Bachelor Thesis
in Information Systems and Management

Optical Character Recognition for Labels Using Deep Learning

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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.

Keywords: Deep Learning, Optical Character Recognition, Scene Text Recognition, Literature Review

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Abbreviations

DL Deep Learning

ML Machine Learning

MLS Machine Learning System

NN Neural Net

OCR Optical Character Recognition

STR Scene Text 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) (Zhao et al., 2020). When compared to traditional methods DL improves automation, effectiveness and generalization (Chen et al., 2021b). DL is a technology based on Neural Nets (NNs) where data is processed in multiple layers to extract complex features to solve a given problem (Shrestha and Mahmood, 2019). DL has only caught on in the recent years as the big computational cost has been met by improvement in computer hardware as well as automatic feature learning (Ponti et al., 2017; Chen et al., 2021b). 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. This is an interesting task as performance of OCR systems in complex scenes is still challenging (Zhao et al., 2020). Such scenes entail natural scenes captured by a camera. OCR in these conditions is also known as Scene Text Recognition (STR) (Chen et al., 2021b). Factors such as complex backgrounds, noise, perspective and variability in fonts, colors and sizes, of scene texts complicate the process (Hu et al., 2020; Chen et al., 2021b). Therefore, it is critical to specify possible factors for the underlying problem and to find criteria for evaluating feasibility in order to find viable approaches.

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 (Arpteg et al., 2018). Therefore, it is useful to propose several approaches that might solve the problem from different angles and different with properties.

The problem has to first be analyzed in depth in order to find viable approaches for the solution. This includes defining requirements such as detecting alpha-numeric strings or suitability despite inadequate image conditions (Ghosh et al., 2017; Hu et al., 2020). 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 STR to dividing the process into text detection and text recognition is centered Chen et al. (2021b) around the requirements which are given by the problem.

Out of the Machine Learning (ML) lifecycle (Data Management, Model Learing, Model Verification, Model Deployment) only the substage Model Selection from Model Learning will only be looked at. Other aspects such as data analysis, implementation, training, deployment and maintenance of a solution in a production environment shall not be performed within the scope of this thesis.

1.3 Methodology

The methodology of this thesis can be labeled as a literature review (Snyder, 2019; Torraco, 2005). The goal is to provide an overview over current DL pipelines and models that can help in choosing which to implement and test in order to solve the specific problem defined in Section 1.2 and more detailed in Chapter 3.

The research question guiding the process is most crucial: Which state of the art DL approaches for STR are viable for the use case of extracting textual label data from images. In order to improve the validity for the subsequent analysis, the problem is disected further. This includes analysing the specific use case as well as researching which qualities have been identified as generally critical for STR systems.

The literature is identified through searching in reputable journals. All research after 2017 which pertains to STR is regarded as relevant. OCR solutions may not hold validity in practice, as the image qualities can vary in the defined problem (Chen et al., 2021b). An important criteria is that the paper contributes to the ML model. This extends to the whole pipeline from preprocessing an image to the final result of the model. Concludent to to the distinction in Section 1.2, contributions to other stages in the ML lifecycle are not examined. Therefore, keywords for the search include: Deep Learning, Scene Text Recognition, Pipeline, Preprocessing, End-to-end, Text Recognition, Text Detection, Text Segmentation.

The identified literature is synthesized into an overview over the five most common approaches for STR. This includes listing important factors for DL such as the number of parameters, or which type of layers are used in order to achieve success. The overview will be organized into the categories for the ML pipeline, such as End-to-End solutions as in Xing et al. (2019) or a split into Text Detection and Text Recognition as in Yang et al. (2021); Chen and Li (2018).

In the analysis possibly viable approaches are compared with the qualities defined in Chapter 3. The approaches are analysed in detail in regards to commonalities as well as differences and the possible effect on the feasibility. The analysis thus shows which approaches are worthwhile to apply the whole ML lifecycle to.

