

Pattern Recognition

Text Extraction from Image using pattern recognition



Under the Guidance of:
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INTELLIGENT CHARACTER RECOGNITION USING FULLY CONVOLUTIONAL NEURAL NETWORKS

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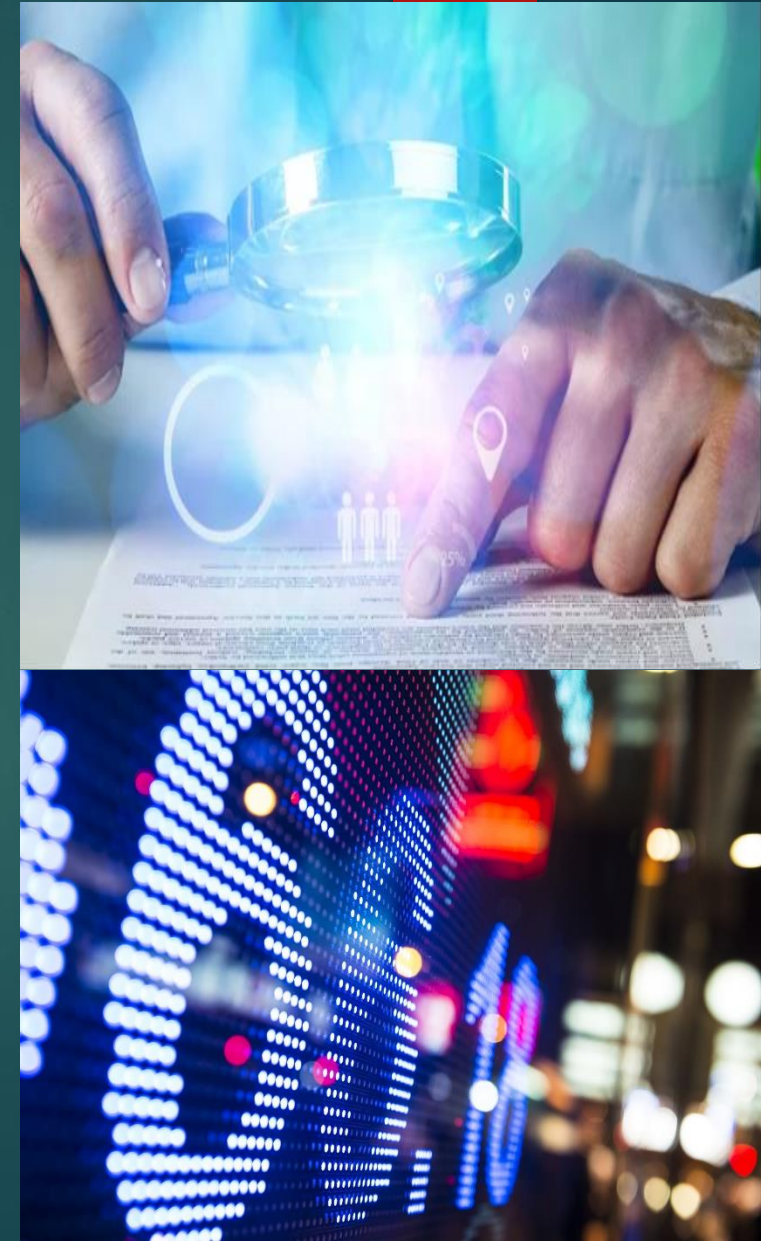
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Introduction

- A method to find accurate character and symbol.
- Finding and isolating handwritten symbols from a close-up grayscale picture.
- Sequence recognition over handwritten text recognition.
- ▶ **Motivation:**
 - Latest text extraction technology from images improves efficiency, accessibility, and innovation in real-life applications across industries.
 - For ex: clinical decision support, Road Safety etc
- ▶ **Model proposed:**
 - character based classification.
 - It predicts both arbitrary symbols as well as words from a lexicon.
- ▶ **Application:-**
 - Vehicle recognition and tracking
 - Medical imaging and analysis
 - Captcha solving



Literature Review

| TITLE | AUTHOR | YEAR | ADAVANTAGE | LIMITATIONS |
|---|--|------|---|---|
| Distance Transform based Text-line Extraction from Unconstrained Hand-written Document Images | Suman Kumar Bera, Soumyadeep Kundu, Neeraj Kumar, Ram Sarkar | 2021 | Placing paragraphs in a one-page document has always yielded impressive results in most cases. | In multi-page documents, if there's a seperator between paragraphs, the method might mistake it for a new line. |
| Accurate, Data-Efficient, Unconstrained Text Recognition with Convolutional Neural Networks | Mohamed Yousef, Khaled F. Hussain, Usama S. Mohammed | 2020 | It worked very well on both short and long lines of text and also can handle different handwriting styles, sizes, and orientations with robustness. | Existing line recognition methods can't handle paragraphs or multiple lines without line segmentation algorithms. |

Technical Details

❖ Datasets are:

