24/24 [==============================] - 126s 5s/step - loss: 17.7654 - val_loss: 18.7542
Epoch 22/25
24/24 [==============================] - 136s 6s/step - loss: 17.5322 - val_loss: 18.4921
Epoch 23/25
24/24 [==============================] - 126s 5s/step - loss: 17.3158 - val_loss: 18.3432
Epoch 24/25
24/24 [==============================] - 124s 5s/step - loss: 17.0306 - val_loss: 18.1717
Epoch 25/25
24/24 [==============================] - 124s 5s/step - loss: 16.8041 - val_loss: 17.7183
```

Figure 4. Epoch analysis.

4. Test Model

Model is tested on the test data image set

Figure 5. Test image result.

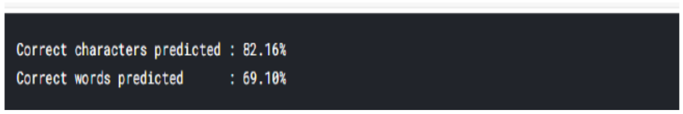


Figure 6. Prediction Accuracy Result.

5. Conclusion

Convolutional Neural Network (CNN) adds its significant improvement to the Manuscript Document Recognition System. This paper tells us the effectiveness of CNN-based classification of data and pre-processing methods. Our model clearly sees handwriting and achieves outgoing predictions of up to 82.16% and accurate predictions of up to 69.16%. However the model can be continuously developed using multiple training samples. This will help the model to learn as well as the generalisesebetter. There are many images in the training set that are completely invisible to the human eye. Deleting such images will aid in the learning of the model.

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