

Deep Neural Network for Handwriting Recognition System

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ABSTRACT: In a large-scale industry or organization, a number of documents will be sent and received. Due to variation in handwriting, interpretation of these texts will be difficult and manual automation of these would be nearly impossible. In our paper, we intend to translate the handwritten texts into digitalized text. Digitized text is useful as it makes information readily available. Some of the previously used approaches for HTR are, Deep Convolutional Neural Network (DCNN), Optical Character Recognition (OCR), Self-organising map and Projection approach. Problems faced here are over-fitting, identification of wrong text, limitations to human handwritten text, slow computation and reduced efficiency with smaller dataset. To overcome these hurdles in the existing system, we have proposed a system based on ANNs (Artificial Neural Networks). Recently, it was discovered that ANNs have an excellent capacity in sequence data analysis such as natural language processing. In our proposed system we are using both Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to recognize the handwritten text efficiently. The classifier has CNN layers to extract features from the input image and RNN layers to propagate information through the image. This helps to optimize the data effectively and increases the accuracy.

Keywords: Convolutional neural networks, Artificial neural network, Recurrent neural network, convert into digital text, natural language processing.

I. INTRODUCTION

Handwriting recognition is undoubtedly one of the most challenging areas of pattern recognition. It is extremely useful in a wide range of real-world practical problems, including documentation analysis, mailing address

interpretation, bank check processing, signature verification, document verification, and many others. Several pattern recognition approaches have been applied to both online and off-line handwriting recognition, including statistical methods, structural and syntactic methods, and neural networks. Some reading systems identify strokes; others try to identify characters, groups of characters, or entire words.

In the problem of handwritten text recognition, neural networks are heavily used for efficiently predicting handwritten symbols. Character recognition has long been a critical area of Artificial Intelligence. Recognition is a trivial task for humans, but to make a computer program that does character recognition is extremely difficult.

Recognizing patterns is just one of those things humans do well and computers don't. One of the primary means by which computers are endowed with human-like abilities is through the use of neural networks. Neural Networks are particularly useful for solving problems that cannot be expressed as a series of steps such as recognizing patterns, classifying them into groups, and series prediction and data mining. ANN approach for character recognition is now gaining importance because of ANN's highly parallel architecture and fault tolerance.

II. LITERATURE SURVEY

M. Ghanim et al. [5] proposed a Arabic Handwriting Recognition using DCNN. CNN algorithm is used to convert typewritten text into digitized text and HAC algorithm for clustering characters. Some advantages of this paper are optimization of the data with better accuracy and easy to recognize different handwriting styles whereas it may recognize words which are not in

dictionary when the written words are hard to read which is a major disadvantage.

Eltay et al. [2] proposed an approach to recognize Handwritten Arabic Texts using Deep learning. Review and investigation of different deep learning architectures and modeling choices for Arabic handwriting recognition has been done and an Adaptive data - augmentation algorithm is used to build this system. Some of the pros of this paper are more data can be used for recognition and it also reduces data over fitting while on the other hand, this system is not efficient for small dataset.

Uddin et al. [1] proposed a literature review for handwritten Optical Character Recognition. Handwritten character Recognition and Printed character Recognition using OCR is used. Some advantages of this paper are processing information is fast and recognition engines which is used with imaging can capture highly specialized data sets whereas OCR systems equipments are expensive and workload to data collectors because OCR has severe limitations when it comes to human handwriting which serve as a major disadvantages.

R.Ezhilarasi et al. [3] proposed OCR for text recognition using recurrent neural network. OCR is used to give an impressive recognition exactness for manually written text using recurrent neural network which is used to improve accuracy. Some of the pros of this paper are it can process any length input and model size doesn't increase for longer input, while on the other hand, the computation of this neural network is slow and therefore training is different which serve as major cons.

Aly et al. [4] proposed a robust digit recognition system using self organising map network. Development of this new efficient deep unsupervised network Deep Convolutional Self-organizing Maps (DCSOM) helps to learn invariant image representation from unlabeled visual data. Some pros of this paper include easy data interpretation and data visualization. On the other hand, if dataset is small then map size is also small. Map size depends on training data and some clusters end up in distant parts of map making it difficult to visualise the similarities between them serves as major cons.

