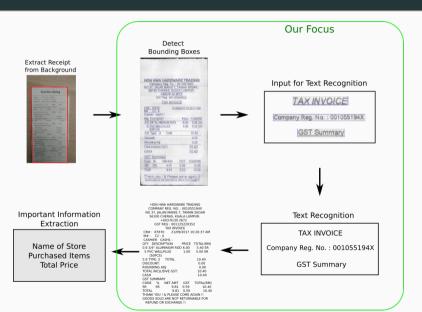
Extract Text from Receipts using Deep Vision

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Text Extraction Pipeline



Text Detection

- ullet First step is to localize text ightarrow bounding boxes
- Receipts with annotated bounding boxes as training data
- Detected bounding boxes as input for text recognition



Figure 1: Bounding boxes used for training.

EAST-Model: Architecture

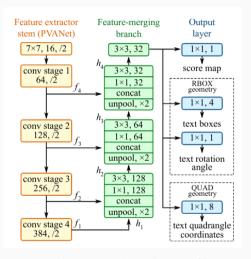


Figure 2: Architecture of the EAST-Network [6].

- EAST: Efficient and Accurate Scene Text Detector by Zhou et al. (2017)[6]
- Fully Convolutional Architecture
- Pre-trained classification net (VGG16) for feature extraction
- U-shaped design to merge features from different levels and keep computational cost small
- Loss function $L = L_{score} + L_{geo}$

EAST-Model: Loss function

Score Loss

- Score map S with value of 1 for every pixel inside bounding box
- Dice score for loss

$$L_{score} = 1 - \frac{2|S_{pred} \cap S_{true}|}{|S_{pred}| + |S_{true}|}$$



Figure 3: Illustration dice loss [4].

Geometry Loss

 Geometry map G storing offset to four corners for every pixel inside a box:

$$G_i = \{x_1, x_2, \cdots, x_8\} \in G$$

Loss

$$I_i = \sum_{i=1}^{8} \frac{\text{smoothed}_{L1}(x_i - \hat{x_i})}{\text{shortest edge}}$$

$$L_{geo} = \frac{1}{N} \sum_{i=1}^{N} I_i$$
 with N pixels

$${\rm smoothed} \iota_1(x) = \left\{ \begin{array}{ll} 0.5x^2 & \text{ if } |x| < 1 \\ |x| - 0.5 & \text{ otherwise} \end{array} \right.$$

Data set Text Detection

Data provided by:

ICDAR 2019 Robust Reading Challenge on Scanned Receipts OCR and Information Extraction

- Data set: 986 receipts in english
- Annotation: Bounding boxes and text
- 626 training images and 360 test images

Results Text Detection

• Best IoU score of 81.86%

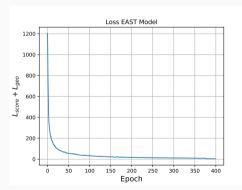


Figure 4: Loss after different number of epochs.

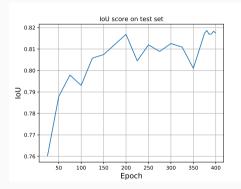


Figure 5: Intersection over Union.

Results Text-Detection - Example



Figure 6: Text detection on test data.



Figure 7: Text detection on test image.

Text-Recognition

- Use ground truth bounding boxes for training
- Crop bounding boxes and scale as preprocessing
- Different approaches have been tested:
 - CRNN
 - DenseNet + RNN + CTC
 - DenseNet + CTC
 - Adding artificial data for training
 - Different CTC input lengths (32 and 64)



Figure 8: Example of text recognition.

Connectionist Temporal Classification (CTC) - Encoding

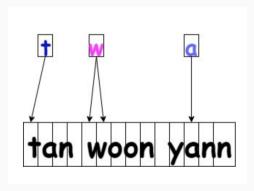


Figure 9: Text encoding mechanism for CTC Loss [2].

- Characters can span over multiple lines
- Introduce blank "-" character to encode duplicate characters (removed in decoding)

Examples:

"aa"
$$\to$$
 "a-a"
"a" = "-a" = "a- -" = "aaa"

ightarrow different alignments represent same text

CTC Loss - Calculation

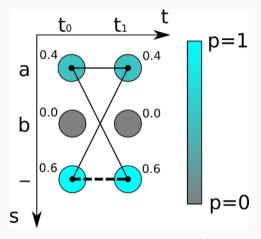


Figure 10: Example CTC Loss calculation [3].

- Output Net: Score for every character for every slot/time step
- Score: Sum output for all possible alignments of ground truth text

Example for ground truth : "a" Possible alignments: "-a", "a-", "a" $Score:\ 0.4\cdot0.6+0.6\cdot0.4+0.4\cdot0.4=0.64$

 \rightarrow Maximize score

Data set Text Recognition

- Cropped bounding boxes for training
- 33626 images as training set
- Additionally create artificial images with data generator [1].

Results Text Recognition - Comparison of different Models

- Word Accuracy: Number of correctly predicted words/sentences
- Levenshtein Score: Similarity depending on number of character differences

	Dense Net 32	Dense Net 64	CRNN 32	CRNN 64	Tesseract
CTC Loss	0.0025	0.0059	0.1332	0.0147	_
Word Accuracy	57.6%	64.2%	54.8%	66.3%	53.6%
Levenshtein Score	85.6%	93.3%	88.4%	93.4%	90.0%

Table 1: Quantitative results of the different methods.

