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in Information Systems and Management

Comprehensive Overview of Scene Text Spotting Methods with Deep Learning

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Declaration

In accordance with §16 para. 10 APO in conjunction with §35 para. 7 RaPO:
I hereby declare that I have written this bachelor thesis independently, have not submitted it for examination purposes elsewhere, have not used any sources or aids other than those indicated, and have marked verbatim and analogous quotations as such.

Munich, the 15.03.2022

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Johannes Reichle

Abstract

What Deep Learning approaches for Scene Text Spotting are there, and what are their shortcomings concerning the problem of extracting textual label data from images taken in real-world conditions? That is the question guiding this thesis. It is essential, as automated digitization has many economic upsides. A taxonomy is created that distinguishes different categories of approaches: Scene Text Spotting can be subdivided into Scene Text Detection and Scene Text Recognition. Both subtasks have different categories of approaches that are examined. A literature review is conducted to identify the most important innovations and gain insight into what shortcomings the field works on and what techniques are used in the process. The most prevalent issue is dealing with curved text robustly. For curved text, detection is improved by segmentation-based approaches, and recognition is improved by rectification and attention-based approaches.

Before analyzing the identified approaches, qualities are identified that serve as criteria for the comparison: appropriateness, performance/robustness, and efficiency. The analysis uses these qualities to compare the different categories. Depending on the specific dataset's properties, different approach categories can shine: regression-based detection efficiently deals with oriented text while segmentation-based detection is needed for curved text. For recognition, sequence-based approaches are the favorite. These entail CTC-based approaches for oriented text that contains longer text instances or alphanumeric strings and attention-based approaches for robustness for curved text. Additionally, CTC is the better choice for efficiency. For the whole task of Scene Text Spotting, the end-to-end differentiable 2-stage approaches that combine detection and recognition by sampling features are the clear favorite over 2-step approaches.

Keywords: Deep Learning, Scene Text Spotting, Literature Review

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Abbreviations

AED Average Edit Distance

AP Average Precision

BB Bounding Box

BiLSTM Bidirectional Long Short Term Memory

CNN Convolutional Neural Network

CTC Connectionist Temporal Classification

DL Deep Learning

DNN Deep Neural Network

EnDe Encoder Decoder

GD Gradient Descent

IOU Intersection over Union

LSTM Long Short Term Memory

ML Machine Learning

MLP Multi Layer Perceptron

MLS Machine Learning System

MSE Mean Squared Error

NED Normalized Edit Distance

NMS Non Maximum Suppression

NN Neural Network

OCR Optical Character Recognition

RNN Recurrent Neural Network

ROI Region of Interest

RPN Region Proposal Network

SSD Single Shot MultiBox Detector

STD Scene Text Detection

STR Scene Text Recognition

STS Scene Text Spotting

TPS Thin Plate Splines

Notation

Calculus

$\frac{\delta \mathbf{y}}{\delta \mathbf{x}}$ Jacobian matrix $\mathbf{J} \in \mathbb{R}^{n \times m}$ of$f : \mathbb{R}^n \to \mathbb{R}^m$

$\frac{\delta y}{\delta x}$ Partial derivative of y with respect to x

$\frac{dy}{dx}$ Derivative of y with respect to x

$\nabla_{\mathbf{x}} y$ or $\frac{\delta y}{\delta \mathbf{x}}$ Gradient of y with respect to $\mathbf{x}$

Datasets

$\mathbb{X}$ A set of training examples

$\mathbf{x}^{(i)}$ The i-th example (input) from a dataset

$y^{(i)}$ or $\mathbf{y}^{(i)}$ The target associated with $\mathbf{x}^{(i)}$

X The $m \times n$ matrix with input example $\mathbf{x}^{(i)}$ in row $X_{u,:}$

Numbers and Arrays

$\mathbf{a}^T$ or A^T Transposed vector or matrix

A Matrix

a Scalar

$\mathbf{A}$ Tensor

$\mathbf{a}$ Vector

Other

$\|\mathbf{x}\|$ L^2 norm of $\mathbf{x}$

$\mathbb{R}$ Real numbers

$f(\mathbf{x}; \boldsymbol{\theta})$ A function of $\mathbf{x}$ parametrized by $\boldsymbol{\theta}$

Chapter 1

Introduction

1.1 Motivation

Digitization is the transformation of analog information into a digital representation (Imgrund et al., 2018). Information systems in conjunction with digitization help optimize efficiency and productivity for business performance and reduce costs (Imgrund et al., 2018). This facilitates the growing need for automation (Imgrund et al., 2018). Additionally, a comprehensive information system with such digitized information allows a company to aggregate and share information to harness its benefits (Goodhue et al., 1992). However, before reaping the rewards, the information must first be digitized. Take technicians, for example, who work in the field with different equipment. It is helpful to digitize the labels of such equipment, to keep an overview of the inventory (Abramowicz and Corchuelo, 2019). The automated process of digitizing such data is called Optical Character Recognition (OCR), the concept of extracting typed, handwritten, or printed text from an image (Zhao et al., 2020). Techniques for this concept have improved a lot due to the advances in Deep Learning (DL) (Zhao et al., 2020). DL improves automation, effectiveness, and generalization (Chen et al., 2021). Applying these new capabilities and finding the right solution in the space of DL for the use case of extracting information of labels is the focus of this thesis. This is an exciting task as the performance of OCR systems in natural scenes is still challenging (Zhao et al., 2020; Chen et al., 2021). Such scenes entail natural scenes captured by a camera (Chen et al., 2021; Baek et al., 2019). Factors such as complex backgrounds, noise, perspective, and variability in fonts, colors, and sizes, of scene texts complicate the process (Hu et al., 2020b; Chen et al., 2021; Baek et al., 2019). In these conditions, OCR is known as Scene Text Spotting (STS) (Long et al., 2021).

1.2 Problem Description

This thesis aims to create an overview of possible DL techniques that facilitate finding a solution for digitization. Which state-of-the-art DL approaches for STS are viable for the use case of extracting textual label data from real-world images.

It is difficult to assess how well a DL approach performs before being implemented and tested on the specific problem or representative dataset (Arpteg et al., 2018). This justifies creating an overview rather than pointing out a single approach deemed the most promising. There are different categories of approaches (Chen et al., 2021; Long et al., 2021). The categories must be distinguished and explained. How the respective issues for the steps are solved must be identified from the literature, listed, and explained alongside.

The definition of the viability of an approach must be determined to judge a technique's shortcomings. What qualities such as detecting alpha-numeric strings or suitability despite inadequate image conditions must a solution have (Ghosh et al., 2017; Hu et al., 2020b)?

The approaches' shortcomings must be identified to compare them. This analysis cannot be performed with quantitative data, as results from different studies are not safely comparable (Baek et al., 2019; Arpteg et al., 2018; Long et al., 2021). Therefore, the comparison must leverage qualitative data concerning the different approach categories.

The article by Ashmore et al. (2021) defines four phases of the Machine Learning (ML) lifecycle: Data Management, Model Learning, Model Verification, and Model Deployment. Only the substage Model Selection from Model Learning will only be looked at in the scope of this thesis. The substage aims at selecting a suitable ML model to perform a given task (Ashmore et al., 2021). The other Model Learning substages, loss function selection, training, and hyperparameter selection (Ashmore et al., 2021), will not be examined. Other aspects such as data analysis, implementation, training, deployment, and maintenance of a solution in a production environment shall not be performed either. Note that is this work is concerned with end-to-end recognition, which aims to detect and recognize every text instance, as opposed to word spotting, which aims to find known words only (Chen et al., 2021; Karatzas et al., 2015).

The overview and subsequent analysis create a foundation for finding the right solution. However, it does not contain any claims about the degree of goodness or the certainty of solving the given problem. Further verification, implementation, and testing can then be performed based on 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 of current DL techniques that can help choose which to implement and test to solve the specific problem of STS, defined in Section 1.2 and further developed in Chapter 4.

The research question guiding the process is most crucial (Snyder, 2019): What DL approaches for scene text OCR are there, and what are their shortcomings concerning the problem of extracting textual label data from images taken in real-world conditions?

It is important to report how the information was found and synthesized (Torraco, 2005). Therefore, each section in the overview contains a paragraph about said information.

Before getting into the current research level, it is necessary to familiarize oneself with the field. A taxonomy is created to clarify the subsequent provision of current research and the analysis. The taxonomy is helpful to classify and give context to innovations in the field. It is formed with the help of overview literature and other related research in the field.

The research strategy is most important for a literature review (Snyder, 2019). The strategy for current innovations includes determining databases and keywords used and enforced exclusion criteria (Torraco, 2005). Innovations are explored through searching in the Google Scholar database. Additionally, literature is selected through citations for literature that has already been identified as impactful. All research after 2018 which pertains to extracting scene text is regarded as relevant. Standard OCR solutions that do not concern scene text may not hold validity in practice, as the image and text conditions can vary in the defined problem (Chen et al., 2021). A criterion for further examination is appropriate citations for the piece of literature in question. Another necessary criterion is that the paper contributes to the ML model. This extends to the whole pipeline from extraction features to the final result of the model. The identified literature is synthesized into an overview aligned according to the taxonomy.

The problem is dissected further to improve the validity of the subsequent analysis. This includes analyzing the specific use case and researching which qualities have been identified as generally critical for scene text approaches. The qualities are taken from the literature covering ML in general to literature covering OCR under challenging scene text conditions.

In the analysis, possibly viable approaches are compared with the required qualities defined in Chapter 4. The comparison is organized according to the taxonomy, which facilitates clarity and comprehensibility. 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. The subsequent analysis highlights different approaches for their theoretical fit as a solution.

In the following, 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 STS relevant for the problem described in Section 1.2. Chapter 2 lays the theoretical foundation for later chapters. This includes general principles of DL and, by extension ML, and STS. Chapter 3 examines current research. The overview is twofold: a taxonomy for the pipeline and its approaches as well as innovations in current research. The resulting overview can be viewed as a basis for a decision to implement a practical solution. In Chapter 4, 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 techniques and enable the discussion in Chapter 5. Here, the results, the availability of a solution, and 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 and an outlook for further research into the topic.

Chapter 2

Theoretical Foundation

This chapter succinctly describes principles that build the foundation for later chapters. Only the most relevant topics are touched upon, necessary details are explained in later chapters. The mathematics that makes the techniques possible is not explained in-depth as it would otherwise exceed the scope of this work. Whenever possible heavy mathematical notation is omitted if it does not aid the reader's understanding.

2.1 Machine Learning

A solid understanding of ML has to be developed first to grasp DL (Goodfellow et al., 2016). This is because DL is a subfield of ML (Chauhan and Singh, 2018). The most well-known definition for ML comes from Mitchell (1997): 'A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, improves with experience E'.

The task that the Machine Learning System (MLS) learns to perform can range from approximating a function (e.g., regression — $f : \mathbb{R}^n \to \mathbb{R}^l$, classification — $f : \mathbb{R}^n \to \{1, \ldots, k\}$) to obtaining a different representation for the data that has beneficial properties for further processing but preserves as much information as possible (e.g., PCA for compression) (Goodfellow et al., 2016). Note that the learning itself is not the task but merely the process of improving on performing the task (Goodfellow et al., 2016). One of the most well-known ML algorithms is Linear Regression. In the following, the algorithm is used as an example for explaining ML principles. As the name implies, Linear Regression is used to predict a value $\hat{y} \in \mathbb{R}$ given the input vector $\mathbf{x} \in \mathbb{R}^n$, which is made up of the features x_i. The goal is to approximate the ground truth y.

Linear is derived from the underlying model shown in Equation 2.1:

$$f(\mathbf{x}; \mathbf{w}, b) = \mathbf{w}^T \cdot \mathbf{x} + b = \sum_{i=1}^{n} w_i x_i + b = \hat{y} \tag{2.1}$$

The scalar product of the weights $\mathbf{w} \in \mathbb{R}^n$ and $\mathbf{x}$ is added to the bias term $b \in \mathbb{R}$. Both $\mathbf{w}, b$ are parameters learned by the model to optimize the approximation (Goodfellow et al., 2016).

The performance of a model measures how well the task can be completed. Depending on the task of the MLS, different quantitative measures are used. The metric Mean Squared Error (MSE) (see Equation 2.2) can be used for Linear Regression.

$$\mathsf{MSE} = \frac{1}{m} \|(\hat{\mathbf{y}} - \mathbf{y})\|^2 = \frac{1}{m} \sum_{i=1}^{m} \left((\mathbf{w}^T \mathbf{x}^{(i)} + b) - y^{(i)}\right)^2 \tag{2.2}$$

Here m denotes the number of examples $\mathbf{x}^{(i)}$ with the associated targets $y^{(i)}$, used to calculate the error (Géron, 2017; Goodfellow et al., 2016). The goal is to minimize the generalization error, which measures the expected performance on previously unseen input (Géron, 2017). The test set is used once the model has been trained. The test set is a part of the available data for use that is only used for confirmation purposes (Géron, 2017; Goodfellow et al., 2016). The generalization error can be divided into three components. The bias error arises from simplifying assumptions for the model; the variance error measures the variation in the model outcome depending on the data used for training. The model's representation capacity influences both these errors, so the relationship is called the Bias/Variance tradeoff. Lastly, the irreducible error stems from not having measured all data and the variation in real data and cannot be reduced (Ashmore et al., 2021; James et al., 2013; Géron, 2017).

The experience part of ML depicts the process where the algorithm is 'experiencing' the training dataset $\mathbb{X}$ and is learning essential properties of the dataset. In general, there are two paradigms for training: supervised and unsupervised (Goodfellow et al., 2016). Linear Regression is an example for supervised learning, as the model uses the ground truth value to learn approximating $y^{(i)}$ for the associated input $\mathbf{x}^{(i)}$ (Alzubi et al., 2018; Goodfellow et al., 2016). For unsupervised learning, on the other hand, the algorithm is not directed to predict a target value but to learn properties about the data and to leverage them for representation tasks like compressing or denoising the data (Goodfellow et al., 2016; Géron, 2017). In most cases, training can be described as an optimization problem, i.e., minimizing a function — the so-called objective or loss function L (Goodfellow et al., 2016). The MSE introduced earlier can be used for Linear Regression (see Equation 2.3). This

objective function has properties that make it suitable for linear output models (Goodfellow et al., 2016).

$$\min_{\mathbf{w},b} \mathsf{MSE}(\mathbf{w}, b) \tag{2.3}$$

Note that for minimization, the MSE is a function of $\mathbf{w}, b$, and not of $\mathbf{x}$. In predicting a value, the MSE is a function of $\mathbf{x}$ parametrized by $\mathbf{w}, b$ (see Equation 2.3). In Equation 2.1 $\mathbf{w}$,b are parameters that must be learned to minimize the generalization error (James et al., 2013; Géron, 2017). For other tasks such as binary classification, the metric (e.g., F_1-Score) and the objective function (binary cross entropy loss) are different (Géron, 2017; Ho and Wookey, 2020). For optimization, the Gradient Descent (GD) algorithm is prevalent, especially in the subfield of DL. As the name suggests, the gradient is used to update the parameters $\mathbf{w}, b$ iteratively to arrive at a minimum of the objective function (see Equations 2.4 and 2.5) (Géron, 2017).

$$\mathbf{w}' \leftarrow \mathbf{w} - \epsilon \cdot \nabla_{\mathbf{w}} \mathsf{MSE}(\mathbf{w}, b) = \mathbf{w} - \frac{2\epsilon}{m} \mathbb{X}^T (\mathbb{X}\mathbf{w} + b - \mathbf{y}) \tag{2.4}$$

$$b' \leftarrow b - \epsilon \cdot \frac{\delta}{\delta b} \mathsf{MSE}(\mathbf{w}, b) = b - \frac{2\epsilon}{m} (\mathbb{X}\mathbf{w} + b - \mathbf{y}) \tag{2.5}$$

Figure 2.1 shows a simplified visualization of potential GD steps towards the loss minimum and an intuition for how the gradients' signs affect the calculated parameters.