Zin et al. [6] proposed a character recognition system by projection approach. Segmentation is carried out mainly on labelling and projection concept. Pros of this paper include better accuracy in recognition of cursive words compared to other techniques. But still its maximum accuracy is only around 65% which is a drawback.

III. PROPOSED SYSTEM

Our proposed system uses ANN integrated with CTC loss and decoding algorithm to convert the handwritten text to digital or machine text. The fundamental steps that should be followed to accomplish our goal are:

Data Acquisition:

Dataset is the origin of knowledge for our Machine Learning models. Henceforth, feeding well-defined data and selecting the suitable dataset is crucial for obtaining profitable outcomes. Thus we have used the IAM dataset for our proposed system.

This dataset comprises about 1539 forms filled out by approximately 657 writers. Data is annotated on line level and word level. It has the most unique words out of all other handwriting recognition system datasets.

Data Preprocessing:

Data Preprocessing is that step in which the data gets transformed, or Encoded, to bring it to such a state that now the machine can easily parse it. In other words, the preprocessing is done to make things easier for the classifier.

Preprocessing techniques includes contrast normalization, and random modifications to the original dataset to enlarge the datasets

Classification:

Artificial Neural Network(ANN) serves as a classifier for our proposed system. Multiple Convolutional Neural Network(CNN) layers are trained to extract relevant features from the input image. These layers output a 1D or 2D feature map which is handed over to Recurrent Neural Network (RNN) layers.

The RNN propagates information through the sequence. Later on, the output of the RNN is mapped onto a matrix that contains a score for each character per character element. In this system, an implicit word segmentation method based on the decoding algorithm for the RNN output is proposed and evaluated. In this way, the ANN can be fed with line-text images.

Decoding:

Since ANN is trained using a specific coding scheme, a decoding algorithm must be applied to outputs of RNN to obtain the final text. Decoding can take advantage of the Language Model(LM). The loss calculation and decoding from the matrix are carried out by the Connectionist temporal classification (CTC)

operation.ie CTC serves two-fold: (1) as a loss function,(2) as a decoder.

In this system, we have to privilege to choose the decoding algorithm to be applied. the options available are(1) Best Path Decoding(2)Beam Search (3) Word Beam Search. The default decoder set for training is best path decoding algorithm.

IV. SYSTEM ARCHITECTURE

Our proposed system makes use of ANNs to convert handwritten text to digital text. Multiple Convolutional Neural Network(CNN) layers are trained to extract relevant features from the input image. These layers output a 1D or 2D feature map which is handed over to Recurrent Neural Network (RNN) layers. The RNN propagates information through the sequence. Later on, the output of the RNN is mapped onto a matrix that contains a score for each character per character element.

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Preprocessing is done to make things easier for the classifier. Preprocessing operations include contrast normalization, and making random modifications to the original images to enlarge the size of the dataset. Our proposed system uses implicit segmentation , in which the ANN itself is trained to segment the words by learning the white space characters. Since the decoded text might contain misspelled words, a text postprocessing method is applied to them and the final output is displayed.



V. RESULTS

TRAINING THE MODEL:

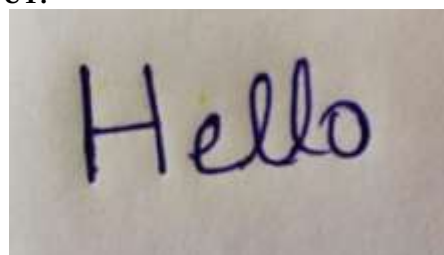
```

python /content/drive/MyDrive/htsr/src/main.py --train --dat

Epoch: 1 Batch: 284/1895 Loss: 12.224536895751953
Epoch: 1 Batch: 285/1895 Loss: 14.413180351257324
Epoch: 1 Batch: 286/1895 Loss: 12.76634407943457
Epoch: 1 Batch: 287/1895 Loss: 13.6570688061820613
Epoch: 1 Batch: 288/1895 Loss: 13.653276443481445
Epoch: 1 Batch: 289/1895 Loss: 13.763181377758789
Epoch: 1 Batch: 290/1895 Loss: 15.124917036334473
Epoch: 1 Batch: 291/1895 Loss: 12.842146873474121
Epoch: 1 Batch: 292/1895 Loss: 12.41551399230957
Epoch: 1 Batch: 293/1895 Loss: 12.604265213012695
Epoch: 1 Batch: 294/1895 Loss: 12.771961212158205
Epoch: 1 Batch: 295/1895 Loss: 14.051325798034668
Epoch: 1 Batch: 296/1895 Loss: 14.1893704452314648
Epoch: 1 Batch: 297/1895 Loss: 12.489302864074797
Epoch: 1 Batch: 298/1895 Loss: 13.051178932138941
Epoch: 1 Batch: 299/1895 Loss: 13.246801184736328
Epoch: 1 Batch: 300/1895 Loss: 14.460000000000003
Executing (6h 16m 21s) Cell
  