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 highlighted 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 ML but also of OCR. In Chapter 3 the problem from Section 1.2 is addressed in more detail. The result shall be a firm understanding of qualities that a solution must possess. 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

Theoretical Foundation

2.1 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

'The prediction error of a model has three components: irreducible error, which cannot be elim- inated regardless of the algorithm or training methods employed; bias error, due to simplifying assumptions intended to make learning the model easier; and variance error, an estimate of how much the model output would vary if different data were used in the training process. The aim of training is to minimise the bias and variance errors, and therefore the objective functions reflect these errors. The objective functions may also contain simplifying assumptions to aid optimiza- tion, and these assumptions must not be present when assessing model performance [59].'(Ashmore et al., 2021) See (Ashmore et al., 2021) for measures, ROC curve and cost curve Difference in Robusteness vs Performance see (Ashmore et al., 2021) (pretty much bias-variance tradeoff) Robusteness: training set does not include all possible ranges of values -> ability to generalize

See (Seshia et al., 2018) for mathematical notation for ML

Define generalization

The model consists of subcomponents organized in directed acyclc graph building a pipeline (Siebert et al., 2021). This directed acyclic graph depicts everything from processing the images to the extracted information (Siebert et al., 2021).

2.2 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].’ (Arpteg et al., 2018)

1. ANN / MLP
   - Architecture → Input, Hidden, Output
   - Feedforward
   - Optimization → Backpropagation, SGD, ADAM, ...
2. Regularization: L0,L1,L2, Dropout, Dropconnect
3. important architectures
   - CNN
   - RNN
   - Specific foundation architectures for relevant approaches
4. transfer learning: reuse parameters from pretrained models

   For reusability: see (Ashmore et al., 2021): ‘Convolutional neural networks (CNN) are particularly suited for partial model transfer [59] since the convolutional layers encode features in the input space, whilst the fully connected layers encode reasoning based on those features.’

Deep Learning in Character Recognition Considering Pattern Invariance Constraints (Oyedotun et al., 2015) 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 (Ouyang et al., 2016) 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 (Srivastava et al., 2021) 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 (Shrestha and Mahmood, 2019) 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

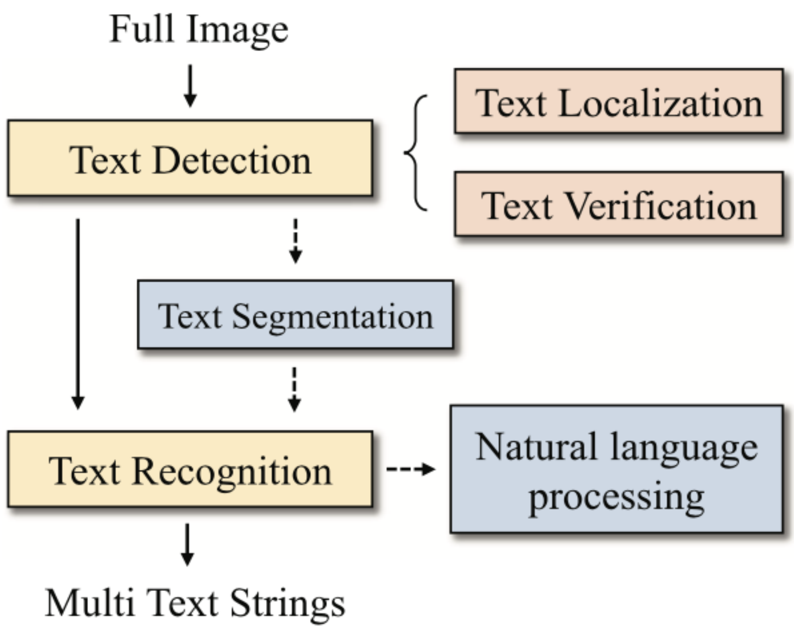
- each connection has weight value
- inputs are multiplied by weight and summed up at each unit
- the sum is used with an activation function (e.g. ReLU, Sigmoid, Tanh, SoftPlus)

2.3 Optical Character Recognition

Deep Learning based OCR (Zhao et al., 2020) 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!!!