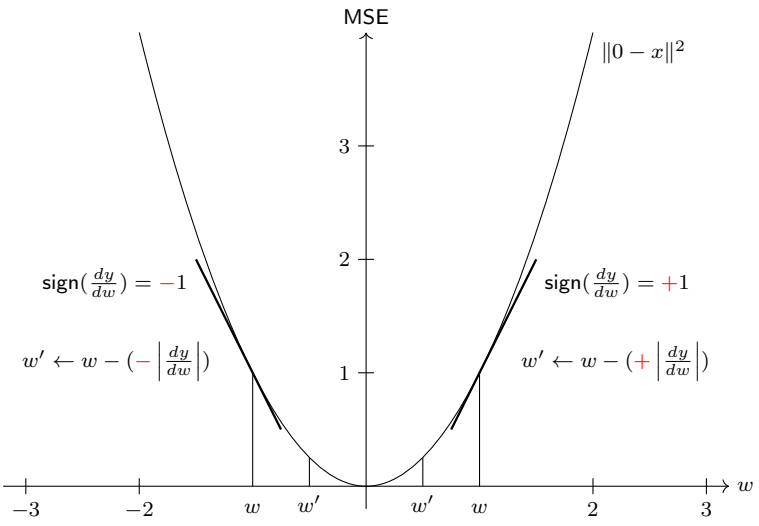
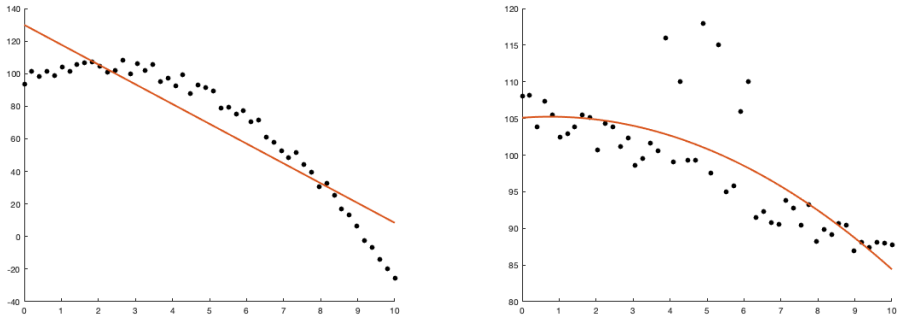


Figure 2.1: Visualization for gradient descent for a 1-dimensional objective function (Goodfellow et al., 2016)

The learning rate constant ϵ can be adjusted to speed up or slow down the 'steps', which can affect the convergence (Goodfellow et al., 2016). More

sophisticated variations of the GD algorithm are more suited for practical application (e.g., RMSProp, Adam) (Géron, 2017). Note that the process minimizes the test error with the test set $\mathbb{X}$. The effect on the generalization error depends on model capacity, which is the space of functions the model enables (Goodfellow et al., 2016). Linear Regression has the capacity to fit data with a linear relationship between features and ground truth. If the underlying relationship is more complicated than that, the model can only underfit the data (model bias) (Goodfellow et al., 2016). Polynomial Regression has more capacity than Linear Regression, for example. Say the actual relationship between features and ground truth now actually is linear; the Polynomial Regression model can overfit for statistical outliers in the training set, which is why in this case, the model with the lower capacity can achieve a lower generalization error (Géron, 2017). Therefore, it is essential to improve the bias/variance tradeoff. Aside from model selection, different techniques are used to prevent overfitting (Goodfellow et al., 2016).



(a) Linear Regression underfit

(b) Polynomial Regression overfit

Figure 2.2: Regression with linear and polynomial model

2.2 Deep Learning

In DL, Deep Neural Networks (DNNs) are leveraged to learn new data representations through multiple layers of abstraction automatically. This makes DNNs powerful function approximators (Goodfellow et al., 2016). DL has only caught on in recent years as the enormous computational cost has been met by improvement in computer hardware and automatic feature learning (Ponti et al., 2017; Chen et al., 2021). In this section, the basics of Neural Networks (NNs) are explained, and popular basic architectures thereof are introduced.

The most basic NN is called a feedforward NN or Multi Layer Perceptron (MLP), where the information only flows in one direction (in contrast

to Recurrent Neural Networks (RNNs) or Transformers) (Goodfellow et al., 2016). The network is made up of so-called artificial neurons. These neurons are arranged as a directed acyclic graph in multiple layers (Goodfellow et al., 2016). The first layer, which receives the input features $\mathbf{x}$, is called the input layer, the last layer which outputs the final estimation of $\hat{y}$ or $\hat{\mathbf{y}}$ is called the output layer, all layers in between are called the hidden layers (Shrestha and Mahmood, 2019). The structure with which the NN is built in terms of how many layers, how many neurons are in each layer, and how they are connected is called architecture (Goodfellow et al., 2016). The number of layers d is referred to as depths, whereas the dimensionality of those layers is called the width w (Goodfellow et al., 2016). A neuron, the basic building block of

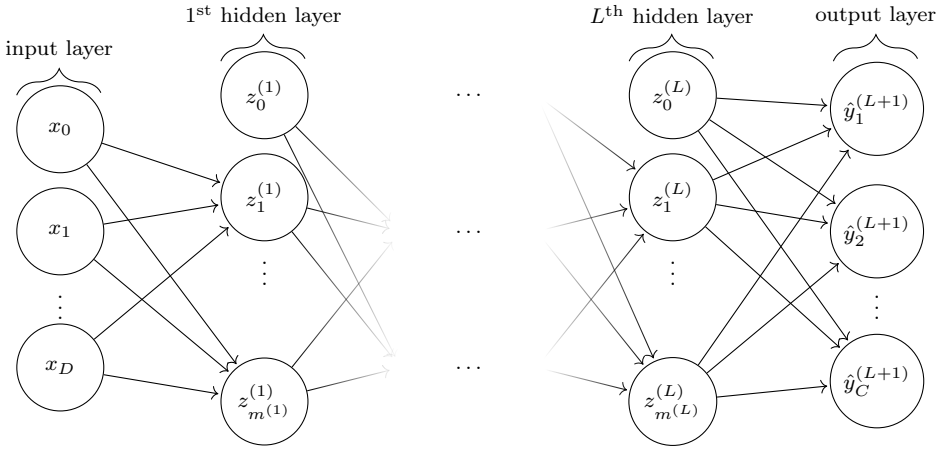


Figure 2.3: Network graph of a $(L+1)$-layer perceptron with D input units and C output units. The l^{th} hidden layer contains $m^{(l)}$ hidden units (Chauhan and Singh, 2018; Goodfellow et al., 2016).

NNs, receives input from neurons in the previous layer and calculates a single value propagated to neurons in the following layer (Shrestha and Mahmood, 2019). The value is calculated by feeding the received information into a Linear Regression model (see Equation 2.1). The resulting value is fed into an activation function g which introduces nonlinearity to allow more complicated transformations of information and representation (Goodfellow et al., 2016).

$$f(\mathbf{x}; \boldsymbol{\theta}) = g(\boldsymbol{\theta}\mathbf{x}) = \mathbf{z} \tag{2.6}$$

Here f denotes the function performed by a layer of neurons (linearity + activation). The parameters of the individual neurons are grouped to $\boldsymbol{\theta}$ ($\boldsymbol{\theta}_{:,0}$ equals 1 for the bias term). Popular activation functions include ReLU, tanh, sigmoid (σ), and softmax (Shrestha and Mahmood, 2019).

$$\mathsf{ReLU}(x) = \max(0, x) \tag{2.7}$$

$$\mathsf{tanh}(x) = \frac{\exp(x) - \exp(-x)}{\exp x + \exp -x} \tag{2.8}$$

$$\sigma(x) = \frac{1}{1 + \exp(-x)} \tag{2.9}$$

$$\mathsf{softmax}(\mathbf{x})_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{2.10}$$

While ReLU is the prevalent function for feedforward NN (Goodfellow et al., 2016), tanh is often used in RNNs like in Sherstinsky (2020); Greff et al. (2017). Sigmoid (softmax) activation functions, used for the output layer, are used to generate a Bernoulli (Multinouli) distribution which is helpful for classification tasks (Goodfellow et al., 2016). For, e.g., regression, the output layer can omit the activation function (Goodfellow et al., 2016). The prediction calculation is a concatenation of the functions defined by the layers and their neurons, the process of which is called forward propagation (Ponti et al., 2017; Goodfellow et al., 2016).

$$\hat{y} = f(\dots f(f(\mathbf{x}; \boldsymbol{\theta}^{(1)}); \boldsymbol{\theta}^{(2)}) \dots; \boldsymbol{\theta}^{(d)}) \tag{2.11}$$

$\boldsymbol{\theta}^{(i)}$ in Equation 2.11 stands for the parameters in layer i with $\boldsymbol{\theta}^{(i)}_{j,:}$ being the parameters the j-th neuron in that layer (Goodfellow et al., 2016). The forward propagation can also be described by a computational graph (see Figure 2.3) (Goodfellow et al., 2016).

The term DNN comes from adding many hidden layers to the NN (Shrestha and Mahmood, 2019). This allows for a more complicated function and more elaborate features or representations that are extracted from the input feature vector $\mathbf{x}$ (Oyedotun et al., 2015). The DNN can be trained as a whole, thus making feature engineering redundant in contrast to standard ML algorithms (Arpteg et al., 2018). The training algorithm is called backpropagation. The training error is calculated through the objective function and is propagated in conjunction with the output of forward propagation on each neuron (Goodfellow et al., 2016). For this, the chain rule of calculus can be used to modularly recursively propagate the loss backward to use GD (see Figure 2.4). The upstream gradient coming from neurons in the next layer is multiplied with the jacobian matrix of the current neuron to produce the downstream gradient that is then used by the preceding layer (Boué, 2018; Goodfellow et al., 2016).

$$\frac{\delta L}{\delta \mathbf{w}} = \frac{\delta L}{\delta \mathbf{z}} \frac{\delta \mathbf{z}}{\delta \mathbf{w}} \tag{2.12}$$

$$\frac{\delta L}{\delta \mathbf{x}} = \frac{\delta L}{\delta \mathbf{z}} \frac{\delta \mathbf{z}}{\delta \mathbf{x}} \tag{2.13}$$

The result of Equation 2.12 is used to update the neuron's weights $\mathbf{w}$ while the result of Equation 2.13 is used for further propagation (Boué, 2018). This

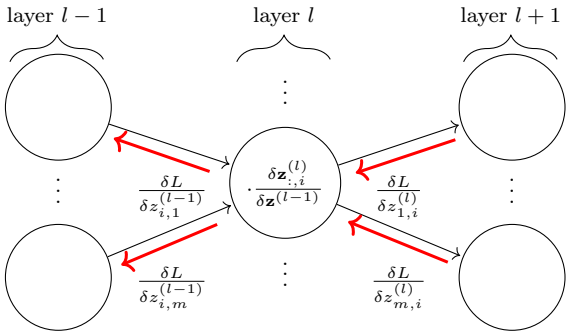


Figure 2.4: Reverse traversing the network's computation graph, $\cdot \frac{\delta \mathbf{z}_{:,i}^{(l)}}{\delta \mathbf{w}_i^{(l)}}$ is used for updating the neurons parameters with gradient descent

calculation is performed until the first layer of the computational graph is reached (Goodfellow et al., 2016). Note that the algorithm can be performed with tensors of arbitrary dimensionality (Goodfellow et al., 2016). When it comes to training DNNs, the problem of vanishing/exploding gradients occurs during backpropagation. This problem can impede convergence (He et al., 2015). Different kinds of NN deal with this problem differently.

2.3 Convoluational Neural Nets

Convolutional Neural Networks (CNNs) are a type of NN that is also acyclic or feedforward, like MLPs (Chauhan and Singh, 2018). CNNs are specialized to process a grid of values $\mathbf{X}$ like an image (Goodfellow et al., 2016). CNNs are extensively used in computer vision (Chauhan and Singh, 2018). They consist of a variety of components: fully connected layer, activation function, convolutional layer, pooling layer (Chauhan and Singh, 2018; Ponti et al., 2017). The fully connected layers are the layers that make up MLPs (Ponti et al., 2017).

A convolutional layer has multiple filters, which consist of multiple kernels (Chauhan and Singh, 2018). For multi-layer input, with d so-called channels, a filter has the same amount of kernels as there are channels (d) (Ponti et al., 2017). Note that the height and width are spatial dimensions, and the depth is referred to as the channel dimension. A kernel is a $n \times n$ square matrix of learnable parameters, so a filter is a tensor $n \times n \times d$. The convolution operation is the elementwise multiplication between the filter and the input's overlapping $n \times n$ subspace (see Figure 2.5) (Ponti et al., 2017). The convolution operation is performed for every space in the input. Spaces can be skipped if stride is introduced (Ponti et al., 2017). Often zero-padding is used to preserve the spatial dimensions between input and output of the layer

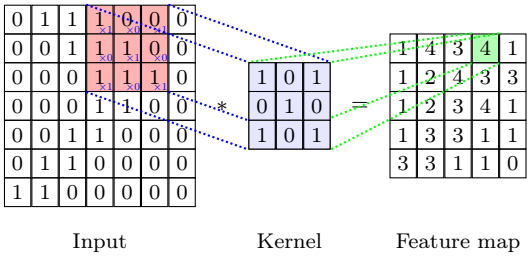


Figure 2.5: Convolution operation of a single kernel (Chauhan and Singh, 2018)

(known as same-padding) (Ponti et al., 2017; Simonyan and Zisserman, 2015). The number of filters a convolutional layer applies is equal to the output channels that the layer has, which are often called feature maps (Ponti et al., 2017). The convolution result is usually fed into a ReLU activation function to introduce nonlinearity like with fully connected layers. The activation is performed on every element in the output and preserves the dimensionality (Ponti et al., 2017). In the explained scenario, the filter is slid across a 2d-surface to perform convolution. Note that this can be restricted to 1d (e.g., audio) or extended to 3d (e.g., CT scans) (Goodfellow et al., 2016).

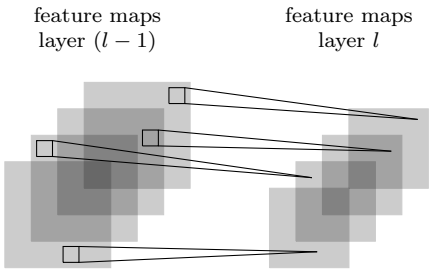


Figure 2.6: Pooling layers preserve channel dimenstions but downsample spatial dimensions

Pooling layers are used to reduce the spatial dimension (i.e., downsampling) of feature maps (Ponti et al., 2017). Pooling layers preserve the number of channels, as the operation is performed to each channel separately (see Figure 2.6) (Chauhan and Singh, 2018). Much like with convolutions (in 2d scenario), the pooling operation is slid across the height and weight dimensions of the channels (possibly with stride), and the pooling operation is performed (Ponti et al., 2017; Chauhan and Singh, 2018). The most popular kind of pooling is maxpooling (Ponti et al., 2017). For the operation, only the

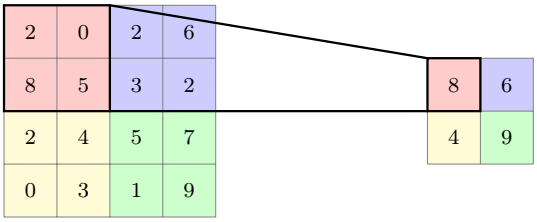


Figure 2.7: 2×2 max pooling operation with stride 2 (Chauhan and Singh, 2018)

maximum value of the current subspace of the current channel is taken (see Figure 2.7) (Chauhan and Singh, 2018).

When it comes to training deep CNNs, the problem of vanishing/exploding gradients occurs during backpropagation. This problem can impede convergence (He et al., 2015). It can be solved by normalized initialization of the network's weights and intermediate batch normalization layers (He et al., 2015; Bjorck et al., 2018). Layer normalization can also be used (Liu et al., 2021; Ba et al., 2016). ResNet introduced residual blocks with skip connections that pass the gradient to later layers to bypass exceedingly deep NN to overcome the degradation problem (where deep NNs perform worse than shallow ones) (He et al., 2015). These skip connections map the identity of the previous layers to later layers (He et al., 2015).

