Bachelor Thesis
in Information Systems and Management

Optical Character Recognition for Labels Using Deep Learning

Johannes Reichle
Matriculation No. 04797218

Supervisor	Prof. Dr. Rainer Schmidt
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Declaration

I hereby certify that I have written this bachelor thesis on my own and that I have not used any sources or aids other than those indicated.

Munich, the XX.XX.2022

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Johannes Reichle

Abstract

Here abstract for Bachelor Thesis.

Contents

List of Figures

List of Tables

Abbreviations

DL Deep Learning

DR data requirement

FR functional requirement

ML Machine Learning

NFR non-functional requirement

NN Neural Net

OCR Optical Character Recognition

Chapter 1

Introduction

1.1 Motivation

Optical Character Recognition (OCR) is the concept of extracting typed, handwritten or printed text from an image. Techniques for this concept have improved a lot due to the advances in the field of Deep Learning (DL) [ZJG+20]. DL is a technology based on Neural Nets (NNs) where data is processed in multiple layers to extract complex features and solve a given problem [SM19]. DL has only caught on in the recent years as the big computational cost has been met by the improvement in computer hardware [PRN+17]. Finding the right solution in the space of DL and applying these new capabilities to the use case of extracting information of labels is the focus of this thesis.

1.2 Problem description

The basic problem of this thesis is finding a viable solution for the extraction of textual information from images with equipment labels. However, it is difficult to assess how well an approach performs before it has been implemented and tested on the specific problem or dataset [ABCFB18]. Therefore, it is useful to propose several approaches that might solve the problem from different angles.

The problem has to first be analysed in depth in order to find a viable approaches for the solution. This includes defining requirements such as detecting rotated text or given computational power of mobile devices the solution. These requirements define properties that an approach must have in order to be classified as viable. Thus the reasearch and subsequent discussion of techniques from end-to-end OCR to dividing the process into text detection and text recognition is centered around the requirements which are given by the problem. Critical factors such as the requirement for data and the complexity

of implementation and training of a DL model also need to be assessed.

Subsequent aspects such as implementation, training, deployment and maintenance of a solution in a production environment shall not be performed within the scope of this thesis. Because these aspects may vary depending on the approach, it is important to consider them when discussing the viability for solving the problem.

1.3 Methodology

The methodology of this thesis can be described as a literature review. As such, the research question guiding the process is most crucial: Which state of the art DL approaches for OCR are viable for the use case of extracting textual label data from images. The following section describes how relevant literature is identified, analysed and synthesised.

1.4 Expected results

In addition to a deeper understanding of the problem and its detailed definition, the literature review lays the foundation for finding the right approach for the extraction of textual information from images with equipment labels through literature review. In the subsequent analysis different approaches are highlight for their theoretical fit as a solution.

In the following section the structure of this thesis is listed and each chapter's expected result is detailed along with its benefits for the overall objective of producing an overview of state of the art OCR relevant for the problem described in Section 1.2. comprehension of the following chapters is gathered. This includes general principles of DL and by extension Machine Learning (ML) but also of OCR. In Chapter 2 the problem from Section 1.2 is addressed in more detail. The result shall be a firm understanding of functional and non-functional requirements both on the technical and the business process side. These requirements are the point of focus for the further examination of OCR techniques. After laying the foundation, in Chapter 4 current research in regards to the identified requirements is examined. The resulting overview can be viewed as a basis for a decision when it comes implementing a practical solution. Therefore it enables the discussion in Chapter 5. Here not only the results and the availability of a solution but also the methodology of this work are assessed critically. The conclusion is a summary of the results compared to the expected results detailed in this chapter as well as an outlook for further research into the topic.