Text Recognition in the Wild: A Survey (Chen et al., 2021b)

- various stages of OCR:
  - text localization: localize text components, group into candidate text regions with as little background as possible, DNN
  - text verification: verify text candidate regions as text or non-text, filter false-positives, CNN
  - text detection: determine whether text is present using localization and verification procedures, basis for end-to-end, can be regression or segmentation based
  - text segmentation: most challenging, includes text line (splitting a region of multiple text lines into subregion of single text lines) and character segmentation (separating text instance into single characters, typically used in earlier approaches)
  - text recognition: translates cropped text instance image into target string sequence, basis for end-to-end, DL encoder-decoder frameworks
  - end-to-end-system: given scene text image → convert all text regions into target string sequences, includes detectoin, recognition and postprocessing, can be seen as indipendent subproblems but also joint by sharing information
- text enhancement: recover degraded text, improve text resolution, remove distortions, remove background → reduce difficulty of recognition



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 (Srivastava et al., 2021) 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 (Goswami, 2018) 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 (Oyedotun et al., 2015) 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 (Ghosh et al., 2017) 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 3

Problem analysis

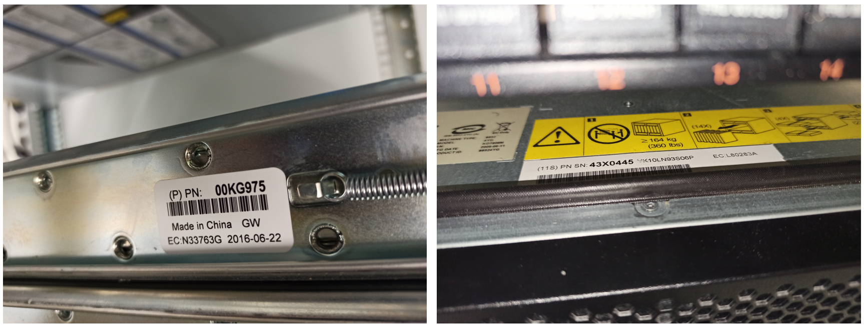
This chapter entails an analysis of the problem which is the research question's foundation. It is crucial, as the quality of requirements ultimately determines the quality of the overview and subsequent analysis.

Requirements for a software system that involves ML and thus DL requirements differs from the traditional approach. The data-driven software components are not entirely defined by the programmer but are influenced by data. The system acts with dependency on the test data (Siebert et al., 2021). This poses a challenge in determining requirements and measuring quality of results (Nakamichi et al., 2020). Instead of categorizing functional and non-functional requirements, like for traditional software projects (Zowghi et al., 2014), qualities that a Machine Learning System (MLS) must possess are defined as proposed. In Nakamichi et al. (2020); Siebert et al. (2021) systematic approaches for identification and documentation of such qualities are detailed. In MLSs various entities interact to in order to produce the desired functionality. The paper Nakamichi et al. (2020) suggests that in order to adequately evaluate the qualities, it is essential to not only consider the model but the entire MLS. These entities are data, model, infrastrucure, environment and platform (also system but as explained shortly, extra granularity would be redundant) (Nakamichi et al., 2020; Siebert et al., 2021).

For this thesis only the model can be assessed because neither of the other entities can be regarded as given. That is why the systematic approaches cannot be performed in the scope of this thesis. For example Siebert et al. (2021) proposes to follow the systematic CRISP-DM approach of identifying qualities. It cannot be performed due to the lack of data and other the other entities. Instead many qualities that are highlighted by research that fit the problem are taken into account along with two critical qualities (alphanumeric recognition, semantic retention) that are directly derived from the use case.