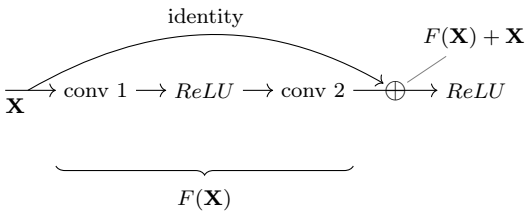


Figure 2.8: Residual block module with skip connection (He et al., 2015)

2.4 Recurrent Neural Nets

RNNs are another popular category of NN used for processing sequential input, like text and speech (Chauhan and Singh, 2018). Figure 2.9 shows a simple RNN. The defining element is the recurrent connection from node $\mathbf{h}$ to itself (Goodfellow et al., 2016). A sequence of inputs $\mathbf{X}$ is iteratively fed into the RNN. The current layer of the network takes $\mathbf{x}^{(t)}$ and $\mathbf{h}^{(t-1)}$ and produces $\mathbf{h}^{(t)}$ (see Equation 2.14). Additionally, $\mathbf{h}^{(t)}$ is used to calculate the

output $\hat{\mathbf{y}}^{(t)}$ (see Equation 2.15), and it is handed to the next layer (Goodfellow et al., 2016). $\mathbf{h}^{(t)}$ is thought of as a hidden state which stores information from previous inputs (Goodfellow et al., 2016).

$$\mathbf{h}^{(t)} = \mathsf{tanh}(b + W\mathbf{h}^{(t-1)} + U\mathbf{x}^{(t)}) \tag{2.14}$$

$$\hat{\mathbf{y}}^{(t)} = \mathsf{softmax}(c + V\mathbf{h}^{(t)}) \tag{2.15}$$

Note that the connection between hidden layers can differ depending on the type of RNN used (Goodfellow et al., 2016). During an execution run, all

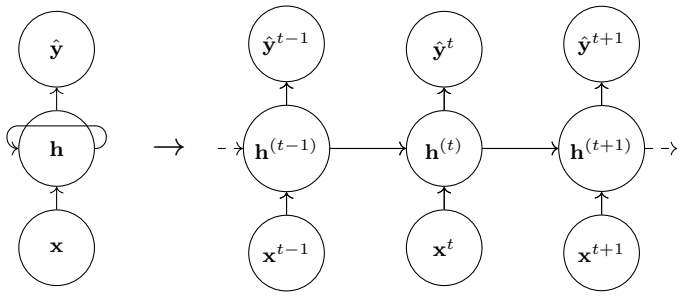


Figure 2.9: Recurrent neural net unrolling (Goodfellow et al., 2016)

unrolled layers share the same weights (U, V, W) (Chauhan and Singh, 2018). This makes gradients from backpropagation vulnerable to exploding/vanishing gradients if the singular values of those weight matrices are > 1 or < 1 (Goodfellow et al., 2016; Pascanu et al., 2013). The example RNN produced an output sequence the same length as the input sequence. However, this does not have to be the case for RNNs (Goodfellow et al., 2016). Depending on the chosen RNN, both the input and the output can either be a sequence of variable length or a vector of fixed length (Goodfellow et al., 2016). Optimization of the parameters of RNNs is performed with (truncated) backpropagation through time (Sherstinsky, 2020).

The Long Short Term Memory (LSTM) network was introduced by Hochreiter and Schmidhuber (1997) and modified by Gers et al. (1999) to improve longer storing of information from earlier layers (Chauhan and Singh, 2018). The LSTM also improves the vanishing gradients problem associated with increasingly deep NNs (Sherstinsky, 2020). The clipping gradients technique is often used to help with exploding gradients (Goodfellow et al., 2016). A so-called cell is shown in Figure 2.10. It shows the basic structure, representing the recurrent building block of LSTMs (Goodfellow et al., 2016). The three gates (input, forget, output) help make the LSTM a widely used NN model.

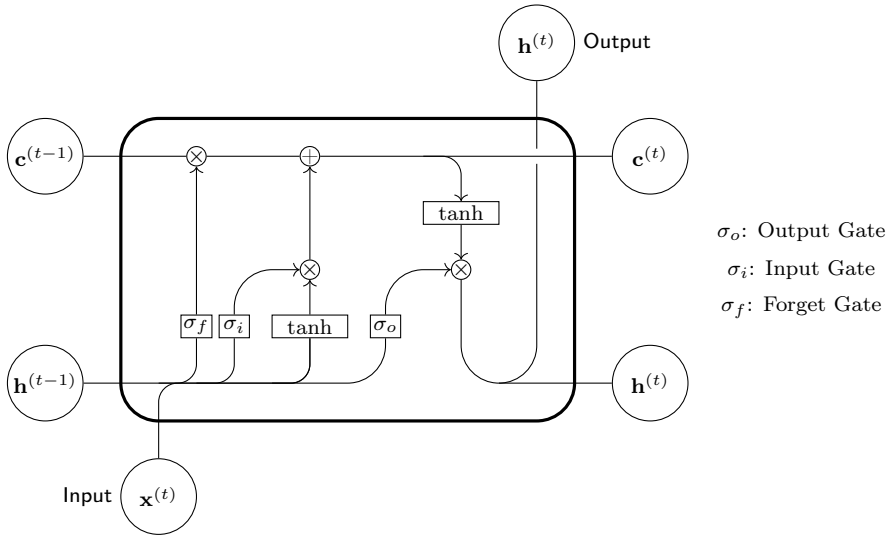


Figure 2.10: Long short term memory cell, merged lines stack vectors, split lines duplicate vector (Goodfellow et al., 2016; Yu et al., 2019)

The gates calculate weights between 0 and 1 (thus the use of σ) used to control the flow of information (Goodfellow et al., 2016). The forget gate is part of a self-loop which helps to accumulate information longer, the input gate helps to focus on the relevant characteristics of the input information, and the output gate removes irrelevant information for the output and the next cell (Goodfellow et al., 2016).

$$\begin{pmatrix} \mathbf{i}_t \\ \mathbf{f}_t \\ \mathbf{o}_t \\ \mathbf{g}_t \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \mathsf{tanh} \end{pmatrix} T \begin{pmatrix} \mathbf{x}_t \\ \mathbf{h}_{t-1} \end{pmatrix} \tag{2.16}$$

$$\mathbf{c}_t = \mathbf{f}_t \otimes \mathbf{c}_{t-1} + \mathbf{i}_t \otimes \mathbf{g}_t \tag{2.17}$$

$$\mathbf{h}_t = \mathbf{o}_t \otimes \mathsf{tanh}(\mathbf{c}_t) \tag{2.18}$$

Equations 2.16, 2.17, and 2.18 show the calculations performed for a single timestep (Xu et al., 2016). σ and tanh denote the application of activation functions after the weight matrix T is multiplied by the stacked input $\mathbf{x}_t, \mathbf{h}_{t-1}$ (Zaremba et al., 2015). $\mathbf{i}_t, \mathbf{f}_t, \mathbf{o}_t$ are the output of the input gate, forget gate, and output gate. $\mathbf{c}_t, \mathbf{h}_t$ are the cell states and outputs to the next step or the prediction sequence (Zaremba et al., 2015).

RNNs are often used with the Encoder Decoder (EnDe) mechanism introduced by Cho et al. (2014). This mechanism is a structure for NN that is used for various problems. Initially, it was designed to use RNNs to transform an input sequence into an output sequence, e.g., translation (Cho et al., 2014). The

output of which can be of variable length (a special token usually indicates the end) (Cho et al., 2014; Asadi and Safabakhsh, 2020). The EnDe mechanism entails two parts: The encoder, which transforms the input into a different representation, compresses all the information from the input into a feature vector; the decoder uses the extracted features to generate the output predictions (Asadi and Safabakhsh, 2020; Cho et al., 2014). The decoder can thus use the whole input context at once (Asadi and Safabakhsh, 2020). The output associated with decoders is sequential (Asadi and Safabakhsh, 2020). The mechanism can be implemented in different ways. Both purely RNNs based (Cho et al., 2014) implementations and mixtures along with CNNs (Ghosh et al., 2017) exist (Asadi and Safabakhsh, 2020). The RNN EnDe can transform a sequence of variable lengths into another sequence with different variable lengths (Cho et al., 2014). The encoder processes the input sequence and crafts a representation vector that encodes information and context for the whole input sequence, which can then be used for every step in the decoder network (see Figure 2.11) (Cho et al., 2014). An example used for an EnDe

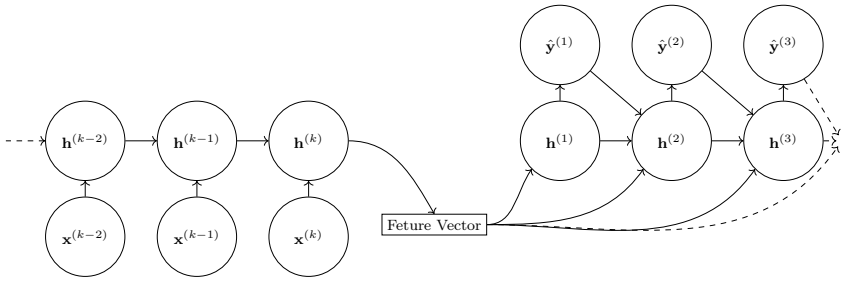


Figure 2.11: Sequence to sequence encoder decoder architecture (Cho et al., 2014)

architecture with a CNN encoder and a RNN decoder would be image captioning (Asadi and Safabakhsh, 2020). The image is encoded into a vector which includes context for the whole image (Asadi and Safabakhsh, 2020).

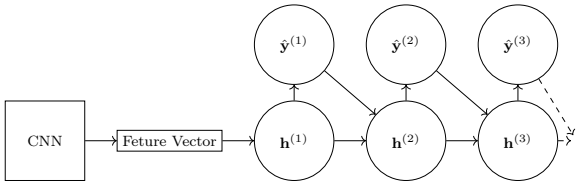


Figure 2.12: Image to sequence encoder decoder architecture (Asadi and Safabakhsh, 2020)

2.5 Scene Text Spotting

OCR is the concept of extracting typed, handwritten, or printed text from an image (Zhao et al., 2020). Achieving satisfactory performance of OCR systems in natural scenes is still challenging (Zhao et al., 2020; Chen et al., 2021). Such scenes entail natural scenes captured by a camera (Chen et al., 2021; Baek et al., 2019). The difficulties arise from diversity and variability of text, complexity and interference from backgrounds, and poor imaging conditions. In these conditions, OCR is known as STS (Long et al., 2021). Before the advent of DL, researchers in the field had to hand-craft features (Long et al., 2021). DL automates the feature generation process with its representation and learning capabilities (Long et al., 2021; Goodfellow et al., 2016). Because of this, DL methods are the preferred tools for performing STS (Long et al., 2021). OCR and STS are often divided into two subcategories (Scene) Text Detection and (Scene) Text Recognition (Zhao et al., 2020; Long et al., 2021; Chen et al., 2021). For Scene Text Detection (STD), the task is to localize text instances in the image, whereas the Scene Text Recognition (STR) task is to recognize/categorize text from already cropped images (Chen et al., 2021). Note that a system that performs both STR and STD in one continuous pipeline is called an end-to-end approach (Chen et al., 2021).

The correct evaluation metrics must be used to assess the performance of developed approaches. The popular protocols Precision, Recall, and the F_1-Score are used to compare approaches for STD (Long et al., 2021). The metrics are derived with values from the confusion matrix (see Tabel 2.1) (Davis and Goadrich, 2006).

		Ground Truth	
		positive	negative
Prediction	positive	True Positive	False Positive
	negative	False Negative	True Negative

Table 2.1: Confusion matrix

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{2.19}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2.20}$$

$$F_1\text{-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2.21}$$

The difference of metrics for the task manifests itself in the way the values of the confusion matrix are calculated (Long et al., 2021). Note that the tradeoff

between False Positives and False Negatives manifests itself in the Precision-versus-Recall curve (Su et al., 2015). F_1-Score is also referred to as the harmonic mean (between Precision and Recall) (He et al., 2018b). STD differs mainly in how the protocols match the prediction to the ground truth (Long et al., 2021). Detectors have multiple predictors which regress the placing and sizing of Bounding Boxs (BBs). More information on this will follow in Chapter 3. Matching is the process of assigning a BB prediction to the ground truth, e.g., Liu et al. (2016a); Liao et al. (2018a). The PASCAL approach defines the Intersection over Union (IOU) (see Equation 2.22).

$$IOU = \frac{\text{area of intersection between truth and prediction}}{\text{area of union between truth and prediction}} \tag{2.22}$$

For PASCAL, the prediction will be matched if the IOU value is larger than a threshold (Long et al., 2021). A match is considered a True Positive. The other values are assigned accordingly (Sun et al., 2019). Other evaluation approaches are mostly based on IOU, e.g., MSRA-TD 500 evaluates the rotation from the BB compared to the truth and the IOU threshold (Long et al., 2021). Long et al. (2021) argues that researchers in the field of STD should consider Average Precision (AP) as the primary evaluation protocol rather than F_1-Score. According to Su et al. (2015), AP can be considered the area under the Precision-versus-Recall curve. F_1-Score, on the other hand, only considers singular instances on that curve (Long et al., 2021) and is sensitive to the tradeoff, while AP is invariant to it (Shi et al., 2017c).

For STR, the evaluation can be based on character-level or word-level. There is no need to match ground truth to prediction, as the image is already cropped (Long et al., 2021). Often lexicons that contain possible words are used by STR. Testing and real-world performance can depend strongly on these lexicons (Chen et al., 2021; Long et al., 2021). The equations 2.23 and 2.24 show metrics based on word-level (Chen et al., 2021).

$$\text{Word Recognition Accuracy} = \frac{\text{correctly recognized words}}{\text{total words}} \tag{2.23}$$

$$\text{Word Error Rate} = 1 - \text{Word Recognition Accuracy} \tag{2.24}$$

An example for a character-based metric would be 1−NED, where Normalized Edit Distance (NED) calculates the distance between prediction and ground truth (see Equation 2.25).

$$\text{NED} = \frac{1}{N} \sum_{i=1}^{N} \frac{D(s_i, \hat{s}_i)}{\max(l_i, \hat{l}_i)} \tag{2.25}$$

D denotes the Levenshtein distance, s denotes the text, l denotes the text length, and N is the total number of text lines (Shi et al., 2017c). For STR, NED is used over the whole dataset (Karatzas et al., 2013).

STS is oriented to both STD and STR. The prediction must be matched to the ground truth, like for STD (Long et al., 2021). For comparing predictions and matching the respective ground truths that have been matched, NED is used (Chen et al., 2021). For end-to-end recognition (Karatzas et al., 2013, 2015), the primary evaluation protocols that are used include Precision, Recall, F_1-Score, and Average Edit Distance (AED) (Chen et al., 2021). A sample is considered a True positive if the NED distance between predictions and matched ground truths equals 0 (Sun et al., 2019) (one sample can have multiple text instances). AED is the sum of NED values divided by the number of pictures (Chen et al., 2021). Note that competitions often define their variants of the metrics, e.g., He et al. (2018b); Shi et al. (2017c). Case sensitivity and matching criteria are examples of changing properties of metrics.

To compare approaches with these metrics, benchmark datasets that have different characteristics are used. Table 2.2 lists a couple of influential bench-

Dataset (year)	**STD**	**STR**	**Text Orientation**	**Characteristics**
ICDAR (2013)	✓	✓	Horizontal	—
IIIT 5K-Word (2012)		✓	Horizontal	Cropped, variance in font, color, size and noise (Long et al., 2021)
ICDAR (2015)	✓	✓	Multi-oriented	Low resolution, small text instances (Liao et al., 2020)
MSRA-TD500 (2012)	✓		Multi-Oriented	Extreme aspect ratios (Liao et al., 2020)
ICDAR MLT (2017)	✓	✓	Curved	Multilingual (Long et al., 2021)
SCUT CTW1500 (2017)	✓		Curved	—
Total-Text (2017)	✓	✓	Curved	—

Table 2.2: Benchmark datasets and their properties

mark datasets and their fundamental properties. ICDAR (2013) references the Focused Scene Text dataset (Karatzas et al., 2013) and ICDAR 2015 to the Incidental Text Competition dataset (Karatzas et al., 2015). The second and third columns indicate whether the dataset provides annotations for the tasks. The Text Orientation column specifies the most complicated orientation present in the dataset (Curved $\subset$ Multi-oriented $\subset$ Horizontal). A collection of images that shows representative examples taken out of benchmark datasets can be found in Appendix A.

Chapter 3

Technique Overview

The objective is to create an overview of techniques in the field. According to the methodology detailed in 1.3, a taxonomy is first introduced, which facilitates the analysis and comparison of techniques. The subsequent search for literature that lays the foundation for an overview of current research is documented. Lastly, the advances in the field are placed in the correct position and analyzed.