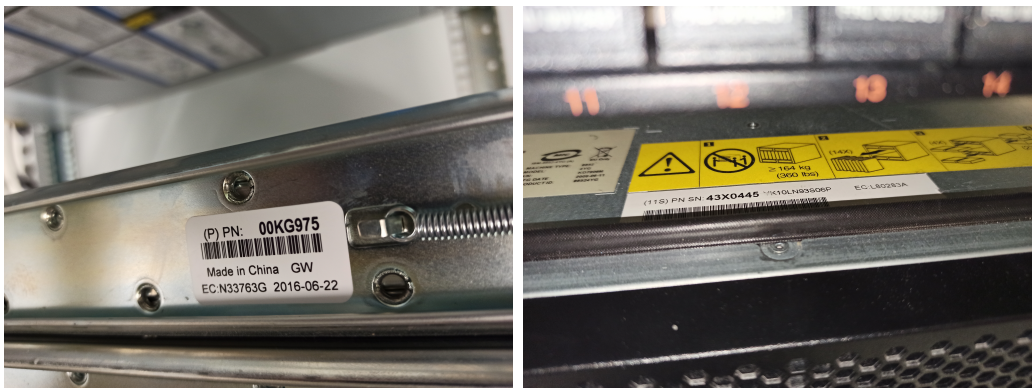
Chapter 2

Problem analysis

This chapter entails an analysis of the problem which is the research question's foundation. It is crucial, as the quality of requirements ultimately determines the quality of the literature review.

For traditional software projects requirements engineering classifies requirements into two categories [ZJJB+14]. Functional requirements (FRs) specify functionality that users can experience [noa98]. Other requirements that are relevant to the project in a way that shapes the target system, defines the development process and manages the development project are refered to as non-functional requirements (NFRs) [KS98, CdPL09]. For DL and thus ML projects, the data requirements (DRs) can be added to these categories. This is because data directly influences the performance of the solution. This results in the need to specify requirements for data that is used in conjunction with the DL system [VB19].

The basic functionality can be described as extraction of textual data from images. The relevant text information is framed by the label. The label contains printed text which can be structured and spaced differently from label to label (see figure 2.1(a)). The goal is to extract the text and keep the semantical meaning behind structure and space. The extracted information then needs to be made available for further processing within a business process. The images can contain alpha-numeric strings. This results in the requirement that the DL model has to be able to recognize sequences that are not part of a predefined lexicon [GVB17]. For ML projects the predictive reliability can be regarded as a FR. To quantify this value a suitable evaluation metric has to be chosen [VB19]. Due to the uncontrolled environment in the practical aspect of taking the images on-site beneficial image properties can not be guaranteed. Robust text extraction can be influenced by factors such as complex backgrounds, lightning conditions, text rotation, font variability and image qualities like blur, noise and low resolution [OOK15, GVB17]. An example for



(a) Positive example (b) Negative example

Figure 2.1: Examples for label images

bad image quality in regards to OCR can be seen in figure 2.1(b). Therefore, these properties have to be accounted for when determining the viability for an approach.

The NFRs that derive from the intended use for the solution with mobile phones are led by power aspects. Not only are mobile phones limited by a finite battery but also by computational power. In this regard NNs can be challenging because they often have an immense amount of parameters which are computationally demanding and can therefore also be a burden for the phone's power supply. The solution will be used on mobile phones that have no access to the internet. Varying aspect ratios in images and such diversities can increase the requirements for preprocessing. Depending on the approach the complexity can change i.e. decrease thus making it more viable. Maintenance of a DL system in regards to changing requirements such as changing the output format are also an important factor.

DRs encompass the data that is required in order to train, tune and test a DL system [VB19]. Difficulties arise from the amount of data needed to train a DL model and from the need to annotate the data for supervised learning [NKK+19]. However, it is possible to pretrain a model on a dataset for a related task. The pretrained model can then be fine tuned to fit the actual task thus decreasing the needed size in the dat set that is specific to the problem [OWZY16]. This procedure allows for achieving good performance. Additionally there's many available pretraining datasets that are labeled [OWZY16]. In the context of requirements, quantity refers to diversity of data [VB19]. When it comes to the quality of data there's three factors: completeness, consistency, correctness. These factors are especially important since better quality as a big influence on performance [VB19]. For completeness, it is important that the dataset that is used for finetuning contains all

edge cases that are relevant for the task [ABCFB18, VB19]. ‘Consistency refers to the format and representation of data that should be the same in the dataset. Correctness refers to the degree to which you can rely on the data actually being true’[VB19]. As implementation and training a DL model is not the subject of this theses these DR are not discussed in detail in the following chapters.