Result Text Recognition - Examples

Correct Predictions



Wrong Predictions



Results Text Recognition - Example Complete Receipt

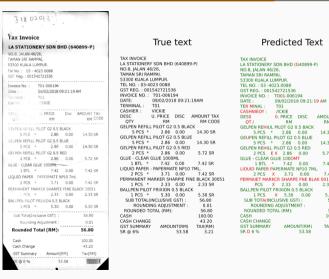


Figure 11: Example text detection on complete receipt.

AMOUNT TAX

14.30 SR

5.72 SR

7.42 SR

7.42 SR

2.33 SR

56.80

0.01

56.80

43.20

.21

TAX(RM)

Summary

- Successfully implemented Text Detection and Text Recognition
- Dense Net and CRNN perform very similar on Text Recognition
- CRNN is faster then Dense Net
- CTC input size important for good predictions

Outlook

- ullet Data augmentation for Text Detection o detect rotated bounding boxes
- Test different architectures of Dense Net and CRNN to improve prediction of long text further
- $\bullet \ \mathsf{Improve} \ \mathsf{image} \ \mathsf{preprocessing} \to \mathsf{improve} \ \mathsf{contrast} \\$
- General hyper parameter optimization

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DenseNet

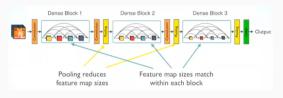


Figure 12: Basic structure of the DenseNet [5].

- Convolutional part build on dense blocks
- Like ResNet each layer receives additional data from all preceding layers, but using concatenation
- Down sample until height of each column is equal 1

Text Recognition Models - Loss

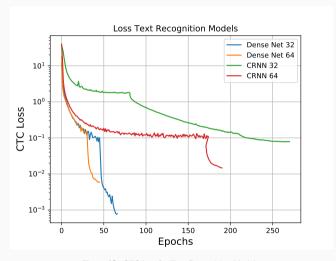
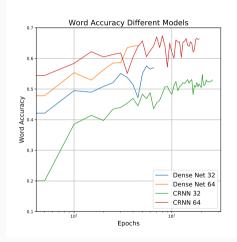
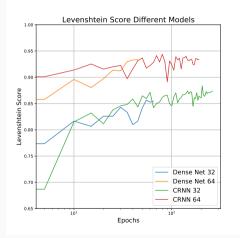


Figure 13: CTC loss for Text Recognition Models.

Results Text Recognition - Score





Results Text Recognition - Example Complete Receipt



AEON CO. (M) BHD (126926-H)
SRD FIR, AEON TAMAN MALURI SC
JLN JEJAKA, TAMAN MALURI SC
JLN JEJAKA, TAMAN MALURI CHERAS, 55100 KUALA LUMPUR
GST ID: 002017394688
SHOPPINS HOURS
OLISTOMER. JEJOSOO'2013.

VALUED CUSTOMER: 1130307913

1× 000005469765	6.65SR
TOPVALU FLOOR C 1x 000001101575 CIF REGULAR 50	5.60SR
Sub-total	12.25
Total Sales Incl GST	12.25
Total After Adi Incl GST	12.25
CASH	50.00
Item Count 2 Change Amt	37.75
Invoice No: 20180314300900	060035
GST Summary Amount	Tax
SR # 6% 11.55	0.70
Total 11.55	0.70
14/03/2018 12:43 3009 (006 0060035

0284846 AMTRUL

True text

AEON CO. (M) BHD (126926-H)
3RD FLR, AEON TAMAN MALURI SC
JLN JEJAKA, TAMAN MALURI
CHERAS, 55100 KUALA LUMPUR
GST ID: 002017394688
SHOPPING HOURS
MON-SUN: 1000 HRS - 2200 HRS
VALUED CUSTOMER: 130307913

1X 000005469765	6.65SR
TOPVALU FLOOR C 1X 000001101575	5.60SR
CIF REGULAR 50	

SUB-TOTAL		12.25
TOTAL SALES INCL G	ST	12.25
TOTAL AFTER ADJ INC	L GST	12.25
CASH		50.00
ITEM COUNT 2 CHA	ANGE AMT	37.75
INVOICE NO:201	803143009	0060035
GST SUMMARY	AMOUNT	TAX
SR @ 6%	11.55	0.70
TOTAL	11.55	0.70
14/03/2018 12:43	3009 006	0060035
0284846 AMIRUL		

Predicted Text

AEON CO. M) BHD (126926-H)
3RD FLR. AEON TAMAN MALURI SC
JLN JEJAKA. TAMAN MALURI CHERAS. 55100 KUALA LUMPUR
GST D: 002017394688
SHOPPING HOURS
MON-SUN:1000 HRS - 2200 HRS

VALUED CUSTOMER: 1130307913

1X 000005469765	6.65SR
TOPVALU FIOOR C	
1X 000001101575	5.60SR
CIF REGULAR 50	

SUB-TOTAL		12.25
TOTAL SALES INCL	SST	12.25
TOIAL AFTER ADI IN	CL GST	12.25
CASH		50.00
IFEM COUNT 2 CH	IAN9E AMT	37.75
INVOICE NO: 20	1803143009	9006003
GST SUAMARY	AMOUNT	TAX
SR 6%	11.55	0.70
TOTAL	11.55	0.70
14/03/2018 12:43	3009 006	006003
0284846 AMIRUL		

Figure 14: Example text detection on complete receipt.