3.1 Pipeline taxonomy

Before getting into the current research level, a knowledge base about the field has to be layed. A taxonomy is created for this, which is helpful to classify

Task	**Approach category**		**Identifying properties**
STD	Seg-free		Localize whole instances, filter out false positives
		One-stage	Regress BBs direclty
		Two-stage	Find ROIs, adjust ROIs for better fit
	Seg-based		Localize text components to reconstruct instance
		Pixel-level	Predict pixel segmentation map
		Component-level	Predict sub-text components
STR	Seg-based		Character segmentation and classification
	EnDe-based		Sequence recognition
		CTC-based	CTC rule transciption
		Attention-based	Attention mechanism
STS	2-step		Images are cropped for STR according to STD results
	2-stage		Features are cropped for STR according to STD regions

Table 3.1: Tasks, method categories and identifying propertis

and give context to innovations in the field (see Table 3.1). The partition of tasks and the categorization of approaches are conducted according to overview literature such as Long et al. (2021); Chen et al. (2021); Cong et al. (2019), and related research in the field such as Qiao et al. (2021); Sheng et al. (2021);

Liu et al. (2020a); Deng et al. (2018). Note that there can be approaches that blend different categories into one. The taxonomy is merely used to facilitate an overview and enable a more transparent comparison. In order to create the overview, the necessary steps in the process of STS need to be highlighted, from localizing possible text instances to predicting the characters or words (Long et al., 2021; Sourvanos and Tsatiris, 2018). Note that details that are not essential are abstracted away. STD and STR only incorporate a part of STS, while end-to-end approaches incorporate both STD and STR techniques to solve STS (Long et al., 2021; Ghosh et al., 2017; Chen et al., 2021). Therefore this section will first discuss the two parts and later combine them.

3.1.1 Scene Text Detection

For STD, two main categories of approaches can be identified: segmentation-based and BB regression-based (see Figure 3.1) (Long et al., 2021; Sheng et al., 2021; Liu et al., 2020a). The regression-based category draws heavy inspira-

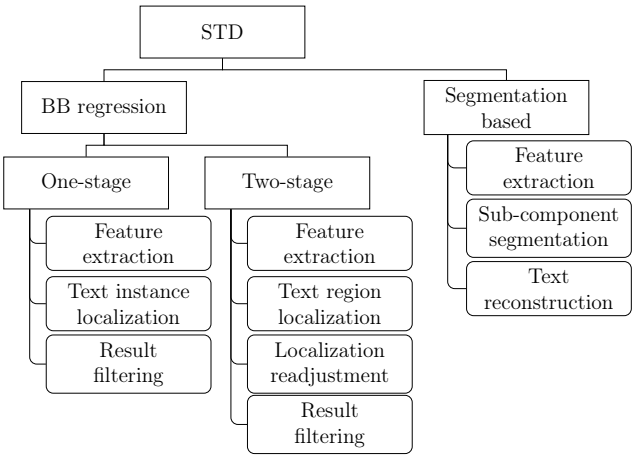


Figure 3.1: Different STD pipelines

tion from the field of object detection (Long et al., 2021; Liu et al., 2020a). This is only natural as text detection can be seen as a type of object detection (Liu et al., 2020a; Long et al., 2021). There are two methods for STD inspired by object detection: one-stage and two-stage (Long et al., 2021). Both localize text instances as a whole in the form of a BB (see Figure 3.2) (Long et al., 2021; Sheng et al., 2021). One-stage approaches are modeled after Liu et al. (2016a), Single Shot MultiBox Detector (SSD), or Redmon et al. (2016), You Only Look Once (YOLO). They have in common that BBs are regressed

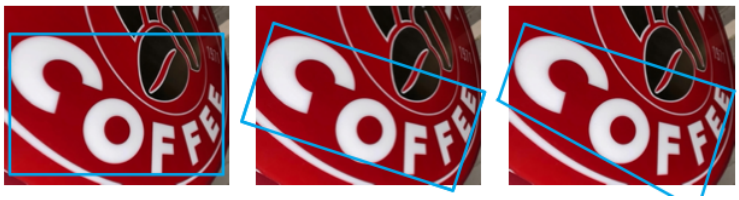


Figure 3.2: Different BB text representation forms (Long et al., 2018a)

once and not changed or optimized afterward (Redmon et al., 2016; Liu et al., 2016a), as opposed to the Region of Interest (ROI) based approach with two stages (Girshick et al., 2014). The basic approach is explained with the example of Liao et al. (2017) (see Figure 3.3), which is based on SSD. Note that the

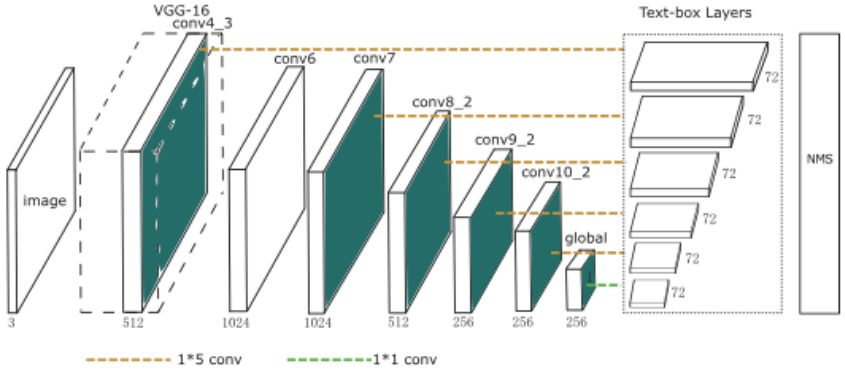


Figure 3.3: Example for a one-stage, BB regression based STD architecture (Liao et al., 2017)

approach is modeled to recognize horizontal text instances (Liao et al., 2017). It uses a convolutional network inspired by the VGG architecture (blocks of two or three 3×3 convolutional layers with same-padding followed by a 2×2 max pooling layer with stride 2) for feature extraction (Liao et al., 2017; Simonyan and Zisserman, 2015). Note that the spatial padding added for convolution ensures that spatial dimensions are preserved (Simonyan and Zisserman, 2015). Afterward come additional layers, which continuously downsample. The output of six of them is separately used as feature maps for BB regression (Liao et al., 2017). The downsampling and BB regression for different layers help detect text instances of different scales (Liu et al., 2016a). Each spatial location on the feature map can be traced back to a region on the input image (Long et al., 2021). The BB regression is carried out by six convolutional text-box layers, which predict how confident (c_1, c_2) the prediction is a text instance or background and where the text instance is (x, y, w, h). Note that the output is not the location of a BB but the offset to the respective anchor box (Liao et al., 2017; Long et al., 2021). Anchor boxes are predefined to bias towards different

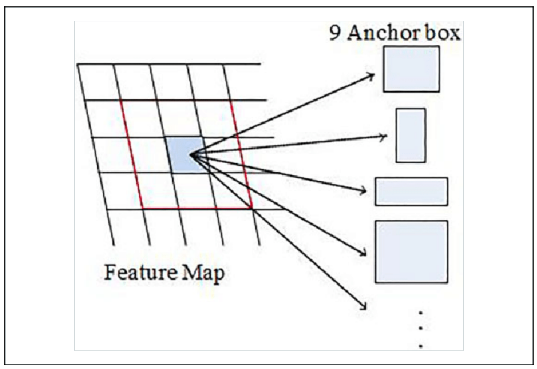


Figure 3.4: Example for possible anchor box placement for one space on the feature map (Zhao et al., 2018)

sizes and aspect ratios (see Figure 3.4) (Liao et al., 2017). The text-box layers are the difference from the SSD approach for standard object detection (Liao et al., 2017; Liu et al., 2016a). These layers use 1×5 filters to adjust to larger aspect ratios (Liao et al., 2017). Each text-box layer has 72 filters (12 anchor boxes $\cdot$ 6 values per prediction), the filters are slid across the input features generating 12 predicted BB per position (Liao et al., 2017). The BBs of all layers are then subjected to the process of Non Maximum Suppression (NMS) to filter out the best BB for each possible text instance (Liao et al., 2017). NMS is a light post-processing step (not part of the DL pipeline). Of all detections which overlap (IOU) more than a threshold ϕ, only the with the highest confidence score (c) is kept (Hosang et al., 2017).

The R-CNN, which builds the foundation for ROI based text detection, was introduced by Girshick et al. (2014) and improved by Girshick (2015) (Fast R-CNN), Ren et al. (2015) (Faster R-CNN), and He et al. (2018a) (Mask R-CNN). Note that two-stage methods are fully differentiable and thus end-to-end trainable since Faster R-CNN (like two-stage methods) (Ren et al., 2015; Long et al., 2021). The two stages consist of ROI regression BB adjustments (Jiang et al., 2017; Ren et al., 2015). The two-stage STD approach introduced by Jiang et al. (2017) (see Figure 3.5) uses Faster R-CNN. Unlike the previous approach, the architecture is designed to detect multi-oriented text instances (Jiang et al., 2017; Liao et al., 2017). Like the one-stage approach, the two-stage approach starts with feature extraction from the image with a convolutional layer (Jiang et al., 2017). Feature extraction CNN is again inspired by the VGG architecture (Jiang et al., 2017), like in the previous approach. Region Proposal Network (RPN) uses the generated feature map (Jiang et al., 2017). Like the previously explained approach, the feature maps are used to regress the offset respective to BBs. However, these are considered regions that probably contain text subject to change and be

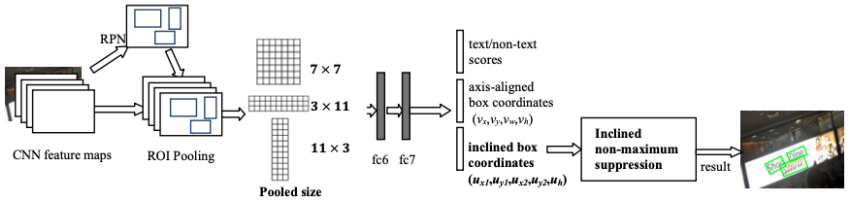


Figure 3.5: Example for a two-stage, BB regression based STD architecture (Jiang et al., 2017)

refined later (Jiang et al., 2017; Lu et al., 2020). The BBs are still axis aligned at this point (Jiang et al., 2017). In contrast to the previous SSD-based approach, only one feature map is used with BB regression (Jiang et al., 2017). The RPN from Faster R-CNN is adjusted to use smaller-scale anchor boxes to adapt to text (Jiang et al., 2017). The resulting BBs are called ROIs (Ren et al., 2015; Jiang et al., 2017). They are used for ROI pooling in conjunction with the original feature maps. This layer uses max pooling to convert the spatial features corresponding to the location of the ROI to a small feature map (Girshick, 2015). In the case of this example, ROI pooling is used to create three feature maps with different aspect ratios ($7 \times 7, 3 \times 11, 11 \times 3$), which are concatenated for the next step (Jiang et al., 2017). The second stage is to predict a confidence score (text, background) for each ROI and to refine them by regressing values (x_1, y_1, x_2, y_2, h) that allow for multi-oriented boxes to account for rotated text (Jiang et al., 2017). At last, the resulting BBs are filtered by inclined NMS post-processing, which is adjusted to the multi-oriented BBs (Jiang et al., 2017).

The basis for the segmentation-based methods is that every part of the text instance can be used to verify that there is text (Long et al., 2021). Because of this, sub-text components can be detected separately and then used to reconstruct a text instance (Long et al., 2021). Segmentation-based methods can be summed up in two categories: pixel-level and component-level (Long et al., 2021). Like BB regression-based methods, example architectures are

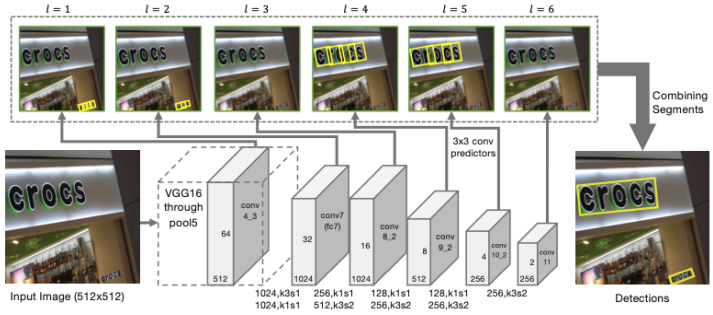


Figure 3.6: Example for a sub-text component, segmentation-based STD architecture (Shi et al., 2017a)

explained to describe their categories more clearly. The first segmentation-based category for STD segment components which are local regions of text that can overlap one or more characters (Long et al., 2021). The architecture (see Figure 3.6) from Shi et al. (2017a) is used as an example for this category. Like the one-stage, BB regression-based STD approach, the feature extraction CNN of this approach is taken from SSD and thus VGG. The difference is reflected in the prediction layers (Shi et al., 2017a; Liu et al., 2016a; Simonyan and Zisserman, 2015). Instead of detecting whole BBs, the network predicts both sub-text components and links at multiple scales (Shi et al., 2017a). The convolutional prediction is carried out with seven 3×3 filters followed by a softmax nonlinearity for normalization. The segments are given by the values $x_s, y_s, w_s, h_s, \theta_s$, which offset an anchor box and confidence scores c_1, c_2 (Shi et al., 2017a). Links (s_1, s_2) are used to combine the segments and are accordingly used to separate nearby words (Shi et al., 2017a). The convolutional

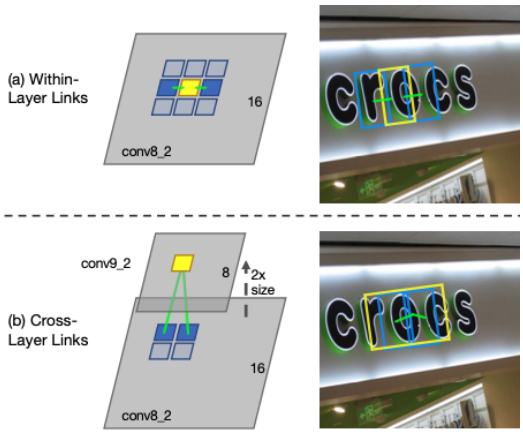


Figure 3.7: Visualization for prediction of links within and across layers for segmentation-based STD (Shi et al., 2017a)

link predictions are then used for text reconstruction post-processing as follows: Within a layer, links connect the neighbors of the space in the predicted feature map (see Figure 3.7 (a), Equation 3.1) (Shi et al., 2017a).

$$\mathcal{N}^{w}_{s^{x,y,l}} = \frac{\{s^{(x',y',l)}\}_{x-1 \leq x' \leq x+1, y-1 \leq y' \leq y+1}}{s^{(x,y,l)}} \tag{3.1}$$

On the other hand, the cross-layer links are found by using the four cross-layer neighbors of the feature map of the preceding predictor (Shi et al., 2017a). (see Figure 3.7 (b), Equation 3.2) (Shi et al., 2017a).

$$\mathcal{N}^{c}_{s^{x,y,l}} = \{s^{(x',y',l-1)}\}_{2x \leq x' \leq 2x+1, 2y \leq y' \leq 2y+1} \tag{3.2}$$

These cross-layer links connect segments on different scales (Shi et al., 2017a). The network architecture is designed so that the preceding feature map is twice

the current size (spatial dimensions), which is necessary to extract the right locations (Shi et al., 2017a). Before reconstructing the text instances, segments are filtered by their confidence scores (Shi et al., 2017a). For reconstruction, the predictions are taken as a graph: segments are nodes, links are edges. Depth-first search is applied to the graph to find connected components and thus text instances (Shi et al., 2017a).

