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From data and algorithms to value creation in the Industry 4.0

TESIS DOCTORAL

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Yo, **Daniel Schmidt**, estudiante del programa de doctorado **Economía y Gestión de la Innovación** de la **Universidad Politécnica de Madrid**, como **autor** de la Tesis Doctoral titulada:

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Resumen

Desarrollar formas de crear, recopilar y poner a disposición de los usuarios los conocimientos es esencial para la mejora de las empresas y el impulso hacia la Industria 4.0. La tecnología digital puede respaldar este esfuerzo y hacer que sea posible compartir estos conocimientos a escala mundial. Para aprovechar al máximo las posibilidades, se requiere la perspectiva holística de una empresa como sistema sociotécnico. En esta red, tanto los trabajadores como la tecnología deben actuar coordinadamente a través de estrategias y conocimientos para lograr resultados positivos. Para un trabajador, esto se da a través del sistema de gestión óptimo, sus conocimientos y la interacción con otros empleados y la tecnología. En la tecnología, los algoritmos y los datos dirigen estos factores. Mediante el uso de estos, esta tesis investiga diferentes direcciones y oportunidades para abordar los retos hacia la Industria 4.0. En un estudio de caso, a través de la utilización de sensores de electroencefalografía, se ha demostrado que el uso de diferentes métodos de gestión ajustada mostró diferencias dramáticas en los patrones cerebrales de los practicantes y un sistema de aprendizaje profundo fue capaz de clasificar los datos registrados con una precisión del 96,5%. Este conocimiento puede utilizarse para comprender las diferencias que presentan los métodos de gestión y cómo se pueden conseguir mejores resultados mediante la gestión ajustada. Mediante el uso del aprendizaje profundo, se demuestran estrategias para el control y la mejora de la calidad. Se logró una clasificación automática de los defectos con una tasa de precisión del 98,4%. Mediante el uso de conocimientos y datos de la industria de la impresión, se ha demostrado que la automatización de un proceso de trabajo que antes era manual es posible y ofrece muchos beneficios y nuevas vías de desarrollo aprovechando la economía digital.

Palabras clave: Algoritmos; Deep Learning; Industry 4.0; Datos; Conocimiento

Abstract

Developing ways to better create, collect, and make knowledge available is essential to the improvement of businesses and the drive towards the Industry 4.0. Digital technology can support this endeavour and make it feasible to share this knowledge on a global scale. To gain full advantage of the possibilities, it requires the holistic perspective of a company as a sociotechnical system. In this network, both workers and technology need to act in coordination through strategies and knowledge to achieve positive results. For a worker, this is given through the optimal management system, his or her knowledge, and the interaction with other employees and technology. In technology, algorithms and data drive these factors. Through the usage of these, this thesis researches different directions and opportunities to tackle the challenges towards the Industry 4.0. In a case study, through the utilisation of electroencephalography sensors, it has been proven that the use of different lean management methods showed dramatic differences in the brain patterns of practitioners and a deep learning system was able to classify the recorded data with an accuracy of 96.5%. This knowledge can be used to understand the differences the management methods have and how better results can be achieved through lean management. Through the use of deep learning, strategies for quality control and quality improvement are demonstrated. An automatic classification of defects was achieved with an accuracy rate of 98.4%. By using knowledge and data from the printing industry, it has been proven that the automation of a previously manual work process is possible and offers many benefits and further paths for development by taking advantage of the digital economy.

Keywords: Algorithms; Deep Learning; Industry 4.0; Data; Knowledge

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List of Abbreviations

(CPD)nA Check Plan Do Act. 33, 35, 36

AI Artificial Intelligence. 15, 16, 75

BSC Balanced Scorecard. iv, 10, 35, 36, 39, 42, 43, 45, 47–51, 54, 55

CMYK Cyan, Magenta, Yellow, Black. 94, 95, 98, 107–109, 114

CNN Convolutional Neural Network. 12, 53, 62

CV Computer Vision. 14

DL Deep Learning. iv, vi, 3, 6, 7, 10, 12, 15, 25, 31, 33, 37, 38, 43, 47, 52, 53, 57, 58, 63, 77–79, 81–84, 127

DNN Deep Neural Network. v, viii, 10, 12–14, 52, 55, 57, 58, 62, 63, 65, 66, 68–72, 80–83, 127

EEG Electroencephalography. 10, 31, 33, 37–40, 42, 44, 47, 50–52, 54, 55, 127

GAN Generative Adversarial Network. 124

HKT Hoshin Kanri Tree. iv, 10, 35, 36, 39, 42, 43, 45, 47–51, 54

KPI Key-Performance-Indicator. 34, 36

LM Lean Management. 15, 33, 38, 39, 42, 55, 73, 76, 77

ML Machine Learning. 9, 25, 77–79

OQC Optical Quality Control. v, 13, 14, 26, 57–61, 63, 67, 80, 81, 83

PFC Prefrontal Cortex. 34, 49, 50, 54, 55

PO Process Owner. iv, 33–36, 39, 40, 42, 45, 48, 51, 54, 55

RAM Random-Access Memory. 63

RGB Red Green Blue. vi, vii, 18–20, 94–96, 103–105, 109, 110, 114

ROI Region Of Interest. ix, 87, 90–93

SM Lean Shopfloor Management. 10, 31, 33–40, 52, 54–56, 127

SVM Support Vector Machine. 78

TPJ Temporoparietal Junctions. 34, 39, 42, 50, 51, 54, 55

1. Introduction

1.1 Research motivation

The rise of digital technology has changed many of the rules by which businesses can and need to operate today. These rules are propagated under the term digital economics [1]. It offers many distinct advantages compared to industrial economics and has and will continue to have a substantial influence on the way organizations operate [2]. All essential business sectors are affected by this, as all businesses are built and grow on the foundation of knowledge [3]. This knowledge can be digitized [4] and is a precondition for the development towards a modern industry [5]. In this way, a business can benefit from these advantages if these are understood and considered in the overall strategy.

Goldfarb and Tucker [6] identify five shifts, which clearly distinguish digital economics from standard economic terms. First, digital technology enables lower search costs for finding information [7]. Now, most information can be found in an instant through a digital search, while prior searches could take a long time and resources, which result in high costs. As the second shift, a lower replication cost is underlined [6]. Although economies of scale also play an important role in industrial production, these benefits appear insignificant next to the near zero cost of copying digital information [8]. The third point adheres to the lower transportation costs, which for physical goods can already take up a high percentage of the end-user price with 10% being in the normal range [9]. Lower tracking costs are the fourth shift and encompass the ability of easily connecting a person or company with information about them, which is in wide use for targeted advertisement [10]. Finally, lower verification costs make it possible to increase trust in the identity of both the customer and the market by making online reputation systems possible [11]. These are the main accelerators of digital economics.

The advantages of the digital economy also come from the exponential growth in some technologies. It is essential to fully comprehend the underlying power of exponential growth [12]. The severity of understanding this has been made clear to us in a different area in the last years through the tragic COVID-19 pandemic [13]. It does not come naturally for us humans to take exponential growth into account [14]. Only in the later stages, where the effects are already felt, does the severity become clear [15]. In this stage, the further outcome can take on dramatic consequences in a small time frame.

All these changes enable and facilitate new business models. One example is the so-called freemium model, which capitalises on the low replication cost [16]. Through this, it is possible that a few paying users can sustain the development of software or other forms of digital content for a large mass of nonpaying users [17]. A similar form is the use of microtransactions in games, where only the most dedicated players are responsible for the large part of the revenue [18]. Another example is the platform-based business, which profits from the lower search costs and therein laying advantages to benefit both the operating company and the user [19]. These are just a few examples, but already show the existing disruptive potential.

This makes it admirable for a company to have a business model that adheres to digital economics, but also to portray itself as having a digital business model. Through this, large future gains can be promised, as most costs are found in the development phase if a scalability of the business is possible [20]. An example has been the company WeWork [21], which provides flexible shared workspaces for entrepreneurs and companies and has branded itself as a digital company, although its core business is more akin to a commercial real estate company [22]. As an important factor, this has led to a meteoric rise and downfall of the company [23]. Though this example can act as a reminder that the advantages of digital economics do not apply to all businesses, this does not decrease the influence it is already having in all areas, including manufacturing.

In the manufacturing world, the disruption through digital technology has been given the term Industry 4.0. In its name, it emphasizes these changes as the fourth industrial revolution, with the first three being the steam engine, mass production, and the rise of digital technology [24]. By applying modern information and communication technology to the manufacturing floor, work processes can become more intelligent and automated [25]. It is expected to have a significant influence on the performance of industries [26]. This can be traced back to the advantages of the digital economy and its exponential growth.

The exponential growth in the digital world has for a long time been attributed to Moore's law and the associated advances in computer hardware, but to a large part is also driven by developments in algorithms. Although its influence is almost general knowledge these days, current developments show a decrease in the expected growth of computing power and that many more factors have been underrated for the overall increases in speed [27]. Only recently has the importance of algorithms for the growth in productivity been proven, with almost 50% of algorithm families experiencing comparable or greater improvements through optimization than in the same time frame through hardware advances [28]. It is predicted that this trend will continue, as the physical limitations for the development of hardware have slowed down the improvement [29]. Though further hardware improvements can be gained through novel approaches, bigger advantages can at least in the near future be expected through the adaption of algorithms to the hardware, performance engineering by reducing software bloat and the creation of new algorithms [30]. This will make the further development of algorithms a crucial task for all businesses.

The audio format Mp3 is just one example of the importance of algorithms in technological development. In a lossless format, a 2 hour audio file would take up more than 1GB in standard settings, while an Mp3 file would only need a mere 50MB for an acceptable audio quality [31]. Even with the improvements in hardware, this would still today make audio streaming almost impossible in practical use and demonstrates the importance of the underlying algorithms.

The influence of data has been in the public mind for a long time, with some even calling it the new oil, as it is the fuel for further development but must be refined to gain any value through better decision making and insight [32]. Data based business strategies form the backbone of some of the biggest companies world-wide [33]. Still, in practice, the focus during the development is often not on the data and its quality, which can lead to considerable negative, downstream effects [34]. This shows the need for an increased focus on the data and its quality.

Combining both the power of algorithms and data, machine learning and especially Deep Learning (DL) have seen a substantial rise in the last years [35]–[39]. Instead of hard-coding rules for different cases, the underlying patterns in the data are extracted to create a data-dependent model and with it the rules [40]. This makes it possible to extract even a large amount of complex rules, which can, for example, be used to classify images [41]. All this makes it an important tool and is the reason for its success in many disciplines.

Although DL has had this much success, with no significant changes, the same level of growth should not be expected. Its current growth has mainly been driven by the increasing use of computing power, which in terms of economic, technical, and environmental terms are not sustainable [42]. A push towards new efficient machine learning approaches is necessary [43]. For simple predictions, human intuition can also offer similar or even better results [44]. This highlights DL as significant but also as one of multiple tools and not as a one-size-fits-all solution, which gives the innovation of new algorithms and software that fit the existing needs an even higher priority.

The resulting opportunities are manifold. It is estimated that alone artificial intelligence could add

814 billion USD just to the UK economy by 2035 [45]. Digital technologies also open a possible way of decoupling economic growth from the environmental throughput, which could make a more sustainable development possible [46]. These gains for a business can only be achieved if the right decisions are made.

This opens up the question, what the hindering points are in applying new digital technologies in the industry. These can differ a lot depending on the company and its current position in the transformation process [47]. But if these hindering points are recognized and removed, major business improvements can be gained by augmenting the customer experience, streamlining operations, or even creating new business models [48]. Therefore, it is important to become aware of the varied dimensions that need to be taken into account to get a full picture of the influencing factors and possible show stoppers.

An important dimension is the human side of the digital transformation process. As an important first step, the necessary skills to tackle new challenges need to be developed within the business [49]. A cultural change needs to occur that allows more risk taking and utilizes the opportunities offered by digital technologies [50]. The cost of experimenting with ideas through digital technology is far less than under other circumstances, where experiments come with a higher price [51]. This high price point forces the limitation of ideas that can be trialed, which has negative consequences, as the complexity of the influencing factors make it very hard to predict a successful influence through this change [52].

The influence of complexity needs to be understood to better react to the resulting challenges. Complexity can already be seen in the decision-making processes of single humans [53]. This complexity further increases with the number of people in the group and their interaction [54]. In a business, multiple groups with competing interests are working together.

This increasing social complexity requires a strategic alignment in the business. Strategic alignment is an outcome and an ongoing process of pursuing the same goals to achieve a continuous improvement and create value for the customer [55]. This becomes even more important in the business model shift from manufacturing companies selling products to selling outcome based services [56]. The strategic alignment process is more complex than dictating absolute goals from the hierarchy but requires a intra-organizational dialog to achieve certain strategic objectives [57]. Algorithms and data can offer new ways to help management in decision-making processes to create a better alignment.

Complexity is also found in technical systems that have interacting parts and interacting machines. The complexity increases from simple machines up to a complete supply chain [58]. In manufacturing plants, both types are found.

This creates a new type of complexity, as also the interplay between those two categories has to be taken into account. It can be described by a socio-technical system that is formed by the human (socio) and nonhuman (technical) parts of the system that have the goal of creating a specific result [59]. This view can also help in the Industry 4.0 implementation by considering the impacts on all parts of the system and seeing these as an integrated network [60]. Not only as a technical system with replaceable individuals who are added and have to adapt [61].

The importance of being able to work with heightened complexity is increasing. Reducing complexity on the customer-facing side and being able to handle the internal complexity with the help of its digital basis has been one of the big drivers for the dominance of the big digital players of Google, Amazon, Facebook, and Apple [33]. This has been achieved through digitalization and the continuous focus on the interaction between technology and its users [62]. These principles can and should also be considered in other industries, where these factors are currently not fully taken into account.

The obstacles that hinder a business the most can differ depending on the company as well as on the development stage in the transformation process. Around 70% of all companies are still in the beginning stages of the digital transformation [47]. The biggest hinderance points for these have been identified as a lack of strategy and too many priorities [47]. In the move towards a maturing digital company, the current hindering points need to be continuously recognised and countermeasures need to be taken.

These changes require that the affected employees do not want to resist and, in the best case, embrace these changes. A digital transformation of the business results in a lot of changes for its workers, by changing the way they work or even making the job redundant [63]. The fears of the employees need to be taken serious and new opportunities need to be made possible and communicated to the employees [64]. It needs to become clear that most current business models will decline and it will be necessary to earn money through new business models.