```

Here, IAM data-set is trained.For each epoch CTC loss value is calculated individually for each batch.Training will stop when character error rate is not improved and the model which has lower error rate is saved.

INPUT:



This is our sample test image not exceeding 32-characters stored in the folder named data. It is then fetched, undergoes preprocessing and sent to the trained model.

OUTPUT:

```

model
├── src
│   ├── DataLoaderIAM.py
│   ├── Model.py
│   ├── SamplePreprocess...
│   ├── createLMDB.py
│   ├── main.py
│   ├── LICENSE.md
│   ├── README.md
│   └── requirements.txt
└── model

/usr/local/lib/python3.7/dist-packages/t
warnings.warn("Layer.add_variable" i
WARNING:tensorflow:From /usr/local/lib/
Instructions for updating:
Call initializer instance with the dtype
Python: 3.7.10 (default, Feb 28 2021, 21
[GCC 7.5.0]
TensorFlow: 2.4.1
2021-03-27 00:05:11.708647: I tensorflow
Init with stored values from /content/dr
2021-03-27 00:05:12.966136: I tensorflow
2021-03-27 00:05:13.038969: I tensorflow
Recognized: "Hello"
Probability: 0.4089355369273926
✓ 6s completed at 6:35 AM
  
```

Machine text from our input handwritten text is recognized and displayed.

ACCURACY:

```
[OK] "that" -> "that"
[ERR:1] "girl" -> "gil"
[OK] "who" -> "who"
[ERR:1] "sand" -> "sard"
[ERR:1] "hulle" -> "hulle"
[OK] "to" -> "to"
[ERR:1] "his" -> "his"
[OK] "is" -> "is"
[OK] "the" -> "the"
[OK] "garden" -> "garden"
[OK] "i" -> "i"
Character error rate: 18.58923148653812%, word accuracy: 74.85258413776038.
```

Character error rate(CER) is number of edit operation performed on the input text by total length of input text. For example, in the above image, "him" is recognized as "his". Number of edit operation is 1(because m is recognized as s) and total length of original text is 3. Therefore, $CER=1/3$. This mismatch in recognition occurs due to many factors like quality of input image, similarities between letters and slanting.

Word accuracy is number of letters recognized correctly by total number of words in validation dataset. For example, consider there is 120 words in a validation dataset. Out of which 89 words are recognized correctly. Then accuracy for the same is calculated as,

$$\text{Accuracy} = 89/120 \times 100 = 74.16\%$$

VI. CONCLUSION

Image recognition is an important aspect for the image processing. The collected dataset is trained using ANN which represents the current state-of-the-art for variety of applications. Thus, we extensively analyzed the model by carefully selecting their parameters and showing its robustness for handling our dataset. In this paper we perform five steps namely, image acquisition, pre-processing, classification, decoding. The input image is preprocessed and fed into Convolutional Neural Network (CNN) for feature extraction and the extracted feature map is handed over to Recurrent Neural Network (RNN). The RNN outputs a matrix that contains a probability distribution over the characters at each image position. The Connectionist Temporal Classifier (CTC) decodes this matrix and final machine text is displayed. Artificial Neural Network (ANN), has good accuracy for handwriting recognition because more training will result in more accurate writing recognition.

VII. FUTURE WORK

This work can be further extended for recognition of other languages. It can be used to convert the fax and newspapers into text format. Before these techniques, approach is mostly focused on efficient feature extraction from these images. Once you have good feature representation of the data, its very easy to build a model. In future, we need systems that can read a character array and modify it to the form that you want.

This project can be further extended to use multi-dimensional LSTM and deslanting technique can be performed at preprocessing level to obtain better accuracy. Eg: like a linguist or auto translation or detected text to voice conversion etc. In a long run, systems or phones would replace the jobs of scanners, dtp operators etc.

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