The paper Deng et al. (2018) introduced a pixel-level STD approach. It adapts the previous component-level STD approach to work on pixel-level (Deng et al., 2018). Pixel-level segmentation approaches mainly rely on fully convolutional neural networks (Dai et al., 2018). Figure 3.8 shows the CNN structure

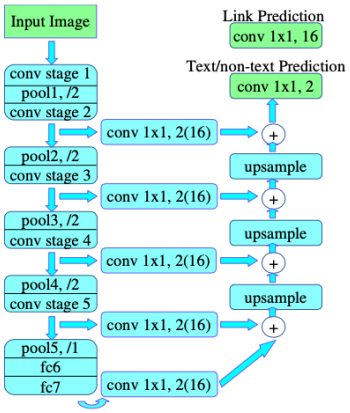


Figure 3.8: PixelNet CNN feature extractor with head structure for pixel segmentation

for feature extraction VGG architecture (until conv5) with the fully connected layers exchanged with another convolutional stage (Deng et al., 2018). Inspired by Long et al. (2015), the structure combines downsampled feature maps with later upsampled ones (Deng et al., 2018). This and similar forms of architecture are often used for pixel-level segmentation (Deng et al., 2018; Yao et al., 2016; Wu and Natarajan, 2017; Long et al., 2018b; Wang et al., 2019a). Continuous downsampling and combining those layers with later upsampled layers helps to combine coarse, higher-level information with fine-grained, lower-level information (Long et al., 2015). The upsampling is performed with bilinear interpolation (Deng et al., 2018). The feature extraction is followed by two heads which either predict text/non-text or links (Deng et al., 2018). This creates dense segmentation maps used to segregate different instances of text (Deng et al., 2018). The 1×1 convolution layers either have 2 or $2 \cdot 8$ filters depending on which head is used. Counted together, the model has 18 output channels (Deng et al., 2018). 2 filters are used to predict text/non-text for each pixel, while the other 16 filters predict the links (Deng et al., 2018). The text/non-text head essentially performs semantic segmentation to categorize

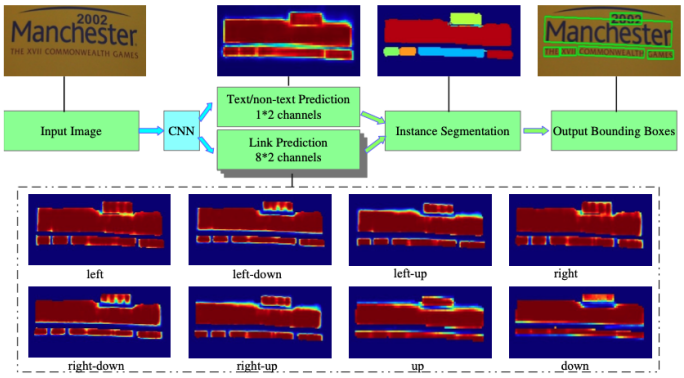


Figure 3.9: Example for a pixel, segmentation-based STD architecture (Deng et al., 2018)

each pixel to its object type (Deng et al., 2018). For every neighbor, there is a negative and a positive score. A pixel has eight neighbors: left, left-down, left-up, right, right-down, right-up, up, down. Each of the $2 \cdot 8$ filters is responsible for a neighbor link (Deng et al., 2018). The output is a dense prediction map with the same spatial structure as the input image (Deng et al., 2018). After both links and text/non-text pixels have been predicted, the text reconstruction post-processing stage starts. They are combined for instance segmentation (Deng et al., 2018). The link layers are used to indicate whether two text pixels are grouped and thus belong to the same instance (Deng et al., 2018). This step must be performed for every pixel and its neighbors (Deng et al., 2018). Noise is filtered out by excluding instances that are too small (< 10 pixels) or too big (> 300 pixels). An oriented bounding box can then be extracted by laying minimum area rectangles over the instances (Deng et al., 2018). Figure 3.9 shows the whole pipeline. Like this approach, pixel-level segmentation approaches often introduced new ways of distinguishing text instances and predicting a variety of different values followed by post-processing to achieve distinguishing different instances (Deng et al., 2018; Liao et al., 2019; Long et al., 2018a).

3.1.2 Scene Text Recognition

For STR, two main categories of approaches can be identified: segmentation-based and EnDe-based (see Figure 3.10) (Chen et al., 2021). Segmentation-based approaches for STR are similar to segmentation-based approaches for STD. After feature extraction, the sub-text components (characters for STR) are segmented (Chen et al., 2021). Instead of reconstructing a BB, the characters are classified to recognize the text and are then used to form the text instance (Chen et al., 2021). Because of their similarity to STD and the re-

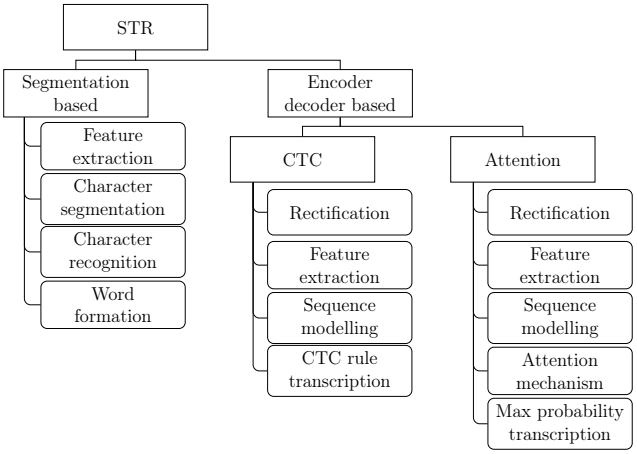


Figure 3.10: Different STR pipelines

cent dominance of EnDe-based approaches (Chen et al., 2021; Long et al., 2021), only the latter will be explained in detail with examples. The approach

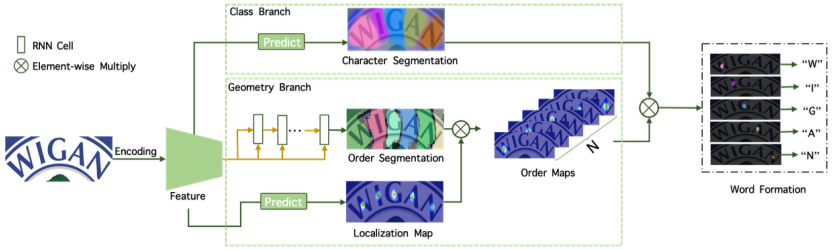


Figure 3.11: Example for segmentation-based STR architecture (Wan et al., 2020a)

from Wan et al. (2020a) can be used as an example, should the reader feel the need to read up on segmentation-based methods for STR that do not include an EnDe mechanism in the sequence modeling and prediction stage. The approach adds a geometry branch parallel to the character segmentation, which helps put the identified characters in the correct sequence (see Figure 3.11) (Wan et al., 2020a).

For EnDe-based STR, there are two main categories: Connectionist Temporal Classification (CTC)-based and attention-based (Chen et al., 2021; Cong et al., 2019). These two categories can mainly be distinguished by how the decoder works (Chen et al., 2021). The previous stages in the pipeline are similar (Long et al., 2021; Chen et al., 2021). Often preprocessing stages are performed to remove distortions, rectify curved text, remove disruptive background, improve resolutions or recover degraded text. Especially recti-

Figure 3.12: Application of spatial transformer network to rectify curved text (Liu et al., 2016b)

fying curved text (see Figure 3.12) with the help of spatial transformer networks (Jaderberg et al., 2015) show significant improvement for STR performance (Long et al., 2021; Chen et al., 2021). A spatial transformer has three stages: First first part regresses values ($\boldsymbol{\theta}$) used as parameters for the transformation (Jaderberg et al., 2015). The dimensions of $\boldsymbol{\theta}$ depend on which type of transformation is intended to be performed (Jaderberg et al., 2015). The transformation that is most often used is based on Thin Plate Splines (TPS) (Bookstein, 1989; Jaderberg et al., 2015). Each pixel location on the input image (x_i, y_i) is then transformed to a pixel location (x'_i, y'_i) in the output image (see Equation 3.3) (Liu et al., 2016b).

$$\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \boldsymbol{\theta} \cdot \begin{pmatrix} x'_i \\ y'_i \\ 1 \end{pmatrix} \tag{3.3}$$

The third part uses bilinear interpolation with the four nearest pixels of the input pixel to determine the intensity of the output pixel (Liu et al., 2016b). The spatial transformer can be trained with the propagated recognition loss (Liu et al., 2016b; Jaderberg et al., 2015).

For feature extraction, different CNN architectures can be chosen. The tradeoff between performance and memory & computation cost determines what CNN should be chosen (Chen et al., 2021). An example of a deep and powerful CNN are ResNets (He et al., 2015) which are often used for benchmark purposes (Chen et al., 2021; Long et al., 2021). Refer to Section 2.3 for more information on ResNets. Efficient feature extraction can, e.g., be performed with binary convolutional networks (Liu et al., 2018c).

For the sequence modeling and transcription steps, first CTC-based and then attention-based examples are explained. Sequence modeling generates contextual information from a sequence of characters rather than considering

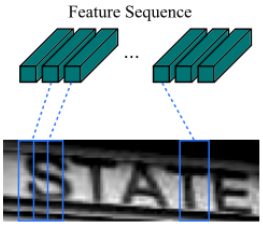


Figure 3.13: Sequential feature extraction from convolution feature maps (Shi et al., 2017b)

every character individually (Chen et al., 2021). For Shi et al. (2017b), the sequence is generated by taking columns out of the feature maps from left to the right (see Figure 3.13) (Shi et al., 2017b). This acts as a connector of visual representation and the sequence representation needed for RNNs (Chen et al., 2021). This is possible because the parts of the feature map corresponding to a spatial region of the original image (Shi et al., 2017b; Goodfellow et al., 2016). This encoding corresponds to a 1d representation that neglects vertical spatial information (Cong et al., 2019). The generated sequence features are fed into a deep Bidirectional Long Short Term Memory (BiLSTM). Figure 3.14 shows one layer, which is made up of an LSTM that processes the sequence in the forwards and another LSTM which processes the sequence backward (Shi et al., 2017b). An LSTM processed a sequence to gather context from earlier input for

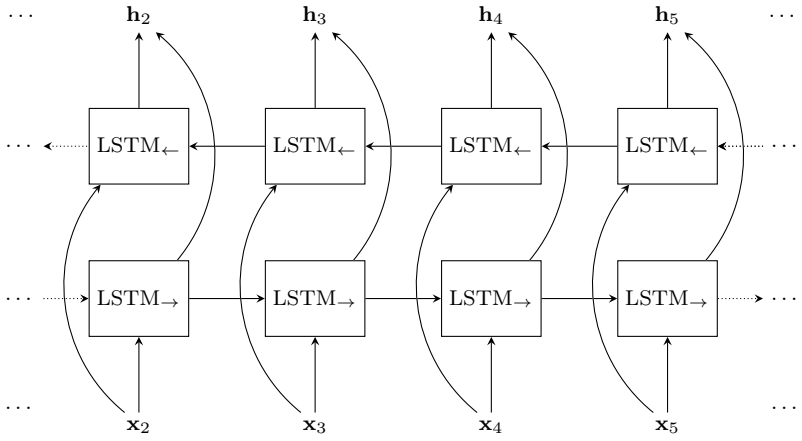


Figure 3.14: Bidirectional LSTM (Goodfellow et al., 2016)

later outputs (Shi et al., 2017b; Goodfellow et al., 2016). The BiLSTM allows gathering context of later input for earlier outputs (Shi et al., 2017b). This is important since a character might comprise more than one step in the sequence data (Shi et al., 2017b). Deep BiLSTMs are computation expensive and are often replaced with less expensive methods like sliding windows or a deep one-dimensional CNN (Chen et al., 2021). The generated encoded features with embedded context are then used for transcribing the final output (Shi et al., 2017b).

The prediction layer uses sequential, context-enriched data to predict a character sequence. The transcription mechanism uses conditional probabilities to convert the per-frame features encoded by the deep BiLSTM into the label sequence, the text instance prediction (Shi et al., 2017b). This process uses the conditional probabilities $p(\mathbf{l}\|Y)$ that are defined by Graves et al. (2006),

which is why the category of approaches is called CTC-based. The CTC probabilities are heavily influencing the model training (Shi et al., 2017b; Graves et al., 2006). $\mathbf{l}$ stands for the predicted character sequence, and Y stands for the per-frame features (Shi et al., 2017b). Each frame $\mathbf{y}^{(t)}$ is a probability distribution over the possible character and a 'blank' character (Shi et al., 2017b; Graves et al., 2006). It is distinguished between lexicon-based and lexicon-free transcription (Shi et al., 2017b). Lexicon-free transcription uses the most probable character or blank (-) at each frame.

HHH-eellll-lll-oo-

Then all duplicate characters are discarded.

H-el-l-o

At last, all blanks are discarded, leaving the final prediction (Shi et al., 2017b).

Hello

For lexicon-based transcription, the combination of Y is checked for similarity to words in the lexicon-based on the Levenshtein distance (like the metrics AED or NED defined in Section 2.5) (Shi et al., 2017b). The process of searching for similarity can be efficiently implemented with the BK-tree data structure (Burkhard and Keller, 1973; Shi et al., 2017b). The word in the lexicon with the largest probability to be derived from Y is chosen (Shi et al., 2017b).

For an attention-based example, the approaches introduced by Shi et al. (2016); Ghosh et al. (2017) are used. For attention, two approaches are explained as they are semantically different in that (Shi et al., 2016) employ a sequence attention mechanism, while Ghosh et al. (2017) employ a visual attention mechanism. Figure 3.15 shows the architecture of the sequence attention mechanism-based approach (Shi et al., 2016). After the feature extraction stage, the last convolutional feature map generates feature vectors like in Figure 3.13, where the feature column channels are flattened into a feature vector per column (Shi et al., 2016, 2017b). Like in the CTC-based approach, BiLSTMs are used for sequence modeling to infuse context (Shi et al., 2016, 2017b). The attention mechanism then uses the sequence, which is explained in (Chorowski et al., 2015). Here the attention weights $\boldsymbol{\alpha}_t$ are used to determine which part of the input $\mathbf{h}_t$ is essential (see Equation 3.4) (Shi et al., 2016). This is possible because the $\mathsf{softmax}$ has non-negative outputs between 0 and 1 (see Equation 3.5). Equations 3.5 and 3.6 show the time calculation of those weights at each time step (Shi et al., 2016). The output $\mathbf{g}_t$ is fed into

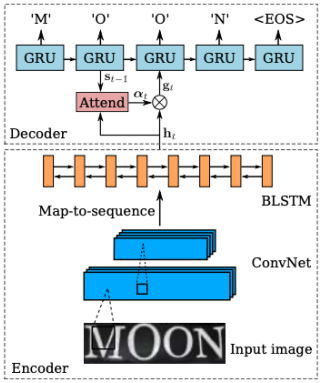


Figure 3.15: Encoder decoder based STR architecture with sequence attention mechanism (Shi et al., 2016)

a Gated Recurrent Unit, which is a RNN very similar to LSTMs (it has two gates instead of three) (Dey and Salem, 2017).

$$\mathbf{g}^{(t)} = \boldsymbol{\alpha}^{(t)} \otimes \mathbf{h}^{(t)} \tag{3.4}$$

$$\boldsymbol{\alpha}^{(t)} = \mathsf{softmax}(\Phi(\mathbf{s}^{(t-1)}, \boldsymbol{\alpha}^{(t-1)}, \mathbf{h}^{(t)})) \tag{3.5}$$

$$\Phi = A \cdot \mathsf{tanh}(W\mathbf{s}^{(t-1)} + V\mathbf{h}^{(t)} + U(F\boldsymbol{\alpha}^{(t-1)}) + b) \tag{3.6}$$

The Gated Recurrent Units use softmax to output a probability distribution over the possible characters (alphanumeric characters + 'end-of-sequence' token) (Shi et al., 2016). The prediction/transcription stage is similar to the following approach and will be explained after the visual attention mechanism.

The approach from Ghosh et al. (2017) is inspired by Bahdanau et al. (2016); Xu et al. (2016): It uses a CNN for spatial encoding of the input image, which the attention mechanism uses directly. The attention mechanism then helps the subsequent LSTM to choose the most relevant parts of the image for each time step (Ghosh et al., 2017). Figure 3.16 shows the network architecture (Ghosh et al., 2017). The CNN performs feature extraction (Ghosh et al., 2017). The used encoder CNN was proposed by Jaderberg et al. (2014) (without the fully connected layers) (Ghosh et al., 2017). The attention mechanism is placed between the encoder CNN and the decoder LSTM (Ghosh et al., 2017). Note that some approaches consider the attention mechanism part of the decoder (Shi et al., 2019, 2016). The feature map is separated into feature vectors $\mathbf{x}^{(i)}$, representing different image parts. The mechanism uses a weighted combination of the softmax activation ($\boldsymbol{\beta}^{(t,i)}$) of the MLP output ($\Phi$) and the respective feature vector to encode the relative importance of the image parts at each time-step (see Equations 3.7 and 3.8) (Ghosh et al., 2017; Xu et al., 2016). It calculates which vertical parts of the image are most

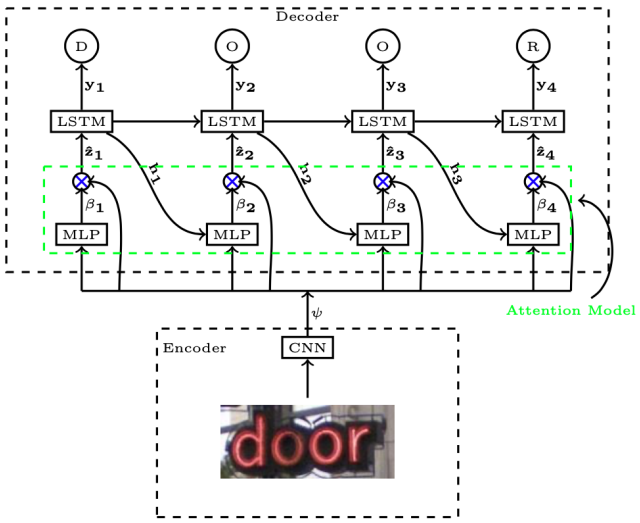


Figure 3.16: Encoder decoder based STR architecture with visual attention mechanism (Ghosh et al., 2017)

important (Ghosh et al., 2017).

$$\hat{\mathbf{z}}^{(t)} = \sum_{i=1}^{K} \boldsymbol{\beta}^{(t,i)} \cdot \mathbf{x}^{(i)} \tag{3.7}$$

$$\boldsymbol{\beta}^{(t,i)} = \mathsf{softmax}(\Phi(\mathbf{x}^{(i)}, \mathbf{h}^{(t-1)})) \tag{3.8}$$

In contrast to the previous approach, this attention mechanism considers the whole image while the previous one considers one time-step concerning the previous step (Shi et al., 2016; Ghosh et al., 2017).