- IAM
- RIMES
- NIST

► Work analysis:

- Traditional feature extraction along with HMM

➡ ANN or GMM

➡ Long term dependency

- Advanced feature extraction

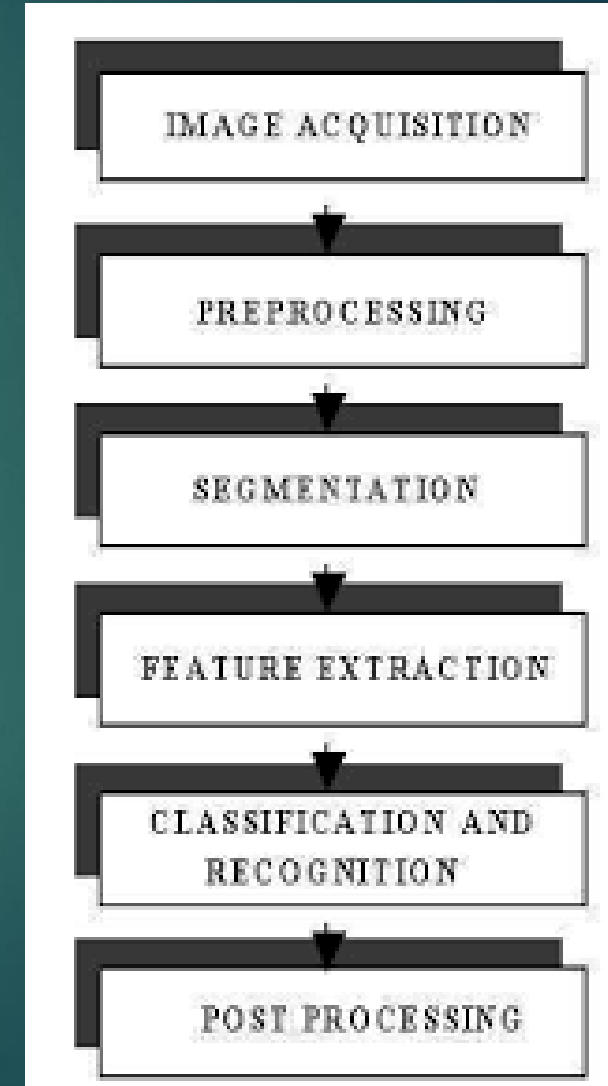
□ LSTM:

➡ Naïve approach along with RNN

➡ Multidimensional RNNs

□ CNN-LSTM network

➡ used CTC techniques



Technical Details

► FCN along with CNN, RNN

- The algorithm consists of four consecutive stages which will be described next:

❑ Symbol alignment

- predicts the number of symbols in a block and resamples the block to a canonical width \times height.
- convolutional layer = $C(d, h \times w, \text{padh} \times \text{padw})$

Where d =filters, $h \times w$ =spatial size, padding= $\text{padh} \times \text{padw}$

- $P(s)=s \times s$, where $P(s)$ = pooling layer of stride, s =stride

❑ Symbol prediction

- It reduces a $32 \times 16N$ input image to a $(2N + 1) \times 111$ prediction

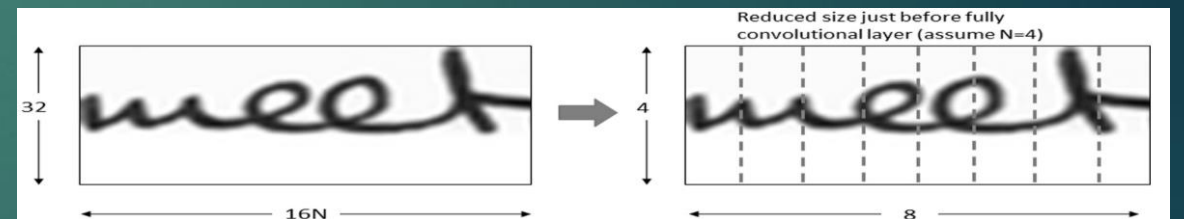
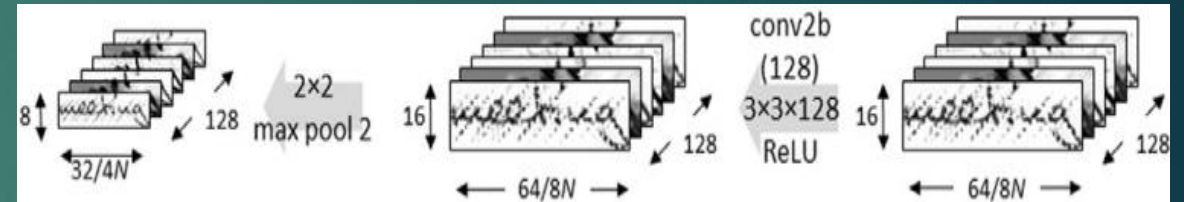
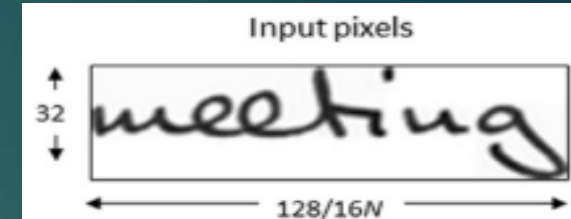
Where N =desired output

(i) Even filter intuition

- even tap filter = pad of $F_w/2 - 1$, where F_w is the width of the filter.