When it comes to documenting the identified qualities, both Nakamichi et al. (2020) and Siebert et al. (2021) define a meta model for qualities that combines qualities with measurement methods and values and assignes them to an entity of the MLS. The implementation and testing phase are not performed in the scope of this thesis and the difficulty in assessing the performance ahead of those phases, prevents complicates the evaluation of measurements. Additionally, experimental results from literature can only be compared as long as factors such as hardware, platform, source code, configuration and dataset are uniform (Arpteg et al., 2018). This applies to studies that create an overview such as Chen et al. (2021b); Long et al. (2021). These studies can only be regarded as guiding values. That's why measurements are not defined, as evaluation would only deliver a false sense of certainty.

The problem can be depicted by a use case. This use case sets the foundation for determining requirements for an approach because qualities derive from the intended purpose of use (Siebert et al., 2021). For this thesis, the basic use case is as follows: A technician takes a photo of a device label with his smart phone. The resulting image contains printed textual information which must be extraced by an application on the smart phone. Space and structure of this information can vary from label to label (see figure 3.1). The text,



(a) Positive example (b) Negative example

Figure 3.1: Examples for label images

spacing and structure carries semantic information which can be important for later processing in the scope of a business process (Chen et al., 2021b). The goal is to extract the text and preserve semantics from structure and space. This means text and the respective coordinates, height, width and a possible rotation angle must be output as the result (Yang et al., 2021). Those values can then be transformed into other formats such as JSON or HTML as needed. The labels can contain arbitrary alpha-numeric strings such as serial numbers (see figure 3.1). This results in the requirement that the DL model has to be able to recognize sequences that are not part of a predefined lexicon (Ghosh et al., 2017). The qualities for the MLS that can be derived directly from the use case (see table 3) can be regarded as excluding criterias, because an approach that does not possess the qualities in question, cannot be regarded as viable for the use case.

Alphanumeric recognition	Recognize alphanumeric strings such as serial numbers
Semantics retention	Retain semantics given implicitly be space and strucure of text in labels

Table 3.1: Qualities specific to use case — exclusion criterias

In addition to the qualities that arise directly from the use case, literature reveals a number of common qualities in regards to MLS (see table 3), some of which can be regarded as relevant and other do not hold any importance for the specific use case. **here important qualities explained (example:**

Imporant Qualites	Unimportant
Performance	Interpretability
Robustness	Reusability
Maintainability	Fairness
Performance efficiency	Security / Data protection

Table 3.2: Qualities identified through literature

robustness) Due to the uncontrolled environment of STR in the practical aspect of taking the images on-site beneficial image properties can not be guaranteed (Chen et al., 2021b). Robust text extraction can be influenced by factors such as complex backgrounds, text form (text rotation, font variability, arrangement), image noise (lighting conditions, blur, interference and low resolution) and access (perspective, shape of text) (Oyedotun et al., 2015; Ghosh et al., 2017; Chen et al., 2021b). Therefore, these properties have to be accounted for when determining the viability for an approach. An example for bad image quality in regards to OCR can be seen in figure 3.1(b).

Chapter 4

Current Research

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

model-pruning → remove connections for better performance

'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.'(Arpteg et al., 2018)

include Pipeline differences

Two models that can be used in conjunction **detection** (Beom, 2021b)
uses RetinaNet structure (Lin et al., 2018)
applies techniques from textboxes++ (Liao et al., 2018)

character recognition (Beom, 2021a)
needs cropped text area as input
uses CRNN (Shi et al., 2015) → 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 (Smith, 2007)

- 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 (Zhou et al., 2017)
SOFT: Softmax-free Transformer with Linear Complexity (Lu et al., 2021)
Generative Pretraining from Pixels (Chen et al., 2021a)

- 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 (Yang et al., 2021)

- 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 (Xu et al., 2021)

- 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(Arpteg et al., 2018) 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.' (Arpteg et al., 2018)

5.3 Outlook

What to do next: next steps Data Collection, Data Cleaning, Data Labeling, Model Training, Model Evaluation, Model Deployment, Model Monitoring Watanabe et al. (2019)

Chapter 6

Conclusion

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Appendix A

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