The prediction stage goes as follows: Like the CTC-based approach, the networks output vectors at each time step represent a probability distribution over all possible characters (Ghosh et al., 2017). Again, the transcription process can be used with a lexicon and without (Ghosh et al., 2017). The basic process without a lexicon leverages the beam search algorithm (Ghosh et al., 2017) to find the sequence $\mathbf{w} = [c_1, c_2, \ldots, c_n]$ with the highest probability (Ghosh et al., 2017). For lexicons, the beam search algorithm is adjusted so that any sequences that do not belong to a word in the lexicon fall out of contention (Ghosh et al., 2017). Besides using a lexicon, the approach can also incorporate language priors into the beam search process. These priors leverage knowledge about the recognized language (Ghosh et al., 2017).

3.1.3 Scene Text Spotting

As mentioned, STD and STR are only parts of the task at the center of this thesis. STS can be performed in two ways (see Figure 3.17). (1) Run STD,

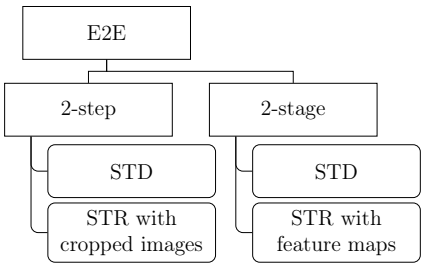


Figure 3.17: Different STS pipelines

crop the image at the resulting bounding boxes, run STR. (2) Run STD, crop feature maps, run adjusted STR (Chen et al., 2021; Long et al., 2021). 2-step methods can modularly be combined (Liao et al., 2017; Shi et al., 2019). The STD approach from Liao et al. (2017) can be combined with the CTC-based STR from Shi et al. (2017b). Note that the 2-step modular approaches can still be adjusted to fit together better (Liao et al., 2017).

The 2-stage approach used as an example was introduced by Busta et al. (2017). The approach essentially combines BB regression-based ROI STD with EnDe-based CTC STR. After extracting features with a CNN, the approach first generates ROIs. All ROIs with a certainty score above a threshold is passed over to the recognition module (Busta et al., 2017). The combination

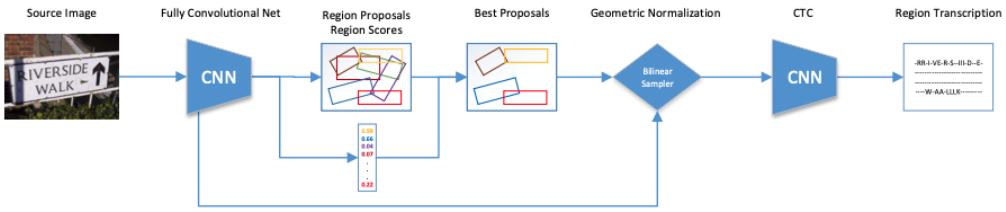


Figure 3.18: 2-stage STS architecture (Busta et al., 2017)

of detection and recognition is made possible by bilinear sampling (Busta et al., 2017). This technique helps collect the correct spatial features in terms of placing, size and rotation to pass to the recognition part (Busta et al., 2017). Note that the transformation normalized the rotation of the ROIs (Busta et al., 2017). At this point, ROIs with a confidence score under a threshold are discarded (Busta et al., 2017). Sampling is the process of selecting the right spatial features from the respective ROI area that can be used for recognition (Liu et al., 2020b). This is inspired by the ROI pooling used in two-stage STD approaches where the pooled features are used for refinement, as in Jiang et al. (2017). The transformed ROI features are then processed by a CNN,

which transforms the feature maps into one feature map whose height is defined by the predictable characters and the width is defined by the spatial features of the ROI (Busta et al., 2017). The resulting values can be transformed into CTC probability distributions (Busta et al., 2017; Graves et al., 2006). Then the CTC transcription rule can be applied to generate the final result. As with standard ROI-based approaches, text instances can be mapped to multiple predictions (Ren et al., 2016; Busta et al., 2017). Instead of performing NMS with the help of the certainty score of ROIs, the filtering is performed with certainty scores which are generated in the recognition phase of the model (Busta et al., 2017).

3.2 State-of-the-Art Methods

This section documents the search for literature that provides the content for the subsequent overview of innovation. Essential DL techniques, notable advances, and properties are researched and presented. Note that not the whole introduced approaches are explained, but only the innovation that improves upon previous work. It is important to report how the information was found and synthesized (Torraco, 2005). The strategy for researching current research is most important for a literature review (Snyder, 2019). This includes databases and keywords that were used and exclusion criteria that were enforced (Torraco, 2005).

The literature is identified through searching in the Google Scholar database. The search is executed with keywords such as, but not only: Scene Text Detection, Scene Text Recognition, Scene Text Spotting. For identified literature, the citations are investigated to find further innovations in the field. An appropriate amount of citations (> 100) for the piece of literature in question is a criterion for examination. This cutoff point is defined to filter the most influential research. All research after 2018 which pertains to innovations for model architecture for extracting scene text is regarded as relevant. Standard OCR solutions may not hold validity in practice, as the image and text conditions can vary in the defined problem (Chen et al., 2021). The delimitation from Section 1.2, of course, holds for this chapter, and only literature which concerns advances for the DL model architecture will be regarded as necessary for the scope of this thesis. This extends to the whole pipeline from extracting features to the final result of the model.

3.2.1 Detection Innovations

The resulting literature for STD and the respective innovation can be found in Table 3.2. The conducted search on Google Scholar yielded twelve results until

Approach category		Source	#cit	Innovation	Orientation	Improvement
Seg-free						
	1-stage	Liao et al. (2018a)	499	Multi-oriented BBs with new quadrilateral representation	m	e
		Liao et al. (2018c)	300	Rotation sensitive features for BBs and insensitive features for text certainty	m	p
	2-stage	Ma et al. (2018)	724	Rotation RPN and rotated ROI pooling	m	p
Seg-based						
	Pixel-level	Deng et al. (2018)	402	Combine text with neighbor predictions for reconstruction	m	p
		Lyu et al. (2018b)	263	Combine corner localization w position sensitive segmentation	m	e
		Liao et al. (2019)	160	Differential binarization for reconstruction	c	e
		Wang et al. (2019b)	122	Efficient segmentation with lightweight feature extractor	c	e
		Xu et al. (2019)	155	Directions away from nearest boundary for textfield representation	c	p
		Wang et al. (2019a)	266	Multiple segmentation maps at different scales	c	p
		Long et al. (2018a)	301	Representation based on a sequence of overlapping circles	c	p
	Component-level	—				
Mix						
		Xie et al. (2018)	137	Segmentation to rescore ROIs with contextual information	c	p
		Dai et al. (2018)	132	Extract finer features, improve NMS with masking	c	p

Table 3.2: Notable innovations for STD model architecture;
c: curved, m: multi-oriented, h: horizontal;
e: efficiency, p: performance

page 10. On page 15, the results started to diverge from the topic, and thus the search was concluded. Research like Xue et al. (2018) was not included since its proposed method concerns the training procedure rather than the model architecture. The investigation into the identified literature's citations yielded another result: Long et al. (2018a).

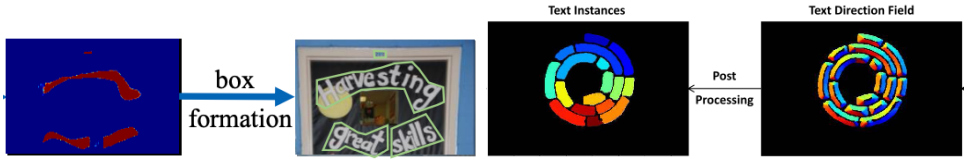
The following approaches are concerned with efficiency for multi-oriented text: The 1-stage BB regression approach by (Liao et al., 2018a) introduced a different representation for BBs, which is multi-oriented. The representation has 13 parameters (Liao et al., 2018a). That is more than usual for multi-oriented BBs (8) (Ma et al., 2018). An efficient approach from Lyu et al. (2018b) uses pixel-level segmentation. A grid subdivides the image, and each grid space of pixels is predicted to efficiently generate a pixel segmentation map (Lyu et al., 2018b). Also, text instance corners are predicted. The

grid segmentation maps are then used to group corners to reconstruct text instances (Lyu et al., 2018b).

The following approaches are concerned with performance for multi-oriented text: The 1-stage STD approach introduced by Liao et al. (2018c) states that predicting both the text certainty scores and the BBs from the same feature maps does not enable the best performance. This is because regression is dependent on orientation and text classification is not (Liao et al., 2018c). Each prediction has two heads: the regression head and the classification head. The classification head is preceded by oriented response pooling, which generates rotation-invariant features from the given feature maps (Liao et al., 2018c). The 2-stage approach STD from Ma et al. (2018) deals with text orientation differently. The RPN generates oriented ROIs, offset by already rotated anchor boxes (Ma et al., 2018). The results are filtered with NMS, which is adjusted to rotation. For the remaining ROIs, the ROI pooling operation is also adjusted to deal with rotation, the results of which are used for the final prediction (Ma et al., 2018). The pixel-level approach by Deng et al. (2018) combines dense predictions maps of text/non-text and neighbor links to reconstruct text instances from pixel-level (Deng et al., 2018).

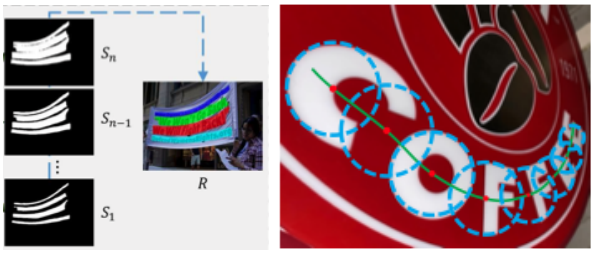
The following approaches are concerned with efficiency for curved text: For Liao et al. (2019), text probability and border pixel-level segmentation maps are used to construct a binary map that represents text/non-text (see Figure 3.19(a)). The construction of the binary map is performed with the newly introduced differentiable binarization function (Liao et al., 2019). The binary map can then be used to generate curved BBs (see Figure 3.19(a)) (Liao et al., 2019). An innovation towards better efficiency based on pixel-level segmentation from Wang et al. (2019b) introduces a light feature extraction network. The network repeatedly upsamples and downsamples the feature maps to improve the representational capabilities of the efficient extractor (Wang et al., 2019b). The generated features are then used to predict text regions and text centers and similarity vectors to distinguish different regions (Wang et al., 2019b).

The following approaches are concerned with performance for curved text: A new representation for curved text was introduced by Xu et al. (2019) (see Figure 3.19(b)). The representation comprises direction vectors that point away from the nearest border. These vectors are predicted by magnitude and direction (Xu et al., 2019). The resulting text direction field can then be used to reconstruct text instances (Xu et al., 2019). Another approach that improves text representation was introduced by Long et al. (2018a). The pixel-level segmentation approach predicts the values used to form the text representation shown in Figure 3.19(d). The representation combines circles with a line to form a curved text instance (Long et al., 2018a). Another way of distinguishing



(a) Binary text segmentation map (Liao et al., 2019)

(b) Textfield with vectors to text center (Xu et al., 2019)



(c) Segmentation scales for label building (Wang et al., 2019a)

(d) Textsnake representation with centerline interconnected circles (Long et al., 2018a)

Figure 3.19: Different curved text instance representation

between text instances is to progressively predict larger-scale text areas (Wang et al., 2019a) (see Figure 3.19(c)). This is achieved by continuously shrinking the image with the help of kernels (Wang et al., 2019a). This helps as the network can recognize at which scale the instances overlap (Wang et al., 2019a). Recent research has brought up approaches that use segmentation and BB regression in the same architecture (Xie et al., 2018; Dai et al., 2018). The approach introduced by Xie et al. (2018) leverages text segmentation to rescore certainty for predicted ROIs to improve NMS. The filtered ROIs are then used to refine BBs regression and text classification (Xie et al., 2018). The innovation by Dai et al. (2018) improves feature extraction for STD by fusing lower-level features. These features are used for ROI proposals and are then used to pool the fused features for the text/non-text classification, BB regression, and text segmentation branches (Dai et al., 2018). Similar to the previous approach, NMS is modified to use a text segmentation map to better work with curved text instances (Dai et al., 2018; Xie et al., 2018).

3.2.2 Recognition Innovations

For STR, the search led to 8 results (see Table 3.3). The last relevant innovation was found on page 13, and on page 18, the search was stopped because the results diverged. The investigation of citations did not lead to new results.

Approach category		Source	#cit	Innovation	Stage
Seg-based		Liao et al. (2018b)	120	Combine different levels of character attention to localize characters and improve receptive fields with deformable convolution	
EnDe-based					
	CTC-based	—			
	Attention-based	Zhan and Lu (2019)	181	Iterative rectification with line fitting transformation	r
		Luo et al. (2019)	174	Rectification by removing character offset	r
		Shi et al. (2019)	349	Rectification based on grids	r
		Cheng et al. (2018)	209	Extract and combine character features in four directions	f
		Li et al. (2019)	141	Simple pipeline combined with neighbor adjusted, robust 2d attention mechanism	a
		Liu et al. (2018a)	112	Adapted attention mechanism to find individual characters and rectify local features for the decoder	a
		Bai et al. (2018)	100	Edit operations (consumption, deletion, insertion) influence probability of prediction	d

Table 3.3: Notable innovations for STR model architecture;
w/: with lexicon, w/o: without lexicon, b: both;
r: rectification, f: feature extraction, a: attention mechanism, d: decoding

The approach from Liao et al. (2018b) works with localizing and classifying each character separately (Liao et al., 2018b), which fits into the segmentation-based category. The innovation leverages deformable convolution (Dai et al., 2017) to decide which spatial information to focus on (Liao et al., 2018b). Additionally, it relies on a fully convolutional attention module that weakens background and highlights characters at pixel-level (Liao et al., 2018b). The attention module is performed at different scales (Liao et al., 2018b; Xu et al., 2016).

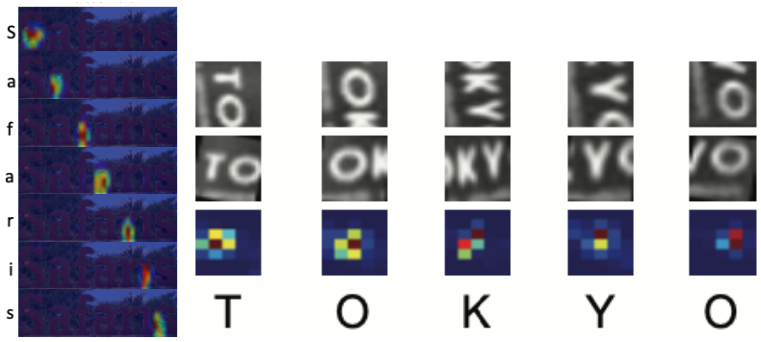
The following approaches are all attention-based. However, their innovation concern different parts of the attention-based STR pipeline. The approaches by Zhan and Lu (2019); Luo et al. (2019); Shi et al. (2019) all improve

(a) center line rectification (Zhan and Lu, 2019) (b) offset rectification (Luo et al., 2019) (c) grid rectification (Shi et al., 2019)

Figure 3.20: Visualization of different innovations regarding rectification

text rectification ahead of the encoding step. From Zhan and Lu (2019) comes a rectification approach that iteratively estimates the fit of a polynomial to the text line and uses that prediction to rectify the text with TPS transformation (Bookstein, 1989; Zhan and Lu, 2019). Rectification is improved by Luo et al. (2019) by removing the vertical offset of characters to straighten the word out by placing a character lower or higher. This works well for slanted images but has problems with curved text in contrast to the other rectification modules (Zhan and Lu, 2019; Liu et al., 2016b; Long et al., 2021). Fractional pickup is also introduced by Luo et al. (2019). It is a mechanism to improve the attention field of vision to lightly include adjacent characters to improve robustness (Luo et al., 2019). Like Zhan and Lu (2019), Shi et al. (2019) estimate the text form by localizing grid control points that surround the text instance from the top and bottom. The grid can then be used with TPSs (Shi et al., 2019).

The approach by Cheng et al. (2018) improves features by extracting features for text in four directions (right, up, left, down) (Cheng et al., 2018). The feature vectors are then used with the other extracted features to act as a gate (similar to LSTMs) (Cheng et al., 2018).



(a) Robust neighbor adjusted 2d attention (Li et al., 2019)

(b) Attention character rectification (Liu et al., 2018a)

Figure 3.21: Effects of innovative attention mechanisms for STR

The following two approaches (Li et al., 2019; Liu et al., 2018a) improve upon the attention mechanism sequence modeling for STR. The innovation by Li et al. (2019) uses 2d attention from (Xu et al., 2016) to use for STR. The mechanism is made more robust by taking each of the eight spatial neighbors into account (Li et al., 2019). Compared to the visual attention mechanism, it can not only decide horizontally which part of the image to focus on but also vertically (Li et al., 2019; Ghosh et al., 2017). The mechanism proposed by Liu et al. (2018a) uses attention to recurrently find characters and TPS to

rectify them to predict the text instance. For each character, the corresponding feature region is extracted and is rectified using a local spatial transformer (Liu et al., 2018a). The last relevant STR innovation improves upon the decoding and prediction process.

The approach from Bai et al. (2018) introduces the concept of edit probabilities. At each time step, the decoder decides which edit operation to perform (consumption, deletion, insertion) based on their edit probabilities (Bai et al., 2018). These operations either forego a time step, add a character to the word or insert a missed character at the previous position (Bai et al., 2018).

3.2.3 Spotting Innovations

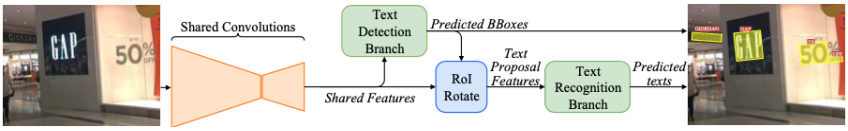
Five results were identified as relevant under the defined criteria for end-to-end STS. The last relevant innovation was found on page five, and on page ten, the topic diverged. The investigation of citations did not lead to new results.

Category	Source	#cit	Innovation	Orientation	Combination
2-step	Liao et al. (2018a)	499	Combine Texboxes++ detection with CTC recognition, used recognition confidence score for	m	one-stage→CTC
	Shi et al. (2019)	349	Textboxes++ BB rectification and grid usage for attention recognition	c	one-stage→att
2-stage	Lyu et al. (2018a)	362	ROI detection followed by pixel and character segmentation	c	two-stage→seg
	Liu et al. (2018b)	355	Bilinear interpolation to transform oriented feature regions into axis-aligned feature maps followed by CTC recognition	m	two-stage→CTC
	Liu et al. (2020b)	100	One-stage with bezier curves instead of anchor fee detection followed by bezier adjusted ROI pooling and a lightweight CTC recognition head	c	one-stage→CTC

Table 3.4: Notable innovations for STS model architecture;
c: curved, m: multi-oriented, h: horizontal;
detection→recognition — seg: segmentation, att: attention

The listed 2-step approaches are not the innovations of the respective methods but rather a way to extend the proposed STD/STR to a STS solution (Liao et al., 2018a; Shi et al., 2019). The STD approach from Liao et al. (2018a) can be extended with the CTC-based approach from Shi et al. (2017b), explained along with the taxonomy. The word probability predicted by the CTC transcription can be combined with the text certainty score of the STD module to improve NMS. The STR approach from Shi et al. (2019) can be extended with the one-stage BB regression-based STD approach from Liao et al. (2017) that was also explained in the taxonomy (Shi et al., 2019).

The field of end-to-end STS has moved towards 2 stage approaches that combine both STD and STR (Lyu et al., 2018a; Long et al., 2021). The innovation from Liu et al. (2018b) combines an oriented detection with combined pixel segmentation and BBs with recognition by using bilinear interpolation to sample and rotate the spatial features corresponding to a text instance to be axis-aligned (Liu et al., 2018b). The subsequent recognition branch is CTC-based. The 2 stage approach introduced by Lyu et al. (2018a) uses a



(a) STS architecture with feature sharing (Liu et al., 2018b)

(b) Rotated to axis aligned sampling effect (Liu et al., 2018b)

Figure 3.22: STS architecture with feature sharing and sampling effect (Liu et al., 2018b)

RPN to propose ROIs, which are used to extract features for both a BB regression branch and a segmentation branch that predicts text instances and characters on a pixel-level (Lyu et al., 2018a). The BBs are used with the text instance segmentation to form the final detection prediction, and the characters are combined to the recognition prediction (Lyu et al., 2018a). The network from Liu et al. (2020b) uses bezier curves to represent curved text (see Figure 3.23). The bezier curve representation is predicted by one-stage, anchor-free regression (Liu et al., 2020b). The spatial features corresponding to the predicted instances are then extracted from the feature maps, rectified, and handed to a lightweight CTC-based recognition branch (Lyu et al., 2018a).

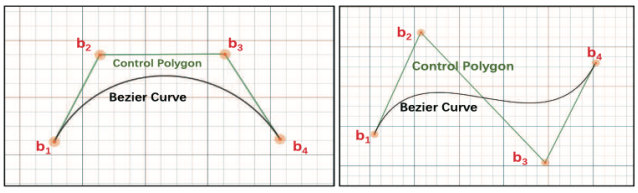


Figure 3.23: Bezier-curves predicted by control points b_i (Liu et al., 2020b)

Chapter 4

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 subsequent analysis.

Requirements for a software system that involves DL and thus ML 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 the 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 MLS must possess are defined.

4.1 Use Case

A use case can depict the problem. This fictitious use case sets the foundation for determining requirements for an approach because qualities derive from the intended purpose of use (Siebert et al., 2021). Table 4.1 gives an overview of the relevant properties derived from the use case. For this thesis, the primary

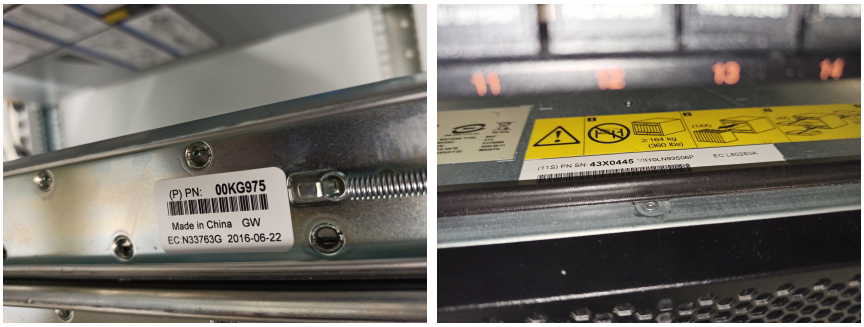
Offline Capabilities	Perform extraction process offline
Alphanumeric recognition	Recognize alphanumeric strings such as serial numbers
Semantics retention	Retain semantics given implicitly be space, strucure and rotation of text in labels

Table 4.1: Qualities specific to use case — exclusion criterias

use case is as follows: A technician takes a photo of a device label with his smartphone. For this, the technician is situated in locations like a cable shaft. Due to this, there is no internet availability. The process from taking the image

to storing the extracted text must work offline safely. The resulting image contains printed textual information, which an application on the smartphone must extract.

The space and structure of this information can vary from label to label (see Figure 4.1). The text does not have to be oriented horizontally. The text, spacing, and structure carry semantic information, which can be crucial for later processing in the scope of a business process (Chen et al., 2021). The goal is to extract the text and preserve semantics that is implicitly provided through structure and space. This means text and the respective coordinates, height, width, and a possible rotation angle must be output as a result (Yang et al., 2021). Those values can then be transformed into other formats such as JSON or HTML as needed.



(a) Positive example (b) Negative example

Figure 4.1: Examples for label images

In addition to this, the labels can contain arbitrary alphanumeric strings such as serial numbers (see figure 4.1). This results in the requirement that the DL model recognizes sequences that are not part of a predefined lexicon (Ghosh et al., 2017; Chen et al., 2021). The qualities for the MLS that can be derived directly from the use case (see Table 4.1) can be regarded as excluding criteria because an approach that does not possess the qualities in question cannot be regarded as viable for the use case.

4.2 Quality Identification

In the article Ashmore et al. (2021), the qualities are identified and assigned to different challenges in working with MLS: Development, production, organizational challenges. Because only the Model Selection substage of the lifecycle is performed, the defined challenges and their qualities are not relevant for this thesis, as they concern the operational aspect of MLSs.

In Nakamichi et al. (2020); Siebert et al. (2021), systematic identification and documentation of qualities are detailed. In MLSs various entities interact to produce the desired functionality. The paper Nakamichi et al. (2020) suggests that to evaluate the qualities adequately, it is essential to consider the model and the entire MLS (see Figure 4.2). These entities are data, model, en-

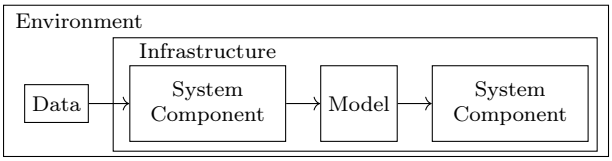


Figure 4.2: Machine learning system entities (Nakamichi et al., 2020)

vironment, system/infrastructure (Nakamichi et al., 2020; Siebert et al., 2021). The article Siebert et al. (2021) differentiates between system and infrastructure.

The infrastructure represents given hardware and available libraries, whereas the system depicts the software that surrounds the model in the runtime environment. The data view pertains to development and runtime data (Siebert et al., 2021). The model consists of subcomponents organized in a directed acyclic graph building a pipeline. This directed acyclic graph depicts everything from processing the images to the extracted information (Siebert et al., 2021). The environment entity covers the external aspects of the MLS, which may interact with it (Siebert et al., 2021). In the scope of this work, the environment entails mainly the conditions in which images are taken.

For this thesis, the entities data and system cannot be regarded as given. The entities environment and infrastructure are only loosely defined through the use case. That is why the systematic approaches cannot be performed in the scope of this thesis. For example, Siebert et al. (2021) propose to follow the systematic CRISP-DM approach of identifying qualities. It cannot be performed due to the lack of data and the other entities derived from the use case.

Table 4.2 lists all qualities that pertain to the model entity and that were found in the literature. Different qualities are *grouped* for their similarities. Because of their properties, they can be evaluated jointly. When 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 assigns them to an entity of the MLS. The implementation and testing phases are not performed in the scope of this thesis, and the difficulty in assessing the performance ahead of those phases prevents 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). Comparing models through the results of different papers is troublesome because different papers might use different evaluation and testing environments (Baek et al., 2019). This applies to studies that present an overview, such as Chen et al. (2021); Long et al. (2021). These studies can only be regarded as guiding values because the performance for a specific dataset cannot be predicted without testing on it (Arpteg et al., 2018). That is why targets for measurements are not defined, as evaluation would only deliver a false sense of certainty.

Quality	**Sources**
Appropriateness	
Appropriateness	Siebert et al. (2021)
Suitability	Siebert et al. (2021)
Model Fitness — Quality of Output Data	Nakamichi et al. (2020)
Performance	
Performance	Ashmore et al. (2021); Vogelsang and Borg (2019)
Accuracy	Nakamichi et al. (2020)
Model Fitness — Degree of Correctness	Nakamichi et al. (2020); Zhang et al. (2020)
Development correctness	Siebert et al. (2021)
Relevance / Bias-Variance tradeoff	Siebert et al. (2021); Zhang et al. (2020)
Trained Model Generalization Performance	Nakamichi et al. (2020)
Appropriateness	
Robustness	
Robustness	Ashmore et al. (2021); Hu et al. (2020a); Siebert et al. (2021)
Robustness Against Change of Input Data	Nakamichi et al. (2020)
Robustness Against Noise Data	Nakamichi et al. (2020)
Reusability	Ashmore et al. (2021)
Interpretability	
Interpretability	Ashmore et al. (2021); Siebert et al. (2021); Zhang et al. (2020)
Understandability	Nakamichi et al. (2020)
Transparency	Arpteg et al. (2018)
Model Explainability	Vogelsang and Borg (2019)
Comprehensibility	Ashmore et al. (2021)
Comprehensiveness	Ashmore et al. (2021)
Fairness	
Fairness	Siebert et al. (2021); Zhang et al. (2020)
Freedom from Discrimination	Vogelsang and Borg (2019)
Performance Efficiency	
Resource Utilization	Siebert et al. (2021); Nakamichi et al. (2020)
Execution efficiency	Siebert et al. (2021)
Temporal Performance	Nakamichi et al. (2020)

Table 4.2: MLS qualities identified for model entity

4.3 Quality Relevancy

In addition to the qualities that arise directly from the use case, the literature reveals several common qualities in regards to MLS (see Table 4.2), some of

which can be regarded as relevant, and others do not hold any relevance for the specific use case (see Table 4.3). The qualities are taken from the literature covering ML in general to literature covering STS. Only qualities that concern the model will be looked at, as the model is the focus of this thesis. The qualities may, however, be influenced by other entities.

Relevant	**Irrelevant**
Appropriateness	Fairness
Performance	Interpretability
Robustness	Reusability
Performance efficiency	

Table 4.3: Condensed qualities for model entity

The appropriateness quality refers to the ability to perform the type of task required by the use case (Siebert et al., 2021; Nakamichi et al., 2020). For this thesis, this applies to STS models. Additionally, the properties derived from the use case (see Table 4.1) can be grouped under this quality. The offline capabilities are always given in the approaches outlined in Chapter 3. Semantics retention is controlled by the text representation output of the STD model (axis-aligned, multi-oriented, or quadrilateral bounding box, text/non-text map). Alphanumeric recognition is dependent on how well STR performs without a lexicon.

'An ML model is performant if it operates as expected according to a measure (or set of measures) that captures relevant characteristics of the model output' (Ashmore et al., 2021). For the performance quality, a measure is chosen depending on the type of task to be solved (Siebert et al., 2021). The F-Score is an example of a metric used to compare different models (Chen et al., 2021; Long et al., 2021). Performance is usually measured with a test dataset that is independent of training and validating a model to approximate the generalization performance (Goodfellow et al., 2016; Nakamichi et al., 2020).

The robustness of a model concerns environmental uncertainty (Ashmore et al., 2021). Due to the uncontrolled environment in the practical aspect of taking the images on-site beneficial image properties can not be guaranteed (Chen et al., 2021). 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., 2021). Therefore, these properties have to be accounted for when determining the viability of an approach. Some of these factors do not change the expected prediction (noise), others do (text form)Hu et al. (2020a). An example of poor image quality regarding STS can be seen in figure 4.1(b). Note that the datasets introduced in Section 2.5 include the

challenging image properties, as STS is defined with robustness in mind. For example, Karatzas et al. (2013, 2015); Ch'ng and Chan (2017) define their challenge with different image properties concerned with robustness. Additionally, STS is differentiated from OCR by solving more difficult reading problems for more complex images (Long et al., 2021; Hu et al., 2020b; Chen et al., 2021; Baek et al., 2019). Therefore, the difference in performance and robustness is negligible for STS.

Performance efficiency addresses time and resource utilization when the model is in use. This does not involve the training phase but the execution or prediction (Siebert et al., 2021). The efficiency refers to low latency needs and minimizing resource needs such as memory usage or power consumption (Nakamichi et al., 2020; Siebert et al., 2021; Sourvanos and Tsatiris, 2018). This quality is crucial for mobile devices in conjunction with DNN (Sourvanos and Tsatiris, 2018; Niu et al., 2019). The infrastructure heavily influences performance efficiency (Nakamichi et al., 2020; Siebert et al., 2021). Because the efficiency needs fall mainly on the model, it is categorized as such and thus deemed relevant in the scope of this thesis.