(ii) Filter receptive field

- It finds which part of the image affects one pixel on the map.



Technical Details

❑ CER and vocabulary matching

step-1: Normalized character error rate

$$\text{CER} = \frac{R + D + I}{R + D + I + C}$$

Where R = number of characters replaced, D = number of characters deleted, I = number of characters inserted, and C = number of correct characters

step-2: CER Computation

$$C_{i,j} = \min(C_{i-1,j} + 1, C_{i,j-1} + 1, \text{Diag})$$

where:

Diag =

$$\begin{cases} C_{i-1,j-1}, & \text{if } P_i = L_j \text{ where } p_i = \text{ith character of prediction and } L_j = \text{jth character of label} \\ C_{i-1,j-1} + 1, & \text{otherwise} \end{cases}$$

step-3: CER-based vocabulary matching

$$W(p) = \arg \min_{L \in V} \text{CER}(p, L) + (1/1 + C(L)) , \text{ where } C(L) = \text{frequency of occurrence of a given word}$$

❑ Lexicon based prediction

- Lexicon CNN can predict words from a given lexicon optionally.
- It helps find common words like "the", "her", and others.

Technical Details

► IAM Results:

■ Prediction:

| Input | Label | Prediction |
|--------------------|-------------|--------------|
| <i>5 Ye-es</i> | 5Ye-es | SYe-es |
| <i>President's</i> | President's | Preseciten's |
| <i>live pool</i> | Liverpool | livepool |
| <i>up</i> | up | ey |
| <i>only</i> | only | outle |
| <i>,</i> | , | , |
| <i>the</i> | the | the |

■ Comparison

Comparison of results on IAM dataset to previous methods.

| Model | WER | CER |
|--------------------------|-------------|-------------|
| Our work | 8.22 | 4.70 |
| Voigtlaender et al. [19] | 9.3 | 3.5 |
| Poznanski and Wolf [52] | 6.45 | 3.44 |
| Dutta et al. [17] | 4.80 | 2.52 |

► RIMES Results:

■ Prediction:

| Input | Label | Prediction |
|--------------------|-------------|-------------|
| <i>permet</i> | permet | puent |
| <i>vous</i> | vous | vur |
| <i>XEXGR52.</i> | XEXGR52 | XEXGGR52 |
| <i>commandées,</i> | commandées | commandores |
| <i>Ces</i> | ces | Cs |
| <i>effet,</i> | effet | effett |
| <i>département</i> | département | tiprtement |

■ Comparison

Comparison of results on RIMES dataset to previous methods.

| Model | WER | CER |
|--------------------------|-------------|-------------|
| Voigtlaender et al. [19] | 9.6 | 2.8 |
| Our work | 5.68 | 2.46 |
| Poznanski and Wolf [52] | 3.90 | 1.90 |
| Dutta et al. [17] | 1.86 | 0.65 |

■ Comparison of results on RIMES and IAM:

(i) error-rate

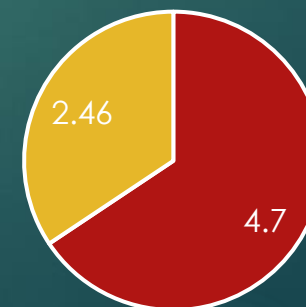
(ii) accuracy

(iii) performance

(iv) probabilistic CER

| Fine-tuned | Lex. CNN | Prob. CER | IAM | RIMES |
|------------|----------|-----------|-------------------|-------------------|
| X | X | X | 4.70(8.22) | 2.46(5.68) |
| X | | X | 5.05(8.62) | 2.55(5.98) |
| X | X | | 6.50(18.30) | 4.15(15.91) |
| X | | | 7.09(17.77) | 4.74(19.91) |
| | | | 8.86(21.80) | 5.03(20.05) |

CER



■ 1st IAM ■ 2nd RIMES ■ ■

Summary

- The proposed model introduces a novel character prediction method, diverging from conventional recurrent neural networks.
 - This approach suggests an alternative to using RNNs followed by CTC for character cleanup.
 - It proposed a novel approach for character correction.
 - It helps for recognize speech and symbols using punctuation.
 - Without using RNNs , advanced results have been achieved on IAM and RIMES datasets.
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- Ex: Amazon Textract is a one of the leading technology in this field.
 - So, in Future research should expand is broad and promising, with potential applications across diverse domains, driving innovation in artificial intelligence and computer vision technologies.

References

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