Chapter 3

Theoretical Foundation

3.1 Machine Learning

1. Loss Function / Error Metrics
2. Supervised — Unsupervised / Categorization
3. Optimization techniques: Stochastic-Batch Gradient Descent, GD Momentum, Adam
4. Bias-Variance tradeoff / Overfitting — Underfitting

3.2 Deep Learning

‘ One of the main differences from traditional ma- chine learning (ML) methods is that DL automatically learns how to represent data using multiple layers of abstraction [5], [6]. In traditional ML, a significant amount of work has to be spent on “feature engineering” to build this representation manually, but this process can now be automated to a higher degree. Having an automated and data-driven method for learning how to represent data improves both the performance of the model and reduces requirements for manual feature engineering work [7], [8].’ [ABCFB18]

1. ANN / MLP
    - Architecture → Input, Hidden, Output
    - Feedforward
    - Optimization → Backpropagation, SGD, ADAM, ...
2. Regularization

3. important architectures
    - CNN
    - RNN
    - Specific foundation architectures for relevant approaches
4. transfer learning: reuse parameters from pretrained models

Deep Learning in Character Recognition Considering Pattern Invariance Constraints [OOK15] Deep Learning: neural network architecture of more than a single hidden layer as opposed to shallow networks Features of deep networks: distributed representation of knowledge at each hidden layer, distinct features are extracted by units or neurons in each hidden layer several units can be active concurrently Each layer extracts moredefined/advanced features → hierarchical representation of features

Common problems with training deep learning

- saturating units
- vanishing gradients
- over-fitting & underfitting

Classification of deep learning architectures

- Generative Architectures:
  not deterministic of class patterns that input belong to → sample joint statistical distribution of data
  unsupervised learning: greedy layer-wise pre-training
  Use auto encoders (generative) when a lot unlabelled but not a lot labelled data → generatively train network and then fine tune with labelled
- Discriminative Architectures:
  required to be deterministic of correlation of input data to the classes of patterns therein
  supervised learning
- Hybrid
  combination of discriminative and generative
  generally pre-trained and discriminately fine-tuned for deterministic purposes

Transfer Learning

Factors in Finetuning Deep Model for Object Detection with Long-tail Distribution [OWZY16] finetuning: appraoch dat initializes model parameters for target task from parameters pretrained on another related task

Convolutional Neural Network

Comparative analysis of deep learning image detection algorithms [SDA+21] These layers apply filters to extract patterns from images. The filter moves over the image to generates the output. Different filters recognize different patterns. Initial layers have filters to recognize simple patterns. They become more complex through the layers over time as follows:

Review of Deep Learning Algorithms and Architectures [SM19] Def Neural Network:

- Machine Learning technique that consists of processing units organized in input, hidden and output layers
- the nodes or units in each layer are connected to nodes in adjacent layers
- each connection has weight value
- inputs are multiplied by weight and summed up at each unit
- the sum is used with an activation function (e.g. ReLU, Sigmoid, Tanh, SoftPlus)

3.3 Optical Character Recognition

Deep Learning based OCR [ZJG+20] What is OCR: process of converting images of typed, handwritten or printed text into machine-encoded one includes two sub frameworks: text detection and text recognition (based on position coordinates) **End-To-End also possible** Process can include image processing!!!

no source grid: divides image into parts → each part has own bounding boxes bounding boxes: regressor for box, each bounding box is assigned an anchor box (respective to grid cell) anchor boxes: default 'shape' for bounding box

bounding boxes different stages of convolution / 2-d size → different object size to detect

Text detection

subfield of object detection (e.g. YOLOv4 can be used for text)

Detect position coordinates containing text in input image Text detection more challenging

Two object detection methods — CNN-based

- Region-based
  views detection problem as classification problem
  CNN to extract deep features of proposals by selective search → Use SVM to classify with features
  e.g. R-CNN

- single 'look' extract feature maps on entire image
  directly regress bounding boxes on feature maps
  e.g. YOLO — You Only Look Once, SSD — Single Shot Detection

Non CNN-based: DETR

Comparison Object Detection basic algos

Comparative analysis of deep learning image detection algorithms [SDA+21]
YOLO-V3 outperforms SSD and Faster R-CNN

VGG-16 widely used feature generating architecture

Faster-RCNN

A deeper look at how Faster-RCNN works [Gos18] composed of 3 neural nets:

- Feature Network: pre-trained image classification netork → generate good features
- Region Proposal Network:
  - NN with 3 conv layers
  - one layer splits up network to: classification and bounding box regression
  - bounding box regression → bounding boxes are region of interes (ROI) that might contain an object
- Detection Network: take input from previous nets, generate final class and bounding box, 4 fully connected, 2 stacked common layers shared by classification and bounding box regression layer

Deep Learning in Character Recognition Considering Pattern Invariance Constraints [OOK15] Neural networks can learn features of task on which they are designed and trained Neural networks better than other approaches (e.g. template matching, syntactic analysis) → NNs can learn and adapt to moderate variations (e.g. translation, rotation, scaling, noisy patterns)

Text Recognition

Recognize text based on position coordinates

character based or word based

Visual attention models for scene text recognition [GVB17] Divided into word detection (generate bounding boxes) and word recognition word recognition can be divided into dictionary-based methods and unconstrained methods

End-To-End

Chapter 4

Current Research

no transformers → self-attention mechanism is too computationally expensive???

model-pruning → remove connections for better performance

4.1 Selection

4.2 Review

'The great advances that have been made in fields such as computer vision and speech recognition, have been accom- plished by replacing a modular processing pipeline with large neural networks that are trained end-to-end [37]. In essence, transparency is traded for accuracy. This is an unavoidable reality.'[ABCFB18]

include Pipeline differences

Two models that can be used in conjunction **detection** [Beo21b]
uses RetinaNet structure [LGG+18]
applies techniques from textboxes++ [LSB18]

character recognition [Beo21a]
needs cropped text area as input
uses CRNN [SBY15] → end-to-end learning, LSTM fir arbitrary length of input and output, no need to apply detection and cropping to each single character

Open Source OCR engine [Smi07]

- uses Deep Learning (found c++ code for layers in repo)
- Processing in step-by-step pipeline, some unusual stages
  1. Line and Word finding
  1.1. Line finding

1.2. Baseline Fitting
1.3. Fixed Pitch Detection and Chopping
1.4. Proportional Word Finding
2. Word Recognition
2.1 Chopping Joined Characters
2.2 Accociating Broken Characters
3. Static Character Classifier
3.1 Features
3.2 Classification
3.3 Training Data
4. Linguistic Analysis
5. Adaptive Classifier

Performs poorly with unstructured text with significant noise

An Efficient and Accurate Scene Text Detector [ZYW+17]

SOFT: Softmax-free Transformer with Linear Complexity [LYZ+21]

Generative Pretraining from Pixels [CRC+21]

- unsupervised representation learning (approach transfered from NLP)
- training of sequence Transformer to auto-regressively predict pixels without incorporating knowledge of 2D input structure
- Active part: GPT-2 scale model learns image representations and performs extremely well even when compared to supervised models

Learning High-Precision Bounding Box for Rotated Object Detection via Kullback-Leibler Divergence [YYY+21]

- Deductive approach to rotated object detection
- box is 'translated' to 2D-Gaussian → KLD with prediction and true gaussian as Loss
- LIMIT: cannot be directly applied to quadrilateral detection

DP-SSL: Towards Robust Semi-supervised Learning with A Few Labeled Samples [XDZZ21]

- Semi-supervised learning:
  - provides way to leverage unlabeled data by pseudo labels
  - performs poorly and unstable when size of labeled data is very small (low quality of pseudo labels)

- Data programming:
  - paradigm for the programmatic creation of training sets
  - existing methods rely on human experts to provide initial labeling functions (LF)
- DP-SSL
  - multiple-choice learning (MCL) based approach to automatically generate labeling functions
  - scheme to generate probabilistic labels for unlabeled data

which aspects to compare? quantitative, qualitative

Chapter 5

Discussion

5.1 Analysis

try to find top $3-5$

5.2 Reflection

Challenges DL[ABCFB18] Note that actual experiments with models have to be done Problem: different papers have different components $\rightarrow$ Hardware, Platform, Source Code, Configuration $\rightarrow$ studies can't really be compared

'A major challenge in developing DL systems is the difficulties in estimating the results before a system has been trained and tested.' [ABCFB18]

5.3 Outlook

Chapter 6

Conclusion

Appendix A

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Appendix B

Code