The first quality often found in research not relevant for the use case is fairness. A fair model is free from discrimination bias. For ML, this can be a big problem since discrimination can be influenced through explicit programming in terms of the model and through implicit knowledge from the data (Vogelsang and Borg, 2019). For the use case, however, no relevance is attached. The model can either recognize the text or fail the task.

The interpretability of a model helps to justify the output (Ashmore et al., 2021). The interpretability is twofold: explain what the model has learned, explain how a model given the input comes to the output (Vogelsang and Borg, 2019). This can be challenging for two reasons. ML models can be complex in size and structure (Ashmore et al., 2021). Modular processing pipelines are continuously replaced with end-to-end models facilitating the tradeoff between interpretability and performance Arpteg et al. (2018).

Another quality for a ML model refers to how well a model intended for one task can be reused for another related task. This can be beneficial because transfer learning can speed up the training, thus reducing training costs (Ashmore et al., 2021). Reusability is not relevant in the scope of this work as it targets the training phase of the ML lifecycle. The identified relevant qualities will be used in Section 5.1 to provide properties to judge the merits of a possible solution.

Chapter 5

Discussion

This chapter contains a comparison between the taxonomy categories that were introduced in Section 3.1. The analysis is followed by reflecting on the methodology and the thesis' results.

5.1 Analysis

The comparison in this section is synthesized from information found in literature and some observations regarding recent innovations that are examined in Section 3.2. The analysis is structured similarly to the overview sections: first compare approach categories for STD and STR and then move on towards STS. The approaches' compared aspects are the qualities that were identified as relevant in Section 4.3: appropriateness, performance in conjunction with robustness, efficiency. Note that appropriateness entails the subqualities derived from the use case (see Table 4.1): While the offline capability requirement is met by all of the approaches identified in this thesis, semantics retention and alphanumeric recognition have to be analyzed further. STD is the relevant subtask for semantics retention and STR for alphanumeric recognition.

The main challenges for STD involve the tradeoff between speed and accuracy and representing arbitrary shaped text instances (Wang et al., 2019b). The innovations regarding STD deal with multi-oriented and curved text (as can be seen in Table 3.2). The innovations often include feature extraction and various segmentation innovations that improve text representation and the subsequent text reconstruction, i.e., distinguishing text instances.

Segmentation-free or BB regression-based approaches have trouble with curved text because of the anchor boxes' linear bias (Wang et al., 2019a; Long et al., 2018a). Additionally, the regressed BBs have trouble accurately representing the shape of curved text instances (Long et al., 2021; Wang et al., 2019a). Representing multi-oriented text is not a problem, on the other

Approach category		Shortcomings
Seg-free		Curved text representation (Long et al., 2021; Wang et al., 2019a) Linear anchor box bias with curved text (Wang et al., 2019a; Long et al., 2018a) High aspect ratio test (Shi et al., 2017a; Long et al., 2021)
	One-stage	More efficient, straightforward architecture (Lu et al., 2020)
	Twe-stage	More accurate predictions due to refinement (Lu et al., 2020)
Seg-based		Separating different text instances (Wang et al., 2019a) Text instance construction is complex and computation intensive (Xie et al., 2019; Liao et al., 2019; Qiao et al., 2021) Incorporate several computation intensive stages (Dai et al., 2018) More vulnerable to noise (Long et al., 2021)

Table 5.1: STD approach category shortcomings

hand (Liao et al., 2018a; Jiang et al., 2017). Long aspect ratios are another problem of scene text which degrades BB regression performance (Shi et al., 2017a; Long et al., 2021).

On the other hand, segmentation-based approaches take advantage of the fact that every part of the text instance can locally be verified as such (Long et al., 2021). The bottom-up approach alleviates the problem of long aspect ratios (Shi et al., 2017a). The segmentation-based approaches facilitate a more natural representation of curved text (Dai et al., 2018; Long et al., 2021) (see Figure 3.19).

However, the segmentation pipeline is more computation-intensive, as it incorporates more complex stages (Dai et al., 2018) and complicated text instance construction (Xie et al., 2019; Liao et al., 2019; Dai et al., 2018). The text instance reconstruction goes hand in hand with the separation of different instances. This challenging task is vulnerable to noise (Long et al., 2021) and focuses on many innovations (see Figure 3.19).

When comparing BB regression approaches, one-stage approaches are generally more efficient because of their straightforward architecture, while two-stage approaches can generally predict the more accurately because of the refinement process (Lu et al., 2020). Note that no meaningful comparison of sub-text level or pixel-level segmentation could be identified. To what STD is concerned, the bottom line seems to be: Is curved text detection or efficiency more critical? Table 5.2 shows the synthesized comparison for curved STD

Approach category		Semantics retention	Performance	Efficiency
Seg-free		×	×	✓
	1-stage	×	×	✓
	2-stage	×	✓	×
Seg-based		✓	✓	×

Table 5.2: Curved STD approach category comparison

based on their shortcomings. The table compares the categories seg-free and seg-based and the sub-categories 1-stage and 2-stage.

STR research focuses on accurately recognizing 2d text instances. The innovations found for STR (see Table 3.3) show that the research mainly focuses on robustly recognizing curved text instances (rectification approaches and 2d-attention). It can be noted that the innovative approaches are mostly attention-based.

However, attention also has shortcomings (see Figure 5.3). For segmentation-

Approach category		**Shortcomings**
Seg-based		Accurate detection of individual characters (Chen et al., 2021; Cheng et al., 2018) Disregard for contextual information between characters (Chen et al., 2021) Incorporate several computation intensive stages (Liu et al., 2020b)
EnDe-based		Curved and multi-oriented text (Cheng et al., 2018; Long et al., 2021)
	CTC-based	Prone to overfitting (Chen et al., 2021) Isolated word recognition (Cong et al., 2019) Not applicable to recognition of 2d text instance (Cheng et al., 2017; Xie et al., 2019; Chen et al., 2021)
	Attention-based	Sentence and long sequence recognition (Cong et al., 2019; Chen et al., 2021) Problems without vocabulary (Wan et al., 2020b) Attention drift leads to missing or superfluous characters (Liao et al., 2018b; Xie et al., 2019; Chen et al., 2021) Adapted 2d-attention requires a lot of storage and computation (Xie et al., 2019; Chen et al., 2021)

Table 5.3: STR approach category shortcomings

based approaches, the main shortcomings are as follows. Localizing individual characters is computationally expensive (Zhan and Lu, 2019). A complex pipeline is needed to predict characters and align them (Liu et al., 2020b). Take Wan et al. (2020a), for example, which leverages a separate geometry branch to help with word formation with the predicted characters from the classifying branch. Segmentation is also susceptible to errors (Zhan and Lu, 2019; Cheng et al., 2018; Chen et al., 2021). The nature of scene text reinforces the errors: complex backgrounds, noise, perspective, and other factors (Hu et al., 2020b; Chen et al., 2021; Baek et al., 2019). Additionally, segmentation-based approaches cannot use contextual information between characters (Chen et al., 2021).

EnDe-based STR, on the other hand, is modeled to take contextual information into account (Long et al., 2021; Chen et al., 2021). The problem manifests itself in dealing with 2d-text instances (Long et al., 2021; Liao et al., 2018b). The EnDe basic approaches use decoders that work with sequences (and therefore 1d) (Long et al., 2021; Cheng et al., 2018). The introduced innovations deal with this in two ways: rectify 2d text into 1d text (Zhan

and Lu, 2019; Luo et al., 2019; Shi et al., 2019; Liu et al., 2018a), adapt the attention mechanism to 2d input (Li et al., 2019). Note that CTC cannot be adapted to 2d input (Cheng et al., 2017; Xie et al., 2019), and the attention adaption by Li et al. (2019) is memory and computation-intensive (Xie et al., 2019).

When comparing CTC-based to attention-based approaches, it can be noted that CTC deals better with long text instances or sentences while attention is better with singular words (Cong et al., 2019; Chen et al., 2021). This is because the misalignment in attention can cause missing or superfluous characters (attention drift) (Bai et al., 2018; Liao et al., 2018b; Cheng et al., 2017). Attention-based approaches have the upper hand when incorporating implicit language models or lexicons, but CTC performs better without language priors (Cong et al., 2019). This is especially important because the text in the use case under consideration contains alphanumeric strings which are not part of any lexicon. When it comes to computational efficiency, both CTC and attention are expensive and time-consuming (Chen et al., 2021). For STR CTC seems to be the choice for efficiency and attention for robustness for curved text. Table 5.4 shows the synthesized comparison for curved STR

Approach category		**Alphanumeric recognition**	**Performance**	**Efficiency**
Seg-based		✓	×	×
EnDe-based		✓	✓	✓
	CTC-based	✓	×	✓
	Attention-based	×	✓	×

Table 5.4: Curved STR approach category comparison

based on their shortcomings. The table compares the categories seg-based and EnDe-based and the sub-categories CTC-based and attention-based.

2-stage approaches have the upper hand when it comes to end-to-end STS. These approaches are in focus for research because they have crucial advantages (see Table 5.5) (Chen et al., 2021).

Category	**Shortcomings**
2-step	Error propagation between detection and recognition (Chen et al., 2021; Long et al., 2021) No joint optimization (Qiao et al., 2021; Chen et al., 2021) Computation requirements for two feature extraction CNNs (Liu et al., 2018b; Chen et al., 2021)
2-stage	—

Table 5.5: STS approach category shortcomings

2-stage approaches are more efficient than 2-step approaches because they do not compute feature maps twice (Liu et al., 2018b; Chen et al., 2021). This carries much weight since feature extraction is usually the most time and

computation-consuming step (Liu et al., 2018b). The direct combination of STD and STR also impacts the performance. Because of the connection, both stages are fully differentiable and can be jointly optimized (Chen et al., 2021; Long et al., 2021; Qiao et al., 2021). Without joint optimization, errors in the detection step can be propagated to the recognition, resulting in performance degradation (Chen et al., 2021; Qiao et al., 2021). The resulting comparison

Category	Performance	Efficiency
2-step	✓	×
2-stage	✓	✓

Table 5.6: Curved STS approach category comparison

between the 2-step and 2-stage categories concerning curved STS can be found in Table 5.6.

5.2 Reflection

This thesis aimed to create an overview of STS approaches to facilitate choosing a practical problem. A couple of factors impede this goal. The first is that all entities of a MLS need to be examined to develop a proper solution (Siebert et al., 2021; Nakamichi et al., 2020). Because not all entities (most notably the data entity) are available, this was not possible.

Another reason is the chosen cutoff point of 100 citations as a requirement for impactful literature. Even though it is helpful to filter for the most groundbreaking advancements in the field, newer innovations that have not been revealed long enough to earn enough citations might be left out of the equation.

The analysis does not contain quantitative data on performance or efficiency regarding singular approaches or even task categories. This is because the literature on ML and DL benchmarking suggests that it is not good to combine and compare results from different studies (Baek et al., 2019; Arpteg et al., 2018; Long et al., 2021). There are different rationales for this. Because different studies incorporate different components such as hardware, platform, source code, or configuration, the comparison would be flawed (Arpteg et al., 2018; Baek et al., 2019). Additionally, different studies might present a different interpretation of metrics (Long et al., 2021). Another reason is the benchmark datasets: datasets are used inconsistently in many cases. Often specific images are left out for various reasons (Baek et al., 2019).

Chapter 6

Conclusion

This thesis provides a comprehensive overview of techniques that are used for STS. The associated tasks and the different approaches help compare different solutions for the identified qualified that are important for the use case (appropriateness, performance/robustness, efficiency).

The overview and literature review reveal that STD and STR are concerned with robust performance for multi-oriented and curved text instances. For STD, the more efficient BB regression-based methods can detect multi-oriented text well. Because of BBs' representational deficiencies, pixel-level segmentation-based methods are better for detecting curved text. However, they are more computationally expensive. For the semantics retention subquality for appropriateness, it is, therefore, essential to consider the text properties of the dataset. The attention mechanism has become the primary approach for STR robustness. However, many innovations are concerned with the curved text rectification stage that both CTC and attention-based EnDe solutions share. CTC has the advantage over the attention mechanism for recognition of alphanumeric strings and efficiency, while attention is better with recognizing curved text. For STS research, 2-stage approaches are the focus because of their remarkable efficiency and competitive performance. The efficient combination of STD and STR stages and reuse of feature maps are topics of the innovations in the field.

For future work, it would be helpful to consider different steps in the ML lifecycle (Watanabe et al., 2019) or build a MLS around the identified DL approach for STS (Siebert et al., 2021; Nakamichi et al., 2020). An example would be to design a supervision mechanism for model monitoring that is important for DL in production systems Nakamichi et al. (2020); Watanabe et al. (2019). Another possible step would be to design and carry out a comprehensive study to generate quantitative data regarding the qualities that a STS solution must possess.

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Appendix A

Benchmark Dataset Examples

Figure A.1 shows representational examples taken out of benchmark datasets for STD, STR and STS.

(a) ICDAR (2013) (Karatzas et al., 2013)

(b) ICDAR (2015) (Karatzas et al., 2015)

(c) ICDAR MLT (2017) (Nayef et al., 2017)

(d) IIIT 5k Word (2012) (Mishra et al., 2012)

(e) MSRA-TD500 (Cong Yao et al., 2012)

(f) Total Text (2017) (Ch'ng and Chan, 2017)

(g) SCUT CTW1500 (2017) (Yuliang et al., 2017)

Figure A.1: Benchmark data set examples

Appendix B

Litaratur Qualities

The following tables show qualities that where identified in literature. The qualities are categorized by the MLS entities defined in Siebert et al. (2021). The model entity is the focus of this work and is thus discussed in Chapter 4.

Qualitiy	**Sources**
Relevancy	Ashmore et al. (2021)
Currentness	Siebert et al. (2021)
Completeness	Ashmore et al. (2021); Vogelsang and Borg (2019); Siebert et al. (2021)
Balancedness	Ashmore et al. (2021); Siebert et al. (2021)
Consistency	Vogelsang and Borg (2019)
Intra-Consistency	Siebert et al. (2021)
Inter-Consistency	Siebert et al. (2021)
Accuracy	Ashmore et al. (2021)
Absence of bias	Siebert et al. (2021)
Correctness	Vogelsang and Borg (2019)
Data Representativeness	Nakamichi et al. (2020); Siebert et al. (2021)
Suitability of Training Data	Nakamichi et al. (2020)
Test Dataset Creating Appropriateness	Nakamichi et al. (2020)
Independence of Train and Test Data	Nakamichi et al. (2020); Siebert et al. (2021)

Table B.1: MLS qualities identified for data entity

Qualitiy	**Sources**
Capacity of Data Storage	Nakamichi et al. (2020)
Infrastructure suitability	Siebert et al. (2021)
Deployment Fit-for-Purpose	Ashmore et al. (2021)
Training Process Appropriateness	Nakamichi et al. (2020)
Training efficiency	Siebert et al. (2021)

Table B.2: MLS qualities identified for infrastrucure entity

Qualitiy	**Sources**
Coverage of Usage Environment	Nakamichi et al. (2020)
Coverage of Operation Environment	Nakamichi et al. (2020)
Scope compliance	Siebert et al. (2021)
Social impact	Siebert et al. (2021)
Environmental Impact of training process	Siebert et al. (2021)
Contextual Relevancy	Ashmore et al. (2021)

Table B.3: MLS qualities identified for environment entity

Qualitiy	**Sources**
Suitability of Input Data Quality Maintenance	Nakamichi et al. (2020)
Quality Maintenance for Test Data Appropriateness	Nakamichi et al. (2020)
Security and Privacy Assurance	Nakamichi et al. (2020); Zhang et al. (2020)
Troubleshooting	Arpteg et al. (2018)
Easiness of Resource Update	Nakamichi et al. (2020)
Easiness of Software Update	Nakamichi et al. (2020)
Easiness of System Status Analysis	Nakamichi et al. (2020)
Runtime correctness	Siebert et al. (2021)
Legal and Regularity Requirements	Vogelsang and Borg (2019)
Effectiveness of output supervision	Siebert et al. (2021)
Efficiency of output supervision	Siebert et al. (2021)
Appropriateness of Operation Maintenance	Nakamichi et al. (2020)
Deployment Tolerability	Ashmore et al. (2021)
Deployment Adaptability	Ashmore et al. (2021)

Table B.4: MLS qualities identified for system entity