The focus of the current research towards the Industry 4.0 is on the technical side through a cyber-physical system [65], [66] and the utilization of big data generated by sensors and Internet of things devices [67]–[70]. These are important requirements for the Industry 4.0, but transformation processes often fail if the technical side is the primary focus, which is a big reason for companies experiencing difficulties in their digital transformation process [71]. This is one of the reasons why the European Commission only recently has announced the value-driven Industry 5.0 vision to shift the focus more on human factors and the goal of creating a production that serves humanity and takes the planetary boundaries into account [72], [73]. In this context, sustainable results in the transformation process are only achievable through a connected view and alignment of the social and technical factors. The main challenges in these are the mastery of the underlaying complexities involved and the constant effort of reducing these [74]. These points are not considered enough in the research and should be examined closer.

1.2 Definitions

To ease the understanding of the thesis, the definitions of the most important terms are given in the following:

- Data: The definition as facts in “digital form that can be transmitted or processed” is used with the addition that information and through it a value can be created [75].
- Algorithm: The broad definition as a “step-by-step procedure for solving a problem or accomplishing some end” that contains computer-implementable instructions is used in comparison to the more restricted view as a “procedure for solving a mathematical problem” [76]. This includes any piece of software that terminates in a finite amount of computing steps.
- Industry 4.0: “The general definition of Industry 4.0 is the rise of digital industrial technology. Industry 4.0 transformations allow us to work alongside machines in new, highly productive ways”. The basis is a cyber-physical system that blurs the boundaries of the physical and virtual world and can be created through new technological developments. This cyber-physical system can be controlled by computer-based algorithms and allows to apply the advantages of the digital economy to the production site [77].
- Lean management: A management philosophy based on two key elements: “a systematic approach to process improvement by removing waste in order to maximise value for the end-user of the service and a commitment to respect, challenge and develop the people who work within the service to create a culture of continuous improvement” [78].
- Value: The definition of value is based on the lean management view as something that the customer is willing to pay for, whereby the removal of waste eliminates all non-value-adding steps in the process [79].
- Deep Learning: Grouped within machine learning, DL is a multilayer neural network that tries to mimic the functionality of the brain and is used to learn underlying rules from data.

In contrast to other machine learning algorithms, DL does not need predefined features. The important features are detected from the data. This is achieved by stacking multiple layers of interconnected nodes that represent different levels of complexity, which results in the name of **deep** learning [80].

1.3 Research questions

In industrial businesses, the influence of the social complexity is often underrated [81]–[83]. As manufacturing plants are often highly automized and focused on technology, this is also often the focus of the leadership. In reality, this is just one dimension. A stronger focus needs to be laid on the aspects of social complexity and its interaction with technology. As a foundation, it is important to achieve a strategic alignment, as stated in Section 1.1. Algorithms and data could be tools that help management achieve this goal by providing necessary insights.

This leads to the first research question:

- RQ1: How can algorithms and data be used to improve the strategic alignment in a business?

Management also needs to find alignment in manufacturing processes. Different key performance indicators need to be taken into account in the evaluation. These factors are usually competing, as a gain in one factor has a negative influence on the others [84]. In the production, these are the quality, lead time, and cost. A higher quality, in general, has a negative effect on the lead time and costs. A faster lead time has a negative effect on the quality and costs. Lower costs have a negative effect on the quality and lead time. Algorithms and data could offer new ways of improving all aspects and, therefore, creating large gains in manufacturing.

This leads to the second research question:

- RQ2: How can data and algorithms be used to reduce costs and add value to a manufacturing line?

Social and technical complexity also exists through the interaction with the customer. On the interface, information and products need to be exchanged between the customer and manufacturer. This requires an understanding of both internal processes. Any form of miscommunication can result in delays or even wrong delivery. In the endresult, this can lead to the customer choosing other companies that can better handle this process. This makes it essential to be able to handle this complexity.

In the industry, a job ordering process usually requires a range of experts on the side of the customer as well as the supplier that make sure that the product fulfills all needs. This not only makes it an expensive process but also increases the lead time of the product. An easier process could have a substantial impact on the industry and offer the building block for a platform-based business [85]. Data and algorithms can offer new ways of making this process possible.

This leads to the final research question:

- RQ3: How can data and algorithms be used to reduce the complexity of the customer-manufacturer interaction?

1.4 Industry 4.0 framework integration

To clarify the different approaches in the context of Industry 4.0, a framework defined by Villalba-Diez [86] was chosen for this thesis. As described in Section 1.1, the research needs to take multiple aspects into account to be implementable and benefit businesses in a holistic approach. Within this framework, the concepts of the developed solutions followed in the next chapters are placed. This gives the opportunity of understanding the technical implementations in a wider context.

The framework is shown in Figure 1.1 and is defined by three dimensions. For a business to succeed, it needs to be able to handle not only the technical complexity but also the social complexity that exists within the organisational structure. These challenges are increasing due to growing requirements for the products. A tool with ever-increasing importance in handling these complexities is digitalization. Through the sequence of information, knowledge, and value, businesses can continuously achieve better results.

In this thesis, the intersections on the linear growth line, as a representative subsample of all possible combinations, are further examined. These are four points that describe the two factors of the social and technical complexity axis involved as well as their interaction. The first is the crossing point of a human and machine and its resulting interaction in the Industry 4.0 context. The increased complexity in the case of connections and the production line is found in the following point. With the further increased complexity, the crossing point of management on the social complexity axis and the factory on the technical complexity axis is found. For the highest com-

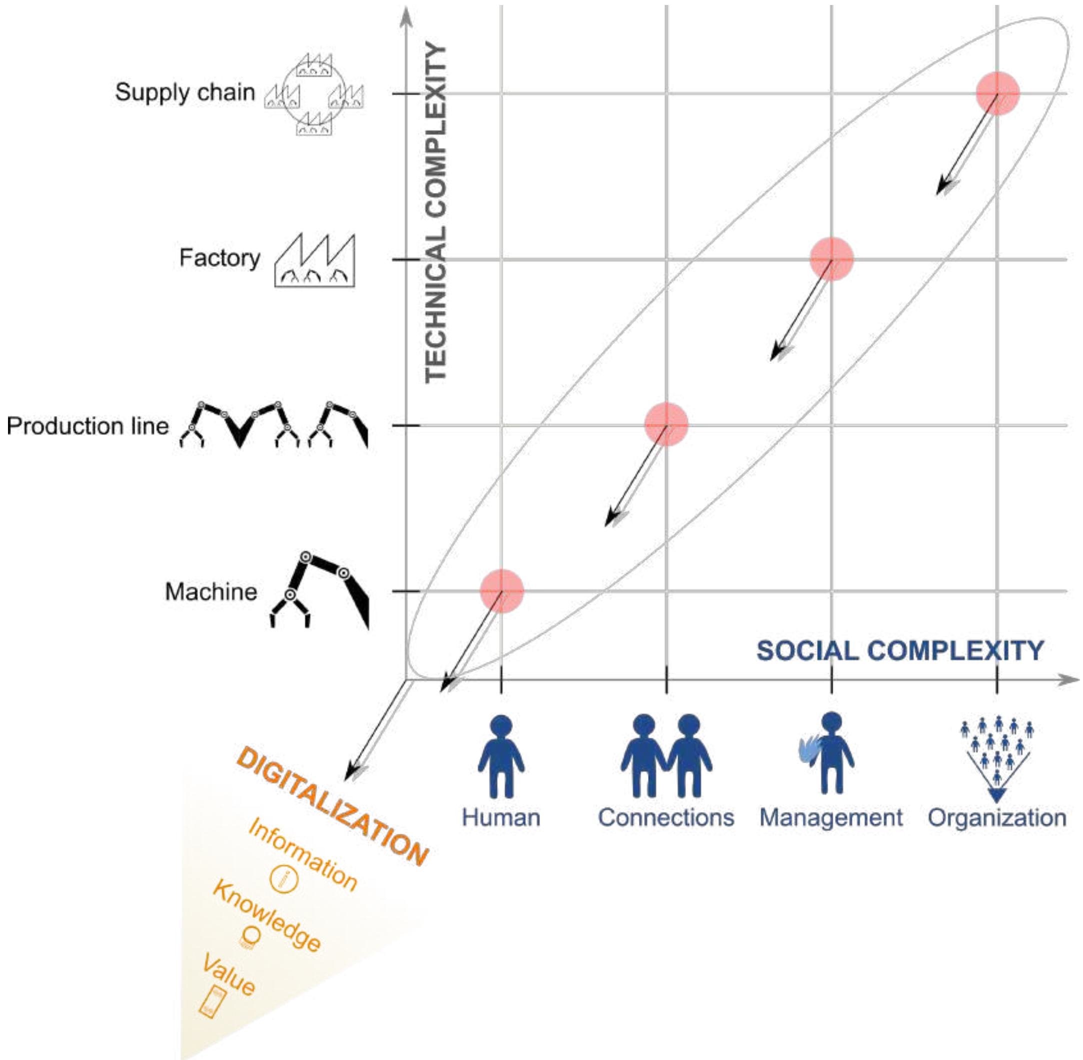

Figure 1.1: Industry 4.0 framework defined by the challenge of handling technical, as well as social complexity. The graphic is based on the work in [86].

plexity in this context, the crossing point is formed by the complete organization and the supply chain.

1.5 Thesis structure

Chapter 2 offers the needed background information for the following chapters by giving an overview of Machine Learning (ML) and further topics related to smart manufacturing and the workflow of the printing industry that is necessary to understand the context of the work.

Chapter 3 investigates the effects of algorithms and data on management. Achieving the shift towards Industry 4.0 is only feasible through the active integration of the shopfloor into the transformation process. Several Lean Shopfloor Management (SM) systems can aid this conversion. They form two major factions. The first includes methodologies such as Balanced Scorecard (BSC). A defining feature are rigid structures that concentrate on predefined goals. Other SM strategies instead concentrate on continuous improvement by giving directions. An example of this group is the Hoshin Kanri Tree (HKT). Evaluations of management systems are usually based on the own experience and the experience of others. A new way of analyzing the dissimilarities, advantages, and disadvantages of these groups is to examine the neurological patterns of workers as they are applying these. This chapter aims to achieve this evaluation through noninvasive Electroencephalography (EEG) sensors, which capture the electrical activity of the brain. A DL soft sensor is used to classify the recorded data with an accuracy of 96.5%. Through this result and an analysis of the correlations of the EEG signals, it has been possible to detect relevant characteristics and differences in the brain's activity. In conclusion, these findings are expected to help assess SM systems and give guidance to Industry 4.0 leaders.

Chapter 4 focuses on the possibilities of using DL in the manufacturing line to increase performance and add value. Rapid and accurate industrial inspection to ensure the highest quality standards at a competitive price is one of the biggest challenges in the manufacturing industry. This chapter shows an application of how a DL soft sensor application can be combined with a high-resolution optical quality control camera to increase the accuracy and reduce the cost of an industrial visual inspection process in the Printing Industry 4.0. During the process of producing gravure cylinders, mistakes like holes in the printing cylinder are inevitable. To improve the defect detection performance and reduce quality inspection costs by process automation, this chapter proposes a Deep Neural Network (DNN) soft sensor that compares the scanned surface to the engraving file and performs an automatic quality control process by learning features through exposure to training data. The DNN sensor developed achieved a fully automated classification accuracy rate of 98.4%. These inspections most often occur at the end of the value chain, insuring the quality standards of the manufactured pieces. The downside to this approach is that defective parts can still continue through the value chain. Wasting a lot of resources and increasing the lead time. To avoid this drain, the machines in the value stream should only produce error-free parts or at least detect them. An optical quality inspection system at every production step would add a high price cost. For this reason, existing sensors should detect unwanted states. With structured data, a person with specific domain knowledge could rate this. This is a tough task, as a lot of unknown factors can influence each step. Therefore, this chapter further proposes steps to improve quality in rotogravure manufacturing using deep learning. Further research will be conducted to expand these results. The proposed procedure will be applied to live data of a rotogravure manufacturing site and the effectiveness of this approach will be analysed.

In chapter 5, the creation of a semi-automatized job entry in the printing industry is described. The digital transformation opens up new possibilities for companies to persist and grow in a competitive environment. This forces a reorganisation of work in the context of a socio-technical system and the reduction of complexity. Through the use of data and algorithms, worksteps can be automated and, when necessary, knowledge is made available in the right moments. A basic requirement for this is that domain knowledge exists to know what happens at every step and why. The order entry process in the printing industry offers a good starting point for implementing this. The underlaying decisions for this process are based on learned general rules and specific preferences. These can each be mapped to algorithms and data, from which further rules are extracted. The goal of this chapter is to develop the basis for this semi-automized process through these algorithms and data.

Chapter 6 closes the work with a summary of the results towards the identified gap in research and possible ways of further finding ways to shrink this gap.

2. Background

2.1 Smart manufacturing

Machine learning

The general objective of machine learning is to generate knowledge out of data. For this, the underlying rules need to be understood, so that the new data can also be interpreted in the correct way. The beginning of modern machine learning is often placed in the early 60s with the development of the *perceptron* [87]. From there, new methods and more data have enlarged the potential of machine learning.

Recent years have seen a rise in Deep Learning (DL), which has been fueled by more available data and computing power [88]. DL builds on the idea of the *perceptron* and the following developments regarding neural networks. It enables computational models consisting of multiple processing layers to learn representations of data with multiple levels of abstraction [89], [90]. Deep Neural Network (DNN)s are constructions created by combining a series of hierarchically superimposed and arbitrarily initialized filters that are capable of automatically learning the best features for a given classification problem due to exposure to training data [91], [92].

An example of this is the Convolutional Neural Network (CNN). For CNNs, the feature extraction is performed by a deep stack of alternatively fully connected convolutional and subsampling max pooling layers. Convolution operations, by means of activation functions, extract the features from the input information which are propagated to deeper level layers. A *ReLu* activation function is a function meant to zero out negative values. The *ReLu* activation function was first presented in AlexNet [93] and solves the vanishing gradient problem for training DNN. *Max pooling* consists of extracting windows from the input feature maps and outputting the max value of each channel. It is conceptually similar to convolution, except that instead of transforming local patches via a learned linear transformation (the convolution kernel), they are transformed via a max tensor operation.

Recurrent Neural Networks (RNN) are another popular alternative. These play an important role for sequential data, such as text or audio, through which, for example, language translation or speech recognition can be achieved [94]. This is done by expanding the feed-forward procedure to further allow previous data inputs to influence the results from new inputs [94].

Long-short-Term Memory (LSTM) networks are a type of recurrent neural network and also have the capability of giving feedback from previous data inputs. By adding new gates, the vanishing and exploding gradient problems are tackled [95]. This offers more possibilities for training but can also increase the complexity and operating costs.

Several DNN architectures have been successfully used to extract statistical information from physical sensors in the context of Industry 4.0 in several applications such as classification problems [96], visual object recognition [89], human activity recognition through wearables [97], [98], predictive maintenance [99], [100], or computer vision [101] among others. More specifically, DNN have recently proved useful for industrial computer Optical Quality Control (OQC) defect detection purposes with promising results by automatically extracting useful features with little to no prior knowledge about the images [102], [103].

The form of the neural network is described as the architecture and is formed by multiple parameters. While statistical ways exist to help select some parameters [104], [105] and a few have become unofficial standards, no clear-cut ways to know the best beforehand exist yet, although recent progress has been made with so called *neural architecture search* [106]. Thus, it is an iterative process of finding the ideal specifications for the architecture by starting with a simple design and seeing which changes improve the results. The final optimal layout therefore depends on multiple factors. More complex features that have to be found in general increase the number of layers needed [107]. But these can also be limited because the training data would not be sufficient for the increasing number of weights or a limit is reached solely because the hardware requirements cannot be met.

Before training the neural network, the dataset is split into three groups. The training, validation, and testing set. After training the DNN with the **training data**, the **validation data** can be used to tune the hyperparameters of the DNN without exposing the **test data** to the DNN. Only at the very end, when no further changes to the DNN are being done, can the testing data be used to evaluate its effectiveness. The set size ratio depends on the amount of data, as the test and validation data should be sufficient to check the validity. While big data cases with millions of examples allow for splits of 99.5% training data, 0.25% validation data and 0.25% test data, cases with examples in the range of 10,000 need a bigger split for the test and validation data [108]. For smaller data collections, the standard is a 80%, 10% and 10% split.

A common method to view the success of the training is the confusion matrix [109]. These are usually separated into the categories True Negative, False Negative, True Positive, and False Positive if only two classes are learned. For a multiclass categorization, it makes sense to have a true and false version for each of the categories. With these values, further values for the evaluation of the model can be computed. The accuracy of the DNN can, for example, be calculated by dividing the sum of the *true* cases through the sum of all cases. For a two-class example through: $(TP + TN)/(TP + FP + FN + TN)$.

Optical quality control

Today's manufacturing industry is increasingly subject to international competition, because of falling transit and communication costs and a faster transportation of goods [110]. Products have become more standardized, as has the technology to produce these [111]. Adding to this, it is becoming increasingly important for companies to cut the environmental footprint by reducing energy and material usage. Only through this is a sustainable use of resources achievable [112]. These conditions intensify the pressure to reduce the costs, but also to increase the speed of the delivered goods. An enormous factor to fulfill these demands will be that only high-quality items are produced.

OQC systems have helped improve the delivered product condition in many fields of manufacturing in the last years. Through the possibilities of digitalization, advances in imaging hardware, and Computer Vision (CV). The sectors concerned include a wide range from food [113], [114] to solar cell [115] and fabric [116] inspection. OQC is crucial to many manufacturing processes to meet customer requirements [117]. On the one hand, the performance of human-centered OQC does not meet the necessary requirements: it is limited by ergonomics and cost, as humans get tired with repetitive OQC tasks and these tasks are usually very labor-intensive. For this reason, automatic detection of visual defects, which aims to segment possible defective areas of a product image and subsequently classify them into defect categories, emerges as a necessary solution to the problem. On the other hand, simple threshold techniques are often insufficient to segment background defects when not applied to a controlled environment characterized by stable lighting conditions. Xie [118] provides a classification of existing methods, but the common practice in industrial environments is that each new feature has to be described manually by experts when a new type of problem occurs: surface defects in industrially manufactured products can have all kinds of sizes, shapes or orientations. These methods are often not valid when applied to real surfaces with rough texture, complex or noisy sensor data. This has the immediate consequence that the classifications are almost always insufficient and cannot be generalized to unknown problems [119]. For these reasons, more robust and reliable results are needed in the detection of defects by more sophisticated methods.

The check is usually only performed at the end of production. Based on the generally high cost of an optical quality control system. Therefore, the defective part still travels along the value stream, and is remade or, if possible, fixed. Depending on the defect and the point during the production, this can have significant effects on the lead time and waste.

Handling complexity

While the general belief is common that higher automation naturally improves the quality of manufacturing, the effects are not always positive and at least on its own should not be seen as a sufficient step towards a higher quality in manufacturing [120]. Sometimes when the complex interplay between the machine and human operator is not fully taken into consideration, this can even expand the problem because of the complexity of the task [121]. This allows two general strategies on how to handle the complexity to improve the quality that don't demand to and should not be applied on their own.

The first is to reduce the complexity of a process step by analyzing it and using tools such as Lean Management (LM) [122]–[124]. The aim of LM is to find less complex ways of achieving the planned results [86], [125]–[130]. The non-value adding steps are removed and continuous improvement becomes a focus.

Another approach is to use tools such as Artificial Intelligence (AI), which can handle a higher complexity as the problem it controls. AI aims to show intelligence by machines [131]. This includes a wide range of subfields with an even wider range of goals. A big subfield of AI is machine learning, through which it is possible to learn correlations and patterns from sample data. Within machine learning, DL has seen an immense surge in the last years. Through it, it has been possible to solve many complex challenges that were assumed to be impossible to solve even with earlier AI tools [93].

The third option is to view LM and AI not merely as side-by-side approaches, but as complementary and integrated parts of each other. In this hybrid, both contribute their strengths. AI can improve the decision-making process by offering new insights. The LM framework is used to incorporate these results. Through this, the human still stays in the focus and prevents the system from becoming a black box.

As AI has become an ubiquitous tool in production, it is becoming an essential building block for many current improvements. One of these developments can be found under the term smart manufacturing [132]. In simple terms, it can be summarized as methods that use the resulting data from manufacturing to improve the performance. This also comprises several subareas, such as predictive maintenance, quality control [133] and quality improvement.

2.2 Printing Industry

The printing industry has been under a substantial transformation process through digitization in the last decades. Many of these changes have not been noticeable to the customer, but have resulted in radical shifts for the industry and its workers [134], [135]. Coming from a long tradition of manual work, many production steps have since been automized or augmented by a digital process, making digitalization possible [136]. This change is set to continue and increase in pace.

Fueled by numerous developments, a digital transformation process is taking place that is affecting all industries and can be seen as a continuation of digitalization [137]. Falling hardware prices in combination with increased computing power not only make it easier and more affordable to record different data points, but also allow more complex calculations to be completed in shorter time [138]. This opens up new ways of using already existing algorithms and big data applications [139]. In addition, new ways of processing data are being contrived to aid the digital transformation process.

In the wake of AI and Industry 4.0, new radical shifts are starting to affect the printing industry. Through AI, it is possible to mimic human intelligence and learn complex underlaying rules from data [140]. Technologies developed within Industry 4.0 allow better connection, information transparency, technical assistance, and decentralized decisions [141], [142]. This will not only influence all digitized and digitizable steps in the production process, but force a reevaluation of the complete process [143]. In the end, it will also force and allow a change of the business model.

New business models use the advantages found in digital economics. A big focus in the printing industry has been the web-to-print model, which allows an easy ordering process [144]. These technologies will further drive business model innovation by harnessing the power of AI [145]. A big part is offering a service.

The service sector is a growing sector of the global economy. Coinciding with its growth, its productivity increases in similar levels to manufacturing [146]. This is also an opportunity of growth for the printing industry in the form of a Product-Service System, that not only offers the physical product but also a range of services that increase the value of the actual product, by setting the focus on the needs of the customer and not on the manufactured product itself [147]. In addition, this can counteract a decline of craft, which is considered one of the biggest causes of low productivity in the printing industry [148] The biggest benefit can be gained if the services are software-based, as no further costs for reproducing this knowledge arise.

A change of services towards software-based systems requires a redesign of tasks, which creates a new division of labor between humans and machines. While the focus for automation used to be more on the tasks that humans cannot do or are unwilling to do, today, it is rather humans doing work that at the moment can't be automated [149]. This forces a reevaluation of processes that, with previous technology, did not seem possible to be automatized.

Printing industry workflow

In the printing industry, a standard workflow involves multiple entities. The steps are visualized in Figure 2.1. These can vary depending on the type of printing and the use of the printed products. A customer needs a set of prints, while the exact design and layout is not sure. The file containing the future print is created by a design agency. It contains the necessary information that should be on the print and is designed to be aesthetically pleasing and follow the norms set by the customer and any regulations. Most often, the result is not in a print-ready form, as the designer usually does not take the printing process into consideration. These changes are done by a reproduction team that has expertise in the specific printing method. Depending on the printing method and some customer-specific preferences, the image data is changed and the necessary properties for the production are chosen. The printing tools are created with this data and are used by the printer.

The reproduction and tool creation are important steps, as they define the outcome of the print. Wrong decisions in this step are often only found during printing and require a complete rework of one or more of the printing tools, if the quality is not satisfying. That is why a lot of knowledge is needed in the job entry for the printing tool, as these parameters and changes to the data are the basis for the print results. Until now, this is a very manual process that offers a lot of room for reevaluation under current technological advances to automate big parts of this.

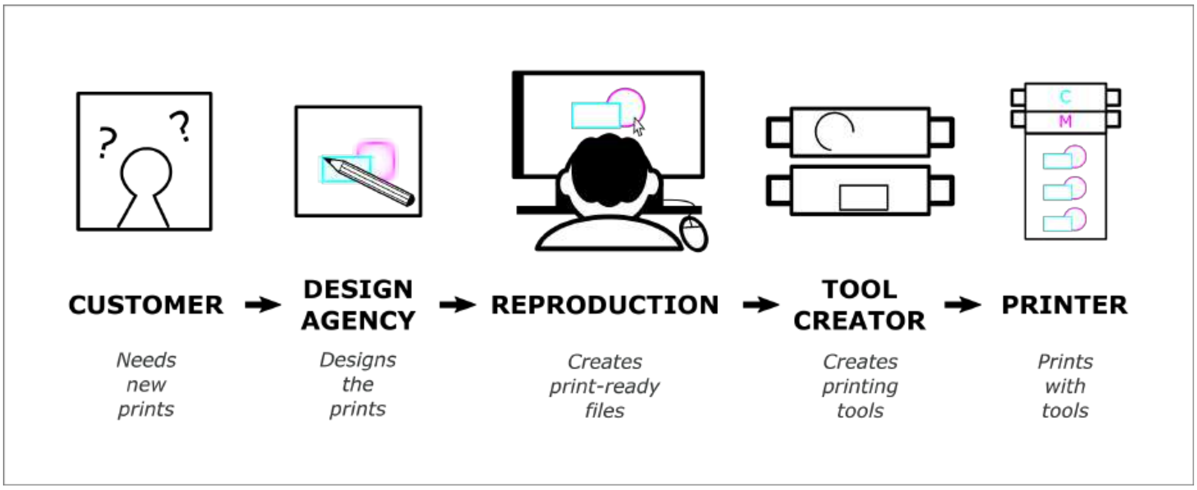

Figure 2.1: Standard workflow in the printing industry.

Color science

Color science is a wide-ranging field with a far-reaching impact in many areas [150]. For printing, it is essential to identify colors and have a way to communicate these. Only through this is it possible to reproduce a print. For this, a color space is needed.

Color space

For image processing, the standard way of handling color is through Red Green Blue (RGB)-values. In this additive color system, the mix of red, green, and blue are used to create a wide range of colors. *RGB* is not a defined color space, as the values are not standardized to any visual color, but color spaces, such as *sRGB* or *Adobe RGB* have been developed with a spectral background, which allows a standardized usage of the defined colors [151]. This is also possible through the *L*a*b** color space.

The *L*a*b** color space has another advantage, as it is much easier to calculate a meaningful distance between colors. For this reason, the *L*a*b** color space is the most used in printing applications as the distances coincide better with the human vision. It can also be communicated through the standardized Delta E value. Many versions of the Delta E value exist, as the model has been refined over the years.

The first version from 1976 is defined as the Euclidean distance for the three values defining the color:

$$\Delta E_{p,v} = \sqrt{(L_p^* - L_v^*)^2 + (a_p^* - a_v^*)^2 + (b_p^* - b_v^*)^2} \tag{2.1}$$

Newer versions, such as Delta E CIE 2000, take the sensitivity of humans to specific colors into account and are therefore recommended. For a value of ≈ 2.3 a just-noticeable distance is given, which implies that this difference is detectable at least half the time for humans [152]. An example of two colors with a just-noticeable distance visible in Figure 2.2 and 2.3 with the RGB-values in the title. A value between 2 and 10 is categorized as perceivable, a value between 11 and 49 shows the colors are more similar than different, and a value of 100 signifies that both are exact opposites [153]. This allows a rough classification of the Delta-E values.

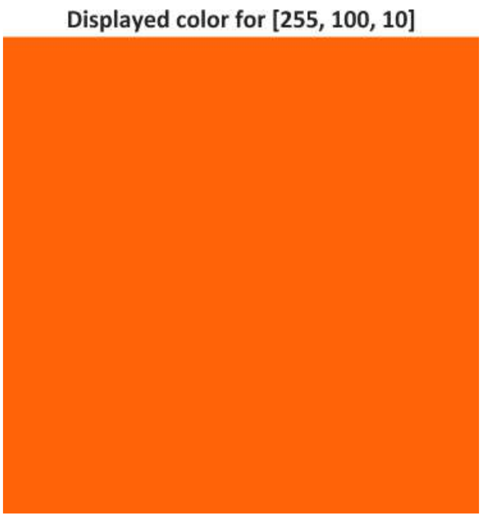

Figure 2.2: Example color used as comparison.

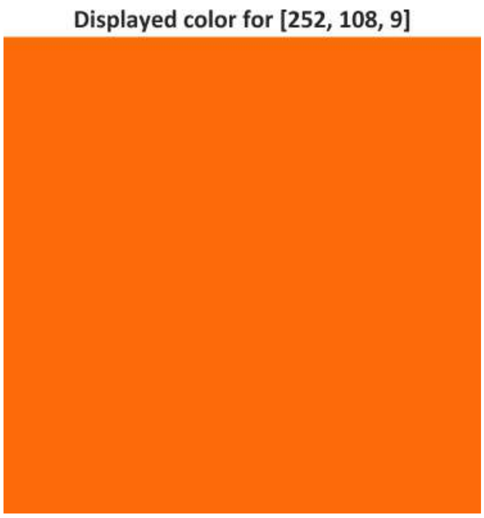

Figure 2.3: Color with a just-noticeable difference to Figure 2.2.

Color classification

The challenge of classifying colors has been a long known one in the printing industry and still is today, as the importance of an exact color, for example, for brand recognition, has been examined [154]. One system that is in wide use to classify colors is the Pantone Matching System® [155]. It is a proprietary color space that not just the printing industry, but also industries such as graphic design, fashion design, product design, and manufacturing utilize. It contains a fixed amount of predefined colors that can be used as a reference for different manufacturers [156].

Color combinations

The exact result of multiple colors overprinting depends on many factors, such as the substrate, the temperature, the exact composition of the inks, and the order of the inks printed. This is very hard to model, as not all parameters are known. Even slight tolerances for the parameters can change the outcome. Still, approximations are possible.

A good approximation can be done through the Kubelka-Munk theory. It has been developed in the early 30s [157], and has since been refined [158], [159] and used in different applications [160]. For it to work, the spectral reflectance functions need to be measured.

If only the *RGB* or *L*a*b** values are known, only a rough approximation can be done [161]. The reason is that different combinations of colors can result in the same or very similar color. It is based on the fact that the spectrum of the mixed color combines the spectra of the colors used for the mix. In the example visible in Figure 2.5, the mixed color was created through a 50% mix of both colors visible in Figure 2.4. A non-distinguishable color could have also been created by mixing a different set of colors.

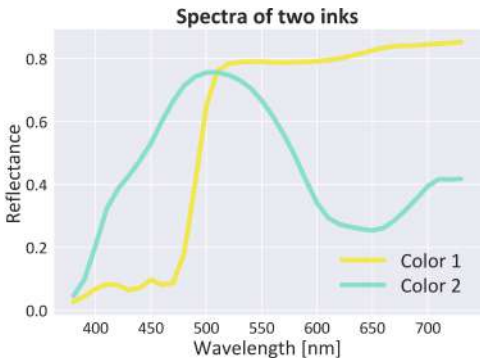

Figure 2.4: Reflectance spectra of a yellow and a turquoise ink that were used to create the mixed color visible in Figure 2.5.

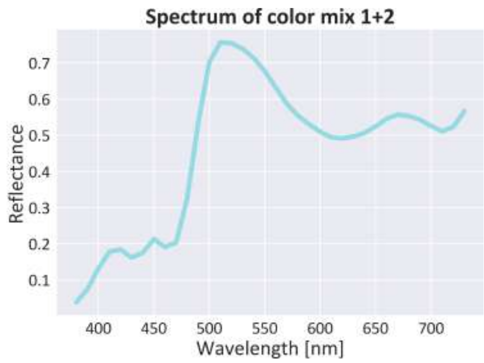

Figure 2.5: Reflectance spectrum of a green color. It was created by physically mixing both colors found in Figure 2.4.

Prepress

Prepress comprises all production steps before printing. With these, it is possible to lessen the impact of technical difficulties that can happen during the printing process.

Color substitution

As demonstrated in Section 2.2, misregistration can occur when elements are created through overlapping colors. Elements created in the artwork can be based on the combination of all available colors defined in the order. The more colors are used for the same object, the higher the chance of a misregistration. Therefore, if it is possible to create a color with less separate colors, this should also be the advisable way.

Trapping

Trapping is the creation of overlaps or underlaps of objects in the prepress stage with the intention of lessening the impact of misregistration on the print [162]. A difference needs to be made between elements, where a trapping can be applied and for those where it is very limited or not possible. In general, this line can be drawn based on the fact if an unambiguous border exists and a continuous area exists. This usually goes along with the fact that the elements are vector-based or raster graphics.

Any kind of photograph is a raster graphic. It is created with a limited number of pixels. Any increases of the resolution are done through interpolation or in current developments through the help of neural networks that have learned to generate visually meaningful results from lower resolution images [163]. An example of a raster graphic within the context of a print can be seen in Figure 2.7.

If possible, the elements are created vector-based, as it allows the optimal quality even after resizing. All information is stored through vectors, which can be translated to raster graphics. An example is visible in Figure 2.6. The PDF format can hold both types within one file. The options to improve the results with raster graphics or more specific elements with unambiguous borders are far more limited than for vector-based elements.

Figure 2.6: Typical example of elements in a print job that start of as vector based.

Figure 2.7: Example for a raster graphic in the same print job as the example from Figure 2.6.

A trapping cannot always be applied to raster graphics in a direct manner. In general, the image data is quite complex and no big continuous areas exist within. Any trapping would change the image content too much. A distinction can be made automatically on a raster image [164].

An indirect way of applying trapping to raster graphics is to add an outline. This needs to be a near opaque color that overprints part of the edges of the raster graphic and a further part outside of it. It can only be used to hide problems visible at the edges. All other raster graphic parts are still affected by misregistration.

A different option that can increase the quality of the complete raster graphic is to change its composition. Almost identical colors can be printed with different combinations of inks. By favouring a combination that limits the number or importance of some colors, the negative effects of misregistration can be reduced. Still, the possibilities for raster graphics are limited.

For the vector-based elements, two further distinctions need to be made. An area affected by misregistration can be caused by an element that is created with more than one color. If one of those moves, both colors in a part can be seen as separate colors, if no other color covers this up. The other option is that the two colors adjoin each other. If one of them moves, it can happen that both colors print together or that there is some area where the underlying substrate is visible. It is also possible that both types happen in combination, if two or more colors overlap and a third color shares the border. In all cases, a trapping can be helpful to improve the outcome.

Elements printed with two separate colors, such as the example after trapping in Figure 2.8, can be printed in one color and would always print the expected outcome as visible in Figure 2.19. This removes all possible negative influences from the misregistration and has no negative effect on the printed outcome.

If the negative effects outweigh the positives, or if elements from different separations are bordering but not forming the same element, other techniques need to be applied. A common one used is trapping. This changes the elements of the separation while trying to create as minimal possible difference to the initial artwork. The first downside to trapping is visible in Figure 2.8. If the elements are too small, a color change is highly visible, as a large share of the area of the elements has been changed. This effect is less noticeable in larger elements and should therefore be avoided for smaller elements. Still, the advantages can be seen in Figure 2.9, where the difference to Figure 2.8 is barely visible.

Figure 2.8: Trapping applied to the Yellow separation, making the Cyan visible.

Figure 2.9: Cyan and trapped Yellow separations after misregistration.

If an element is printed together with the negative element in another separation, it is possible to fill the negative elements in the background and make the positive elements print on top of the filled area. Even then, only specific color combinations give an acceptable outcome and a certain level of tolerance to the intended color is needed. As visible in Figure 2.10, the background color has a considerable influence on the font. On the positive side, misregistration does not have any effect on these areas.

A more appropriate solution for the before-mentioned example is to extend the positive element and let it print before the negative element. In this way, the same results can be achieved even if a misregistration exists. This is only advisable if the color printing on the top is dark enough to overprint it. If the color is not dark enough to mask this extension, it can be visible as a mix of both colors. In that case, the positives and negatives need to be weighed up against each other.

Figure 2.10: Green font overprinting black background.

Figure 2.11: Wrong direction of trapping on the black negative text.

The lighter color needs to be spread into the darker color, as the darker color forms the outline of the elements. This is visible in Figure 2.11, where now only smaller areas have an unwanted white color showing through after misregistration, but also the elements have got smaller. In rare cases, this might be okay, but the general rule is to change the visible output as little as possible.

As trapping is a reoccurring task in the print industry, automatic trapping is targeted. For laser printers and similar devices, this is the standard [165]. For the creation of printing tools, the trapping is often a combination of automatic and manual trapping adjustments. Through this, the best quality can be achieved, which at the moment cannot be achieved in an automatic way.

Different approaches for the automatic application of trapping have been developed. Two general groups exist. The trapping can either be applied to the objects based on the vector image or directly on the pixels through a rasterized image [166]. For both groups, the edges and color values are used to identify the best trapping strategy [167].

Rotogravure manufacturing

Rotogravure cylinders are one of the most important printing methods in the packaging industry and were developed in the early 1890s [168]. Belonging to the family of intaglio printing, which has an even longer history with roots in the fifteenth century, making them one of the oldest printing technologies [169]. The cylinder has cells in the cylinder (Figure 2.12), that fill with ink. This ink gets released during printing, as seen in Figure 2.13, by being pressed against an impression cylinder. In its current form, rotogravure cylinders still work through the same principle as they did in the beginning. Yet, manufacturing rotogravure cylinders has experienced many advances through the help of digitalization.

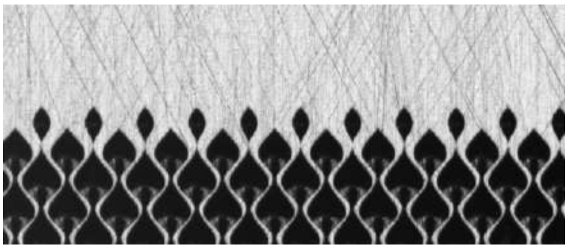

Figure 2.12: Surface of an electromechanically engraved cylinder.

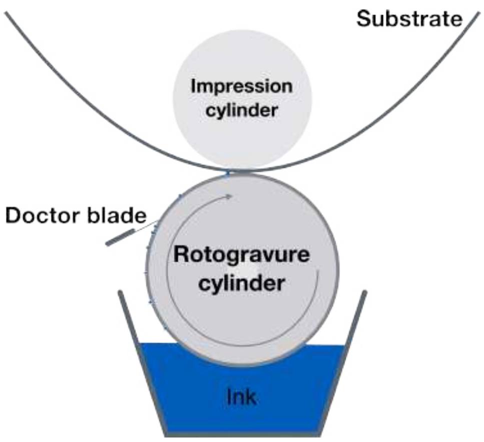

Figure 2.13: Rotogravure printing.

This has allowed the rotogravure cylinder to keep its place as the most important printing method when high print quality and long print runs, starting at a run of at least 100.000 units [170], are needed. These cases have been decreasing. More printing designs are only used for shorter times. This, in turn, increases the need to become relevant for smaller printing runs.

Although manufacturing rotogravure cylinders has this extensive history, the production processes are still prone to errors because of the many influencing parameters and the required high accuracy. Therefore, there is enough room for Machine Learning (ML) techniques, and DL in particular to be applied and to help improve the processes. As the first step of the analysis, the production steps are described.

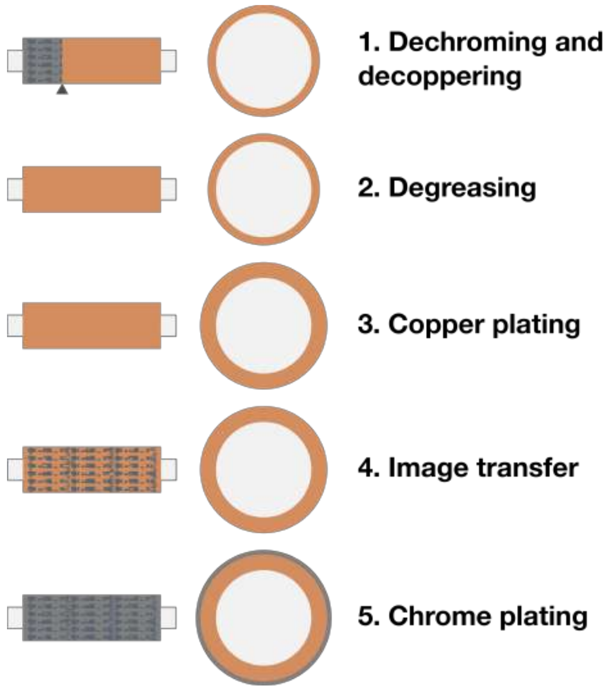

Figure 2.14: The main steps of rotogravure cylinder manufacturing. On the left the on-top view of the cylinder. In the middle a cross section of the cylinder and on the right the description.

The general production process is highly standardized. The key steps can be seen in Figure 2.14. Although the core of the printing cylinder is made of a steel plate that is enclosed by a copper layer, the standard process usually starts with used printing cylinders. These get dechromed and decoppered (Figure 2.14-1). After this, the new production can start. Before a fresh copper layer can be added, the cylinder is degreased (Figure 2.14-2) to remove any kind of contaminant that could have negative effects on the further production steps. If this doesn't happen correctly or if any dirt remains on the cylinder surface, this can lead to defects.

In the next step, a layer of copper is added in a galvanic process (Figure 2.14-3). Because of the earlier production step, and through a multitude of influencing parameters of the coopering machine, holes in the copper surface can emerge. These are already visible in this step. Still, many more difficulties can arise in this process step that are not visible. The major points are the copper hardness or a contamination of the copper that could lead to further problems in the next production step.

The following step adds the desired illustration to the printing cylinder (Figure 2.14-4). Depending on the requirements, a multitude of methods are available to achieve this goal. The most used method is the electromechanical engraving that uses a diamond stylus to remove small cells of varying sizes of copper from the surface that fill with ink during printing and release it on the printing substrate with the help of a doctor blade and a rotary press. In addition, other methods are available, of which many use a laser directly or indirectly to form cells on the cylinder surface. In scarce cases, engraving can even be done by hand. During the process, many kinds of defects can emerge. For the electromechanical engraving, this could, for example, be a broken or fractured stylus or defect in the cylinder surface.

Laser engraving of gravure cylinders (Figure 2.15) is the latest and most exciting development in gravure printing. Laser technology makes it possible to produce cells with variable shapes, which is not possible with electromechanical engraving. These new shapes actually provide a higher print density and it is possible to use inks with a higher viscosity than conventional electromechanically engraved cylinders. Laser engraved cylinders also reduce the influence of print speed on print quality and keep the highlight tone values stable.

Figure 2.15: Printing Cylinder.

Although laser engraving of rotogravure cylinders is a new variant of etching rotogravure cylinders in the rotogravure market, today's systems are still susceptible to errors. Possible errors or optical detectable defects include dents, scratches, inclusions, spray, curves, offset, smearing, and excessive, pale or missing printing or color errors (i.e., incorrect colors, gradients and color deviations from the desired pattern). The most common errors are dents, 32%, while the least common error is smearing, 3%. Due to the different errors and noise levels typical of industrial settings, an automatic error detection based on classical computer vision algorithms was not possible [171]. Most systems aim to select potential faults and present them to the human expert responsible for deciding the presence or severity of faults. Practice shows that about 30% of the possible errors that need to be checked are not relevant. This fact increases both the costs associated with the OQC and the lead time of the overall process. Both factors are crucial to achieving customer confidence and must be systematically optimized.

In the last step, the imaged rotogravure cylinder receives a chrome plating (2.14-5). The reason is that a copper surface would not be hard enough for the pressure needed during the printing process. In this last step, it is also possible that defects, such as holes on the cylinder surface, can occur. A contamination of the cylinder surface or chrome electrolyte could cause such flaws.

Printing

Although automized to a high degree, the printing process offers many challenges which must be taken into account.

Misregistration

The most common and impactful problem during printing is the misregistration of the colors printed. An example of a print with misregistration can be found in Figure 2.16. In the printing press, the colors of the separations are applied one after each other to create a multicolor image. This is visualized in Figure 2.17. A high accuracy of all tools is needed to make an exact fit of the colors possible. This is not without difficulties, as even minuscule deviations from the norm result in large shifts in the long run and the printing substrate can change its form due to the ink applied, which can cause the appearance of gaps or halo artefacts.

Figure 2.16: Print example of a misregistration affecting multiple colors.

During the printing, the misregistration is tried to be kept as low as possible. For this, different forms of techniques have been developed, such as the registration marks visible in Figure 2.18.

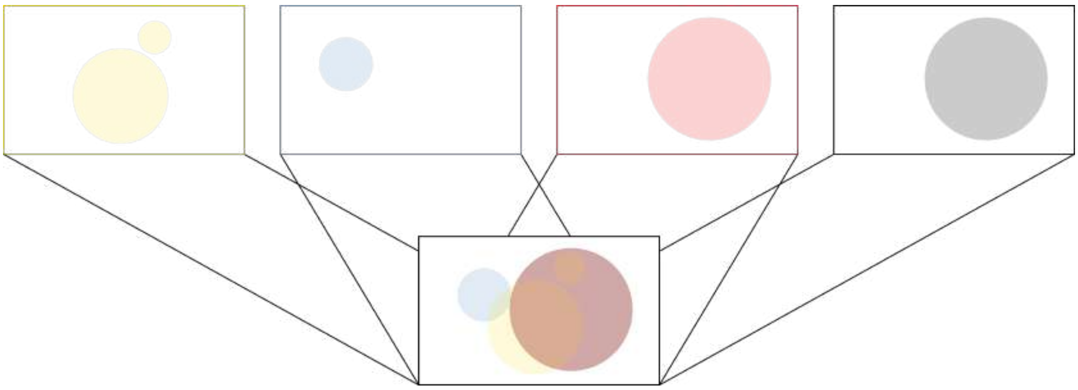

Figure 2.17: The single separations are combined to a composite print.

With these, it is possible to check the current alignment of the color separations and adapt the positions for a better fit. Although these tools are of great importance in reducing the misregistration during printing, it cannot be eliminated by it.

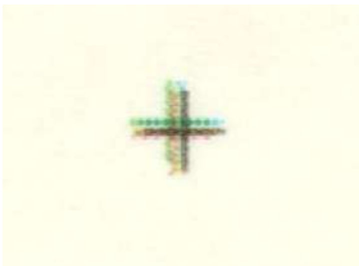

Figure 2.18: Registration marks of multiple separations with a slight misregistration between them.

As an example, different results under misregistration for elements printed with two inks were simulated. A 100% fit of a green font, created by a cyan and a yellow separation, can be seen in Figure 2.19. The possible misregistration results can vary in distance and direction. Already a small misregistration, as in Figure 2.20, can make the result look blurry. Misregistrations can go in any direction as Figure 2.21 and 2.22 demonstrate. The separate colors become visible, and the overlapping part diminishes.

A similar effect appears when elements share the same border. However, if a misregistration occurs, an overlapping area and the color or substrate underneath the other part appears. This can be seen in the example from Figure 2.23 and 2.24. Therefore, further techniques have been developed to reduce the effects of misregistration.

Figure 2.19: Expected outcome for a perfect fit of yellow printing with cyan or a single green color.

Figure 2.20: Slight misregistration between a cyan and a yellow separation.

Figure 2.21: Results of a misregistration, where the yellow separation is a bit higher and more to the left.

Figure 2.22: Results of a misregistration, where the yellow separation is a bit lower and more to the right.

Figure 2.23: Optimal outcome through the standard green font printing on a negative black font.

Figure 2.24: Misregistration of a green text under a black negative text with a negative viewing result.

Moiré pattern

In contrast to other fields, where this effect can be useful [172], the printer tries to avoid a Moiré pattern. This pattern changes the outcome of the print, as can be seen in Figure 2.25, where two overlapping colors create a Moiré pattern. A lower frequency artefact. It originates when two similar but slightly different frequencies intersect with each other. In the print, this can be a displacement, rotation, or a slightly different pitch.

These frequencies are only visible in areas with half-tone, as a full-tone floods the region with ink and no single cells can be found. If two separations of a half-tone image overprint and have this wrong combination of parameters, a Moiré pattern can emerge. If the right parameters are chosen, this effect can be minimized, as seen in Figure 2.26. It is not always predictable, as small variations during production can accentuate or diminish this effect, but specific parameters correlate with a higher change of a Moiré pattern.

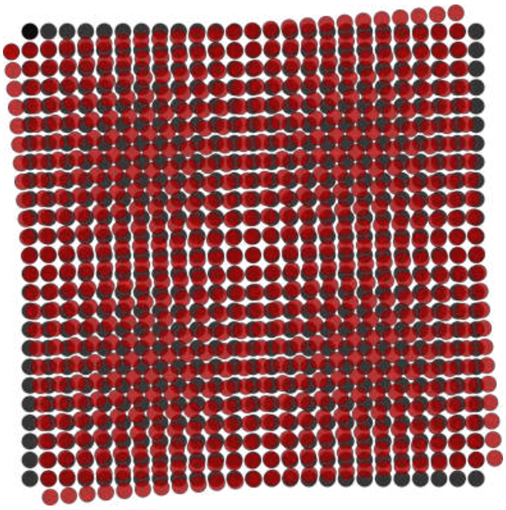

Figure 2.25: Moiré pattern created by a black pattern with a 0° screen angle and a red pattern with 5° screen angle.

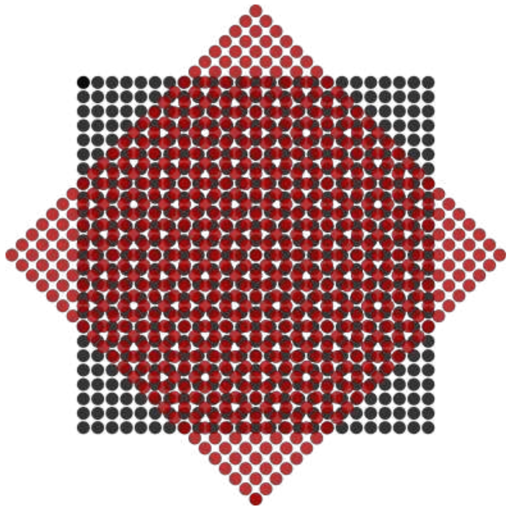

Figure 2.26: Rosette pattern created by a black pattern with a 0° screen angle and a red pattern with 45° screen angle.

As the specific half-tone values of the colors applied are relevant for the existence of a Moiré pattern, these can also be adapted to lessen the impact. The same color can be created by multiple combinations. Through undercolor removal and gray component replacement, the Moiré pattern can be reduced [173]. This offers multiple strategies to reduce the chance of a Moiré pattern.

3. Lean Shopfloor Management Analysis

The purpose of this chapter is to find ways how algorithms and data can be used to improve the strategic alignment in a business. In specific, a method is examined to provide Industry 4.0 leaders with a better understanding of Lean Shopfloor Management (SM) methods through artificial intelligence techniques applied to information collected from portable devices that provide an Electroencephalography (EEG) signal. For this, the initial hypothesis is that Deep Learning (DL) algorithms are capable of characterizing and discerning different types of behavior, once the EEG signal has been properly treated. This is shown in the graphical abstract of the chapter depicted in Figure 3.1. More specifically, the work aims to offer insights into the two major categories of SM systems described in Section 3.1. This is done through the study of the neurological activity of process owners and their leaders performing either method. Non-invasive EEG sensors capture the electrical activity of the brain. A DL soft sensor is used to categorize the data. If the hypothesis is correct, then this would confirm that distinct contrasts in the brain activity during the conduction of different SM systems exist. Furthermore, the correlations of the sensor channels are compared. These correspond to brain regions and show existing differences.

Efficient SM systems will be essential in the transformation process towards Industry 4.0 [174]. Thus, it is of chief benefit to rate these options. Earlier research has focused on the implementation effects of case studies [175]–[178] or used theoretical considerations [179] to assess SM systems. A big detriment is the enormous effort to measure the direct influence of management strategies. For comparison, similar starting positions are necessary. Only then are the outcomes contrastable. The many influencing factors make it challenging to get meaningful results from only a few comparisons. Therefore, alternative concepts that produce more comparable findings are of immense value. Examining the brain activity during the practice of the SM methods opens

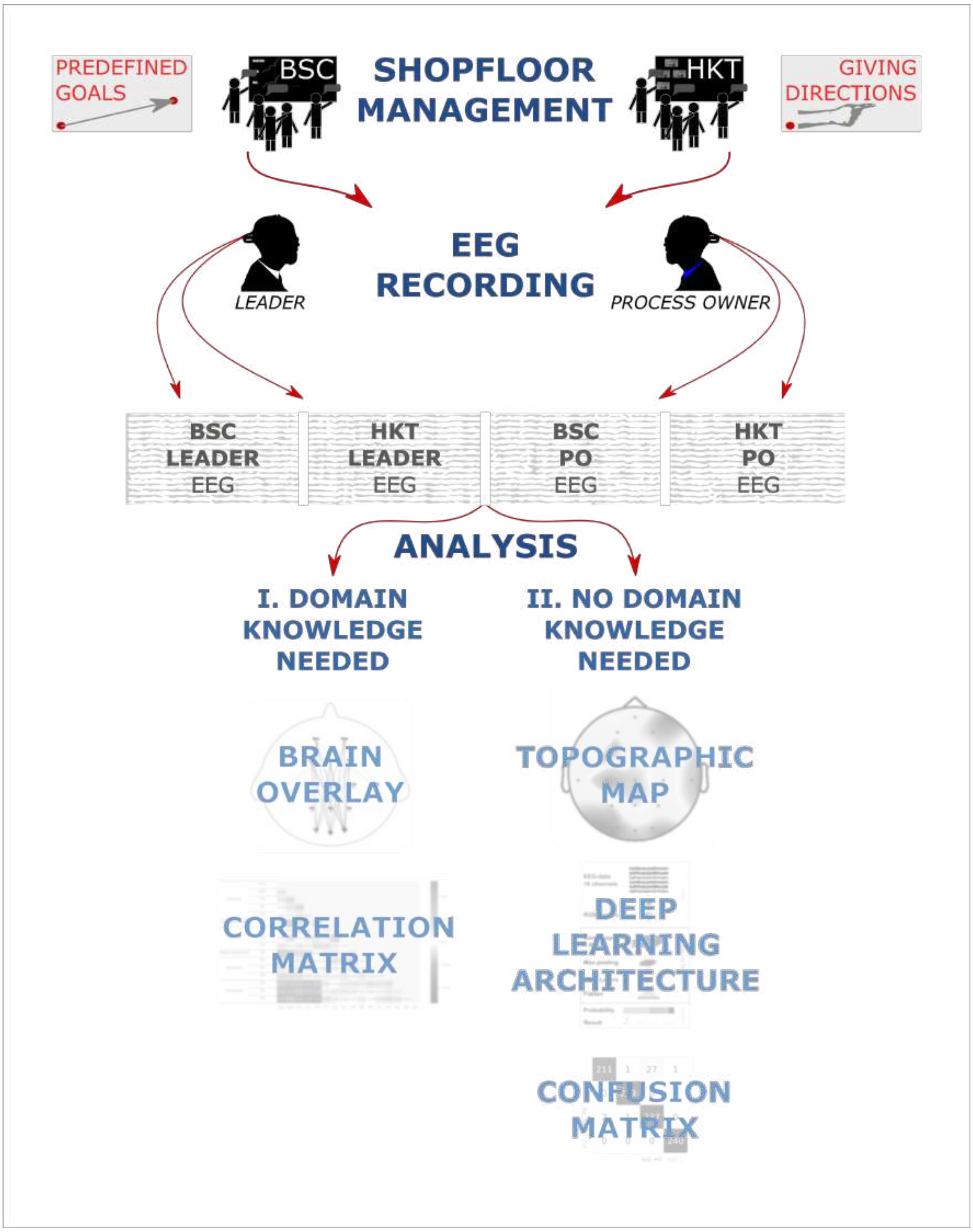

Figure 3.1: Graphical Abstract.

up unique possibilities.

Earlier research demonstrates that significant neurological variations of a Process Owner (PO) using different Lean Management (LM) techniques such as KATA and Check Plan Do Act ((CPD)nA) exist [180]. The aimed added value through this chapter is manifold. Instead of only looking at the brain activity of the PO, this research further takes into account the interaction with his supervisor (in the following "leader") by recording the EEG data of both. It also concentrates on the differences of various *SM systems*. LM and SM have a large overlap, as SM uses many LM methods and tools. The primary distinction is that SM focuses on the aspects of leading and empowering people on the shopfloor [181], the place where the value creation occurs. Furthermore, an alternative way of pre-processing the EEG data for the DL soft sensor is implemented.

Within the Industry 4.0 framework, this affects two points seen in Figure 3.2. First, the human-machine interaction between the user and the EEG-recording device. Second, the management and the factory are influenced by these results. Through this digitalization process, it is expected that an increased value in these areas will be found.

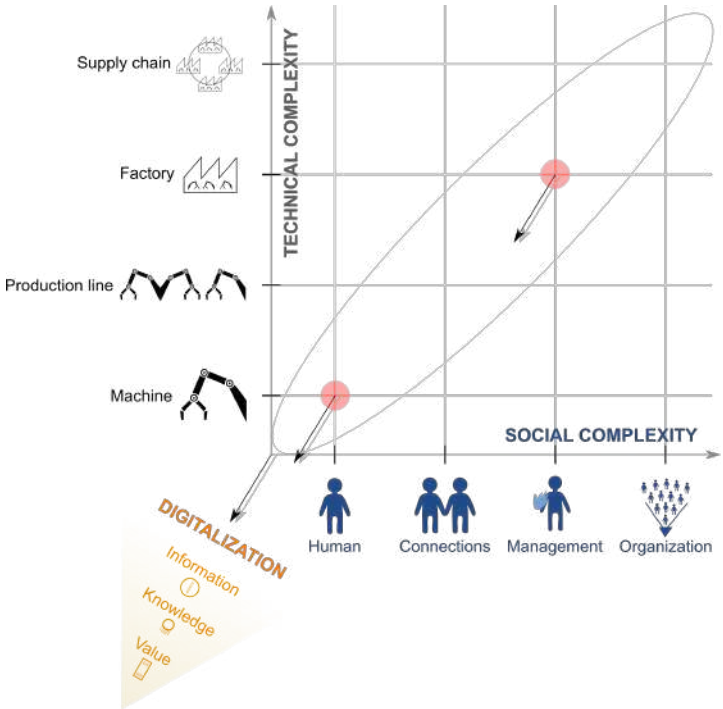

Figure 3.2: Industry 4.0 framework with the main points of this chapter. The graphic is based on the work in [86].

3.1 Management and the brain

Much is still unknown about how the brain functions and above all the human brain. Despite this, many remarkable discoveries of the recent years promote the understanding [182], [183]. These findings can help Industry 4.0 leaders in distinct ways. They make it easier to understand which factors are most important to foster progress. This is attributed to the circumstance that the crucial component in the advancement of a company continues to be using the full potential of the employees [184].

The essential element for continuous improvement through the workers is the ability to form internal goals and to pursue these. In this context, the Prefrontal Cortex (PFC) has been identified as the most important region of the brain that contributes to this [185]. It is the center for cognitive control and makes it possible to act flexible to the outer world. For automatic *"hardwired"* behaviors, it doesn't play any significant role. This leads to the conclusion that substantial activity in the PFC should be expected and seems to be a requirement for a PO practicing an SM system.

Another critical factor is the cooperation between workers to achieve improvements. Understanding the mental state of others is a prerequisite. In this context, there is sound evidence that not only the PFC plays a significant task. Likewise, the left and right Temporoparietal Junctions (TPJ) are indispensable. Though the roles they play seem to differ. While the left appears to be involved in strategic planning of choices concerning humans [186], the right plays a pivotal job for empathy, sympathy and perception [187], [188].

Next to the PFC, the right TPJ additionally seems to play an important role for attention shifting [189]. This is a fundamental aspect in an Industry 4.0 setting, as every part of a manufacturing process is intertwined with other processes. These need to be put into consideration during any change process. Hence it is necessary to be capable of moving the mental focus.

Two distinct SM groups can be identified by focusing on the goal achievement that lays at the core of each management system.

1. Focus on pre-defined goals

   Through pre-defined goals, the focus is set on finding ways to achieve these. This is done through specific key figures, that in the best case give a balanced view on the different achievements or Key-Performance-Indicator (KPI)s [190]–[192].

2. Continuous improvement by giving directions

This group of SM systems only provides a direction (HOSHIN) of improvement. A pre-defined goal is not set. Through this, improvements are approached in a more agile form and can be adapted along the road [122], [193]–[195].

To narrow down the further analysis, one example was chosen for each of the two categories. The Balanced Scorecard (BSC) [196] as a representation of SM systems with pre-defined goals and the Hoshin Kanri Tree (HKT) representing the focus on continuous improvement by giving directions [197].

1. *Balanced Scorecard* is a SM system first described by Kaplan et al. [196] in 1992. The prime goal is to enable a *balanced* view on the driving measures of a business. This works by showing a handful of measurements that allow managers to interpret the complex interactions. Every measurement receives a specific target to motivate the employees to achieve this state. This is in contrast to more traditional approaches. A focus was only set on a few financial performance numbers. These only give a very short-sighted glance on the actual competitiveness of a company.

   One example of a balanced scorecard implementation is visible in figure 3.3 showing the measures of **S**afety, **Q**uality, **D**elivery and **V**alue (*SQDV*). There are many variants in circulation such as **S**afety, **Q**uality, **D**elivery and **C**ustomer (*SQDC*) or **Q**uality, **D**elivery, **I**nventory, and **P**roductivity (*QDIP*) that can also show the priorities of a company by including or excluding specific categories such as **E**nvironment or **S**afety.

   Neely describes the standard way of using *BSC* [198] through the following steps:

   I **Check the current performance.** See how the development is progressing.

   II **Communicate performance** Bring everyone to the same understanding of the current state.

   III **Confirm priorities.** Align the actions needed to improve the performance.

   IV **Compel progress.** Systematically achieve better performances.

   The prime aim is to measure and communicate the achievements towards **predetermined** goals [199]. Niven summarizes balanced scorecard as a conversation tool, a measurement system and a strategic management system [200].

2. *HKT* [197] in contrast is an example of a SM system that focuses on continuous improvement without pre-defined goals. A key feature is the standardization of communication between POs in organizations using the *(CPD)nA* (Check, plan, do, action) framework. Based

on this, a feedback empowerment loop is implemented which makes it possible to build a sustainable process development.

An implementation of the *HKT* can be seen in Figure 3.4. The standard procedure encompasses the following steps as described by Villalba-Diez [201]:

I **Evaluating progress.** Every PO checks if an improvement has been made to his or her *KPI* and places either a red or green magnet on his *(CPD)nA*.

II **Reporting progress.** Only when the *KPI* receives a red magnet, does the progress need to be announced. The others can choose.

III **(CPD)nA.** Every reporting PO ought to follow the *(CPD)nA* behavioral pattern.

IV **Shopfloor visit.** One of the *(CPD)nA*s improvement is checked on site by the complete team.

As shown in Figures 3.3 and 3.4, a visual representation of both types of SM systems displays the main differences between them: BSC is depicting a set of key performance indicators as time series, and the HKT is representing a continuous improvement focused communication network between POs.

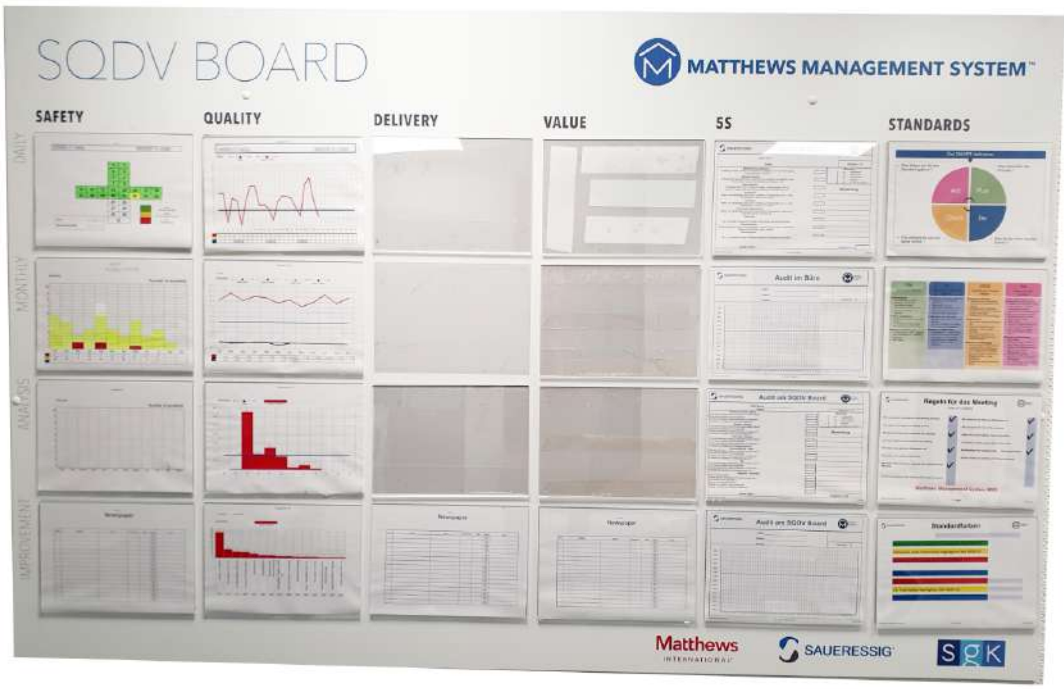

Figure 3.3: SQDV board at Matthews International GmbH, Vreden, Germany as an example of a balanced scorecard management system [196].

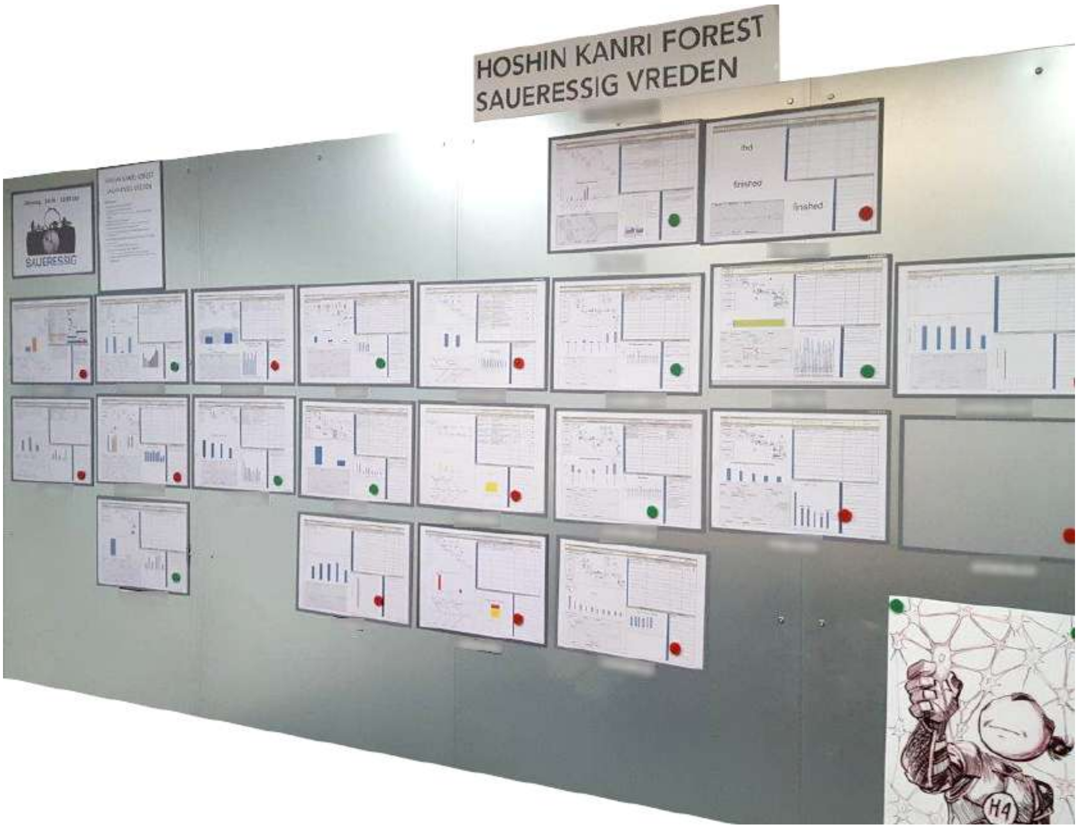

Figure 3.4: Hoshin Kanri Tree [197] at Matthews International GmbH, Vreden, Germany. Process owner names are blurred out for privacy reasons.

3.2 Hypotheses

To analyze the differences of SM systems affecting the brain activity, an experimental setup using EEG recordings can be implemented. Depending on the results to be achieved with the EEG data, distinct methods of investigation are possible. A limited use case is the manual inspection for abnormalities in the EEG data, which can take a long time and presumes at least a basic level of domain knowledge [202]. The frequency analysis has been a more popular method that allows a wider range of applications [203]–[205].

Two distinct techniques are used in this research. These are the correlation function and a DL soft sensor.

1. Correlation Function

   The correlation function has found many use cases. It makes it feasible to classify EEG data [206], identify risk levels for developing schizophrenia [207], detect epileptic stages [208] or to classify EEG Motor imagery [209].

With it, it is possible to determine the similarities between two signals and many application fields use it. In image processing it is for example used for template matching [210] or local image registration [211]. In geology for the location of earthquakes [212].

The cross-correlation function works by sliding one signal along the other, calculating the product between the signals and finding the best fit [213]. Therefore, it is possible to work with time-shifted signals with the cross-correlation function.

2. Deep Learning

   In the last years DL has become a popular technique for analyzing EEG data and has been used to recognize emotions [214], [215], detect Parkinson's [216] and Alzheimer's [217] disease, epileptic seizure prediction [218], the detection and diagnosis of seizures [219] or to decode and visualize the EEG data [220].

   An enormous advantage is that it can handle the complex EEG data with no prior domain knowledge, which allows a wider audience to work with this data. The neural network does this by *learning* the parameters to detect features from examples [221]. This has made it a popular choice for many other fields such as computer vision [222], audio processing [223] or bioinformatics [224]. The key challenge often hindering the further progress with neural networks is the limited data available. This is a prerequisite to represent a high range of input and parameters.

This research aims to expand this approach for the characterization of complex LM / SM associated behavioral patterns in an Industry 4.0 environment. To achieve this, this study outlines the following four research hypotheses (H) and their related LM interpretations shown in Table 3.1. Furthermore, as these hypotheses are based on neurophysiological expert knowledge, management needs to be provided with tools that allow a proper discernment of which behavior is followed, based only on the data. For this reason, a DL-based soft sensor is developed that is able to perform this task. The aim is to examine these with the mentioned methods.

3.3 Materials and Methods

To test the hypotheses, a case study can provide meaningful first impressions if these are valid. Still it is necessary to note that a single study can't give clear-cut proof. In the following the scope of the research is established, the population and sampling is specified, the data collection is further described, as well as the data pre-processing, the standardization procedure and the data analysis.

Table 3.1: Hypotheses regarding the correlations of the brain regions.

#	Hypothesis	Interpretation
H1	The brain patterns of the leaders are expected to show strong correlations between the prefrontal-cortex and the occipital-cortex.	This result can be expected, as the leaders are listening for the majority of the time.
H2	In contrast to *H1*, the brain patterns of the process owners are expected to show significant correlations within the prefrontal-cortex and the occipital-cortex.	This result can be expected, as the process owner speaks for the majority of the time.
H3	Besides *H2*, all subjects are expected to show a high correlation of the prefrontal-cortex.	This could be understood in that way, that the conducted tasks are all executive behavioural patterns.
H4	The brain patterns of *HKT* practitioners are expected to show a strong correlation between the prefrontal-cortex and the TPJ.	The interpretation is that *HKT* is a goal-oriented, context-independent *SM* problem-solving behavioral pattern.
H5	Compared to *HKT*, the brain patterns of *BSC* practitioners are expected to show a weak correlation between the prefrontal-cortex and the TPJ.	This could be understood in that way, that *BSC* is a goal-oriented, context-dependent *SM* problem-solving behavioral pattern.

Scope establishment

For this study, the EEG data from a PO and his supervisor performing a *BSC* and a *HKT* implementation are recorded. All the recordings take place at one corporation. This is an automobile manufacturing facility based in Japan, where LM/SM methodologies were systematically implemented and accompanied by one author of this chapter. The organization of the company can be seen through the HOSHIN KANRI FOREST STRUCTURE in Figure 3.5.

Specifications of population and sampling

For this chapter, data was collected from 14 subject pairs comprising a PO and his supervisor. The age range is between 20 and 60 years with a mean age of 40 years. As far as possible it was made

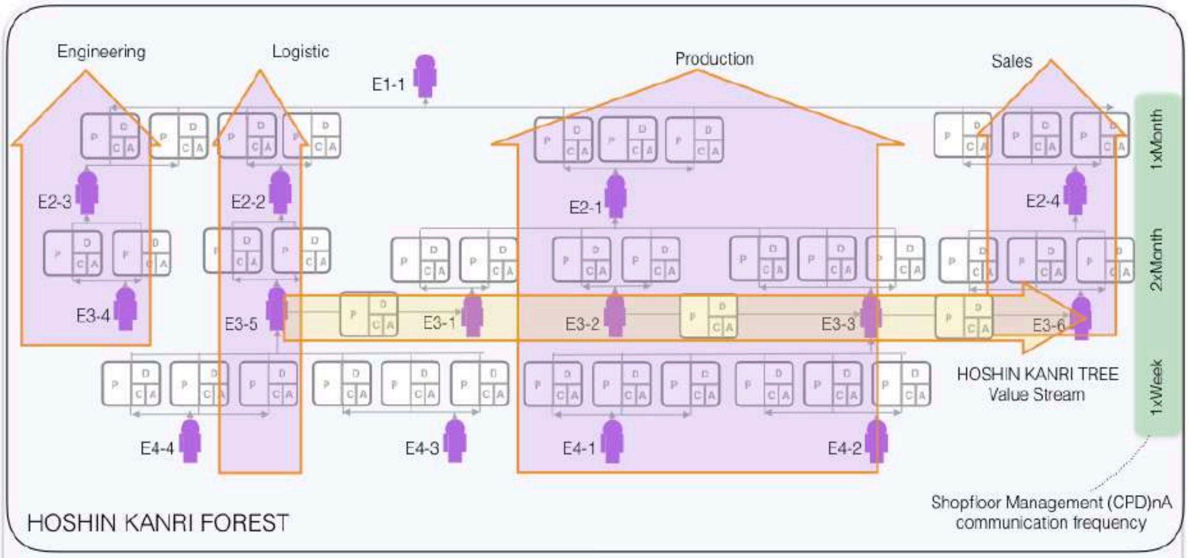

Figure 3.5: Part of the HOSHIN KANRI FOREST STRUCTURE [86]

sure that no significant neurological variations between the subjects should be expected. The subjects were male and had no history of any neurological or psychiatric disorder. Neither was any on chronic medication. All participants were left-hemisphere-dominant persons. Only between the PO and the leader differences could be possible that result from different levels of SM experience. Still, these are not expected to produce significant distinctions for the EEG recordings.

Data collection

To record the EEG data, following 16 channels were chosen as standardized by the American Electroencephalographic Society [225]:

['Fp1', 'Fp2', 'F4', 'Fz', 'F3', 'T7', 'C3', 'Cz', 'C4', 'T8', 'P4', 'Pz', 'P3', 'O1', 'Oz', 'O2']

Through the regulated names, the respective locations on the head during the recording are defined. These can also be seen in Figure 3.6.

The used EEG sensor can be seen in Figure 3.7 and Figure 3.8 and has these specifications [180]:

- Sampling method: Sequential sampling. Single ADC.
- Sampling rate: 128 samples per second (2048 Hz internal).

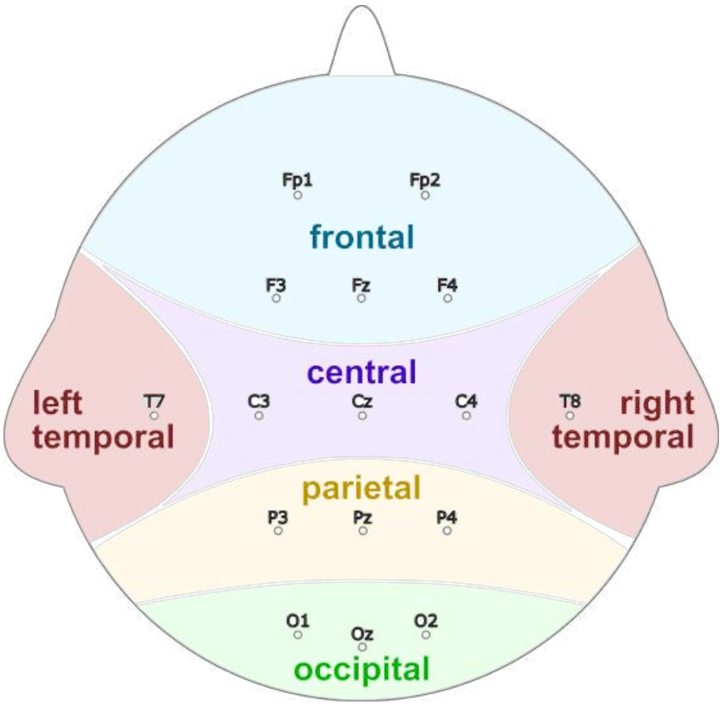

Figure 3.6: The 16 channels with standardized nomenclature that were recorded and the corresponding brain regions.

- Resolution: 14 bits 1 least significant beat = 0.51 μV (16 bit ADC, 2 bits instrumental noise floor discarded), or 16 bits.
- Bandwidth: 0.2 – 43 Hz, digital notch filters at 50 Hz.
- Filtering: Built in digital 5th order Sinc filter.
- Dynamic range (input referred): 8400 μV.
- Coupling mode: AC coupled.

60 seconds were recorded and the hair of all subjects was cut to < 1 mm to receive the best possible quality of the data.

Expected brain patterns

For H1, strong correlations between the prefrontal-cortex and the occipital-cortex are expected. This should show high correlations between the sensors *Fp1-Fp2-F3-Fz-F4* and *O1-Oz-O2*.

For H2, the brain patterns of the process owners are expected to show significant correlations within the prefrontal-cortex and the occipital-cortex. This could be seen in strong correlations within the sensor groups *Fp1-Fp2-F3-Fz-F4* and *O1-Oz-O2*.

In H3, all subjects are expected to show a high correlation within the prefrontal-cortex. This causes high correlations for the sensors *Fp1-Fp2-F3-Fz-F4*.

For H4, the brain patterns of *HKT* practitioners are expected to show a strong correlation between the prefrontal-cortex and the TPJ. This could be seen by high correlations between the sensors *Fp1-Fp2-F3-Fz-F4* and *T7-T8* as well as *P3-P4*.

In H5, the brain patterns of *BSC* practitioners are expected to show a weak correlation between the prefrontal-cortex and the TPJ. This could be seen by low correlations between the sensors *Fp1-Fp2-F3-Fz-F4* and *T7-T8* and *P3-P4*.

Data pre-processing

After recording the EEG data, it needs to be pre-processed to improve the signal-to-noise ratio. This is done in multiple steps and has been achieved with ***Fieldtrip*** [226]. An open access toolbox for pre-processing and analyzing EEG data in ***MATLAB***. A high-pass filter is used to cut out the DC component of the signals, as large drifts were observed in the data. Also, a hardware embedded low-pass filter is used to remove frequencies above 50 Hz. Although it can be possible that gamma waves have an even higher frequency [227], those are usually the result of artifacts during the recording.

In the last step, the data is normalized to the range of -10 to 10, allowing the greatest level of anonymity for the probands. This does not remove any essential information for the further analysis, as relative differences between subjects are not relevant for this study.

Standardization procedure

For every recording, a pair of process owner and his leader are examined. For the first 10 seconds of the recordings, the leader talks, and the PO listens. In the remaining 50 seconds, the process owner presents his results. In this time, the leader observes. This is in contrast to the earlier study [180], where only the process owner of the LM system was recorded without speaking.

During the recording, the pair of PO and leader sit in a room with 50 dBA created noise. This noise level is akin to that of a fridge and makes it possible to have comparable background noises.

Figure 3.7: EEG Low Cost Portable Sensor.

Figure 3.8: EEG Low Cost Portable Sensor.

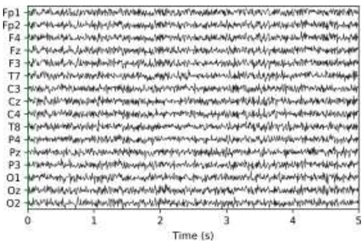

Figure 3.9: 5 seconds of the recorded EEG-data for the HKT leader *Subject* 1.

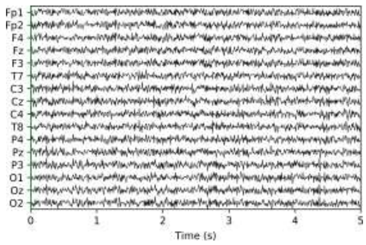

Figure 3.10: 5 seconds of the recorded EEG-data for the BSC leader *Subject* 1.

3.4 Data analysis

In the following section of this chapter, the developed soft sensor is further described. This encompasses the experimental setup 3.4 of the used hardware and software as well as the DL based analysis 3.4.

Experimental Setup

The training and testing of the neural network and the pre-processing has been performed using following hardware:

- *CPU (Central Processing Unit):* Intel(R) Xeon(R) Gold 6154 CPU @ 3.00GHz

- *GPU (Graphics Processing Unit):* NVIDIA Quadro P4000
- *RAM (Random-access Memory):* 192GB DDR4

The source code for the data pre-processing, the training, and testing of the neural network is available under Open Access Repository and was created with ***Jupyter Notebook*** Version 5.7.0.

Correlation Function

For this chapter, the Pearson correlation is calculated which returns a value between -1 for a high negative correlation, 0 for no interrelationship, and +1 for a strong positive correlation [228].

Deep Learning

After the recording and pre-processing of the EEG-data, further steps have to be taken to train the neural network.

1. Data Segmentation

   At first, the pre-processed time-dependent EEG data is split into 0.5 second long segments. It is possible to work with shorter or longer segments such as 1 second [180], [229], but 0.5 seconds was chosen because shorter lengths would decrease the amount of information of a data point and longer lengths would decrease the amount of data points that can be used for training.

2. Image generation

   Through the MNE library [230], [231], these time segments are transformed into topographic maps, as shown in Figures 3.11, 3.12, 3.13 and 3.14. The topographic map displays the activity in the brain, using distinct color tones for the different strengths. To show the brain activity for the complete brain and not just the measured points, the points in between the sensors are interpolated, creating a topographic map for the complete brain. Using more sensors would increase the accuracy of the interpolated area.

   In the example Figures 3.11, 3.12, 3.13 and 3.14, four topographic maps are visible. These show the average brain activity in the first 0.5 seconds for the four different categories.

   The values of the 0.5 second segments stretch to the smallest and largest value, displaying the relative differences on the brain using the *jet* color map as shown in Figure 3.15. This was chosen as the full range of colors is used and the color range does not need to be optimized for the human perception, as this color range is not intuitive for a human [232]. The lowest values are shown as a dark blue, which turns to a green and then to a dark red with the highest value.

The images have a size of 360x360x3 pixel. A different size could have been chosen. Smaller images could decrease the accuracy and larger images would increase the training time.

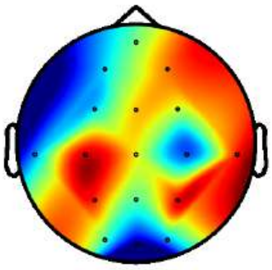

Figure 3.11: *HKT* PO.

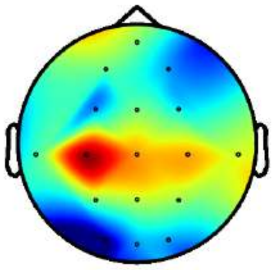

Figure 3.12: *HKT* L.

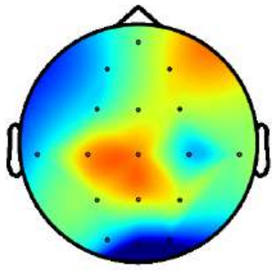

Figure 3.13: *BSC* PO.

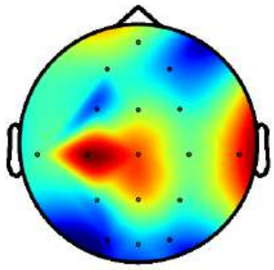

Figure 3.14: *BSC* L.

Figure 3.15: Colormap *Jet* used for the topographic maps

3. Deep Learning Architecture

   With these generated images, a neural network can be trained. In this chapter a convolutional neural network [233] is used, as described in Chapter 2.

   The coarse architecture of the used neural network can be seen in Figure 3.16, the exact composition and the code in the Open Access Repository. Parameters that are set include, among others, the number and the type of layers and the optimizer for the training of the neural network. Here, the *Adam* optimizer is choosen for the training of the network which stands for adaptive moment estimation [234]. The network architecture comprises four repeated layer groups consisting of a convolution, followed by a rectified linear unit (ReLU) activation and a max pooling layer. After this, the network is flattened and a regular, deeply connected neural network layer follows. To reduce the chance of over-fitting, a dropout layer with a ratio of 0.2 is added. The network ends with four outputs that go through the Softmax function to display the probability of the four examined categories.

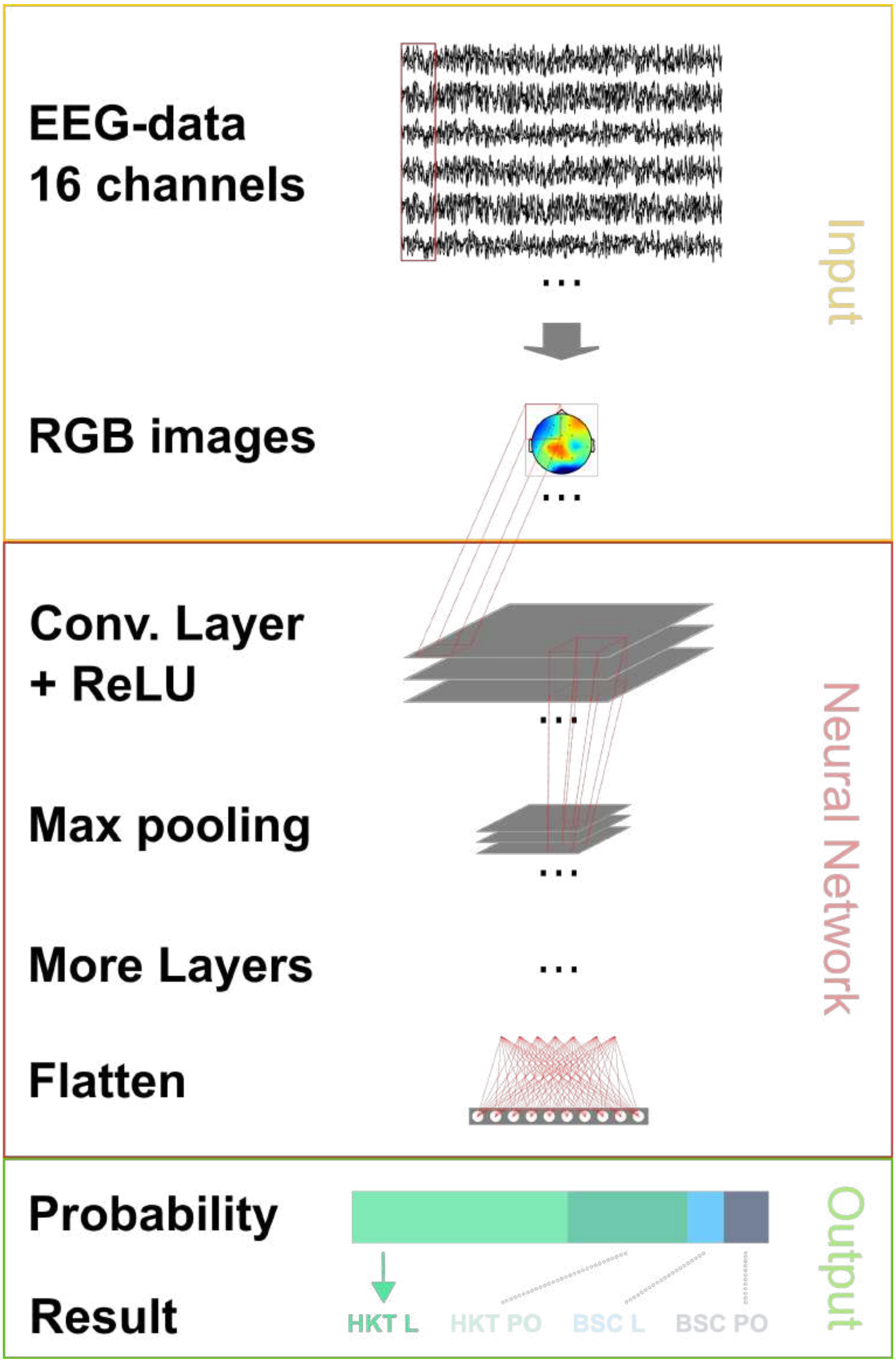

Figure 3.16: Deep Learning architecture for the classification of the EEG-data

3.5 Results

This section presents the obtained results using the recorded EEG-data. It comprises two major parts. Through the analysis of the EEG-data with the help of the correlation function, and through the analysis of the EEG-data with the help of the DL soft sensor. The real-world implications of these findings follow in chapter 6.

Results and Discussion of the Correlation Function

The correlation function can verify the hypotheses presented in Table 3.1. In the following, the results for each hypothesis are examined.

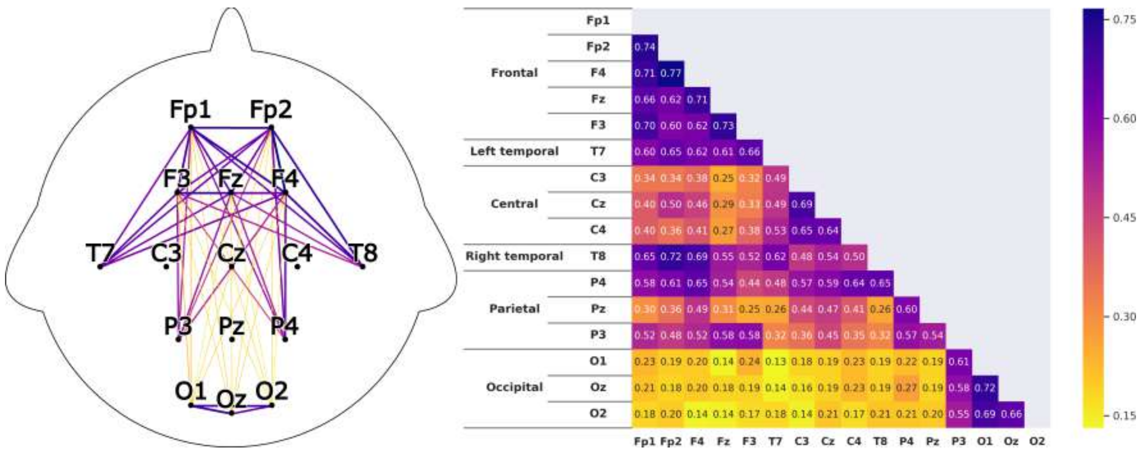

Figure 3.17: Average correlations of the EEG sensors for the *HKT* process owner displayed in two differing layouts. On the left through connecting lines. The strength is visible through the color and the thickness of the line. Only the correlations concerning the 5 hypotheses are shown to have a clearer view. On the right, the correlation matrix for all EEG sensors is displayed.

1. Corresponding to *H1*

   A subject that is listening shows strong correlations **between** the prefrontal-cortex and the occipital cortex. For the recordings, this would mean that a high correlation between the sensors *Fp1-F3-Fp2-F4-Fz* and *O1-Oz-O2* can be found.

   This can clearly be seen in the Figures 3.18 and 3.20. The leaders for both *HKT* and *BSC* show a strong correlation between the prefrontal-cortex and the occipital cortex with values ranging between 0.52 and 0.71 for the HKT leader and values between 0.32 and 0.61 for the BSC leader.

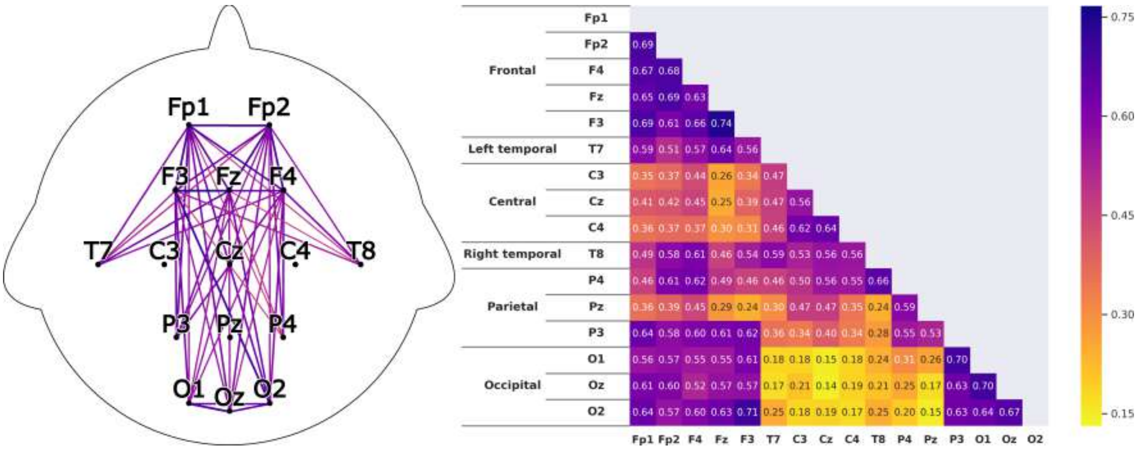

Figure 3.18: Correlations as described in Figure 3.17 for the *HKT* leader.

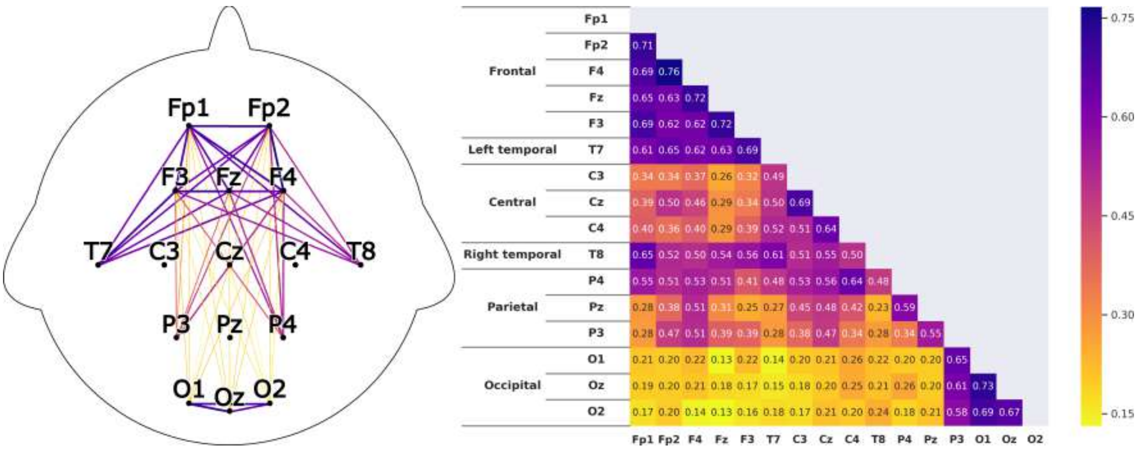

Figure 3.19: Correlations as described in Figure 3.17 for the *BSC* process owner.

2. Corresponding to *H2*

   A subject that is listening shows significant correlations **within** the prefrontal-cortex and the occipital cortex. This would be seen in the recordings through high correlations within the sensor groups *Fp1-F3-Fp2-F4-Fz* and *O1-Oz-O2*.

   This is confirmed in Figures 3.17 and 3.19. Both *HKT* and *BSC* process owner show high correlations within the sensor groups, but not between the sensor groups. The values for the frontal sensor group are in the range from 0.6 to 0.74 for the HKT process owner and 0.62 to 0.76 for the BSC process owner. For the occipital group, the values range between 0.55 and 0.72 for the HKT process owner and 0.58 to 0.73 for the BSC process owner. The values between the frontal and occipital sensor groups only reach up to 0.23 for both HKT PO and BSC PO.

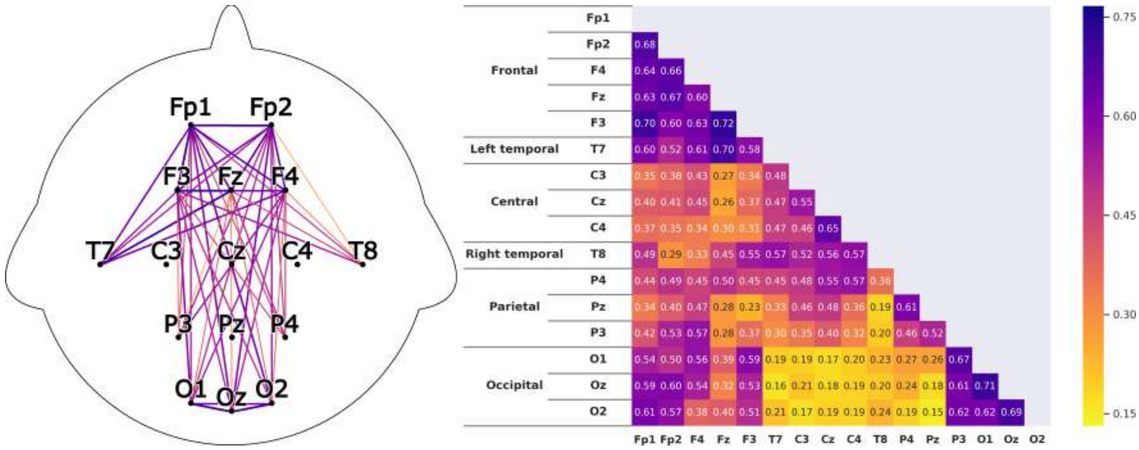

Figure 3.20: Correlations as described in Figure 3.17 for the *BSC* leader.

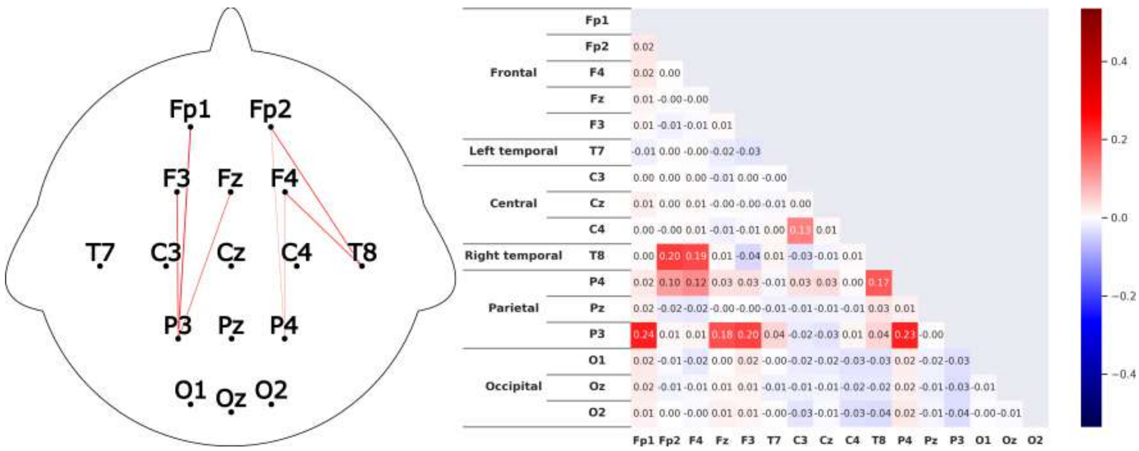

Figure 3.21: Difference of the results between the HKT process owner and the BSC process owner as described in Figure 3.17. Colorscale maximum and minimum are set to the +maximum and -maximum absolute value of the examined differences.

A clear difference between the leaders and process owners can be seen in Figures 3.23 and 3.24, where the biggest differences are the connections between the frontal and occipital group.

3. Corresponding to *H3*

   To confirm an executive behavioural pattern in the neurological activity, a strong correlation in the PFC should be found. For the recordings, this would mean that a high correlation between the sensors *Fp1-F3-Fp2-F4-Fz* should be expected in all four examined categories.

   This is confirmed in Figures 3.18, 3.17, 3.20 and 3.19 showing very high correlations within the frontal sensor group. The minimum value for the weakest correlation of the four subject

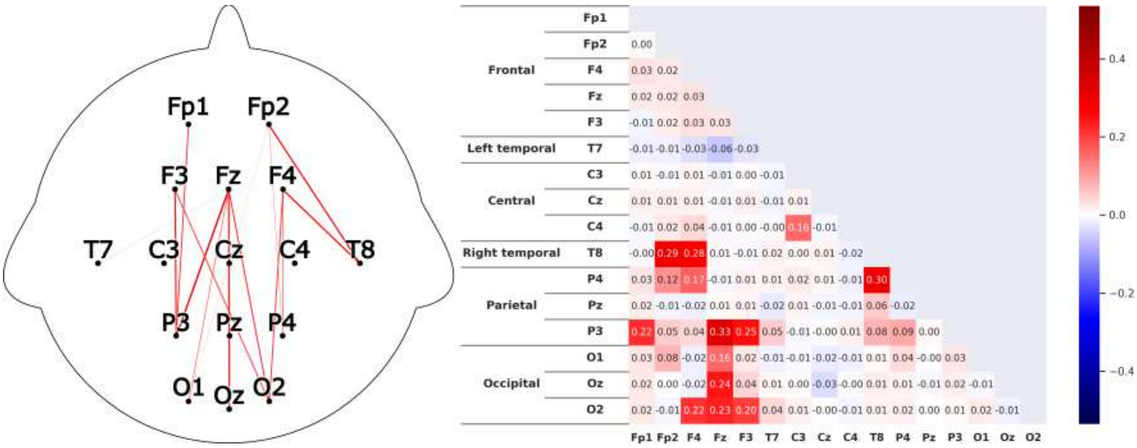

Figure 3.22: Difference of the results between the HKT leader and the BSC leader as described in Figure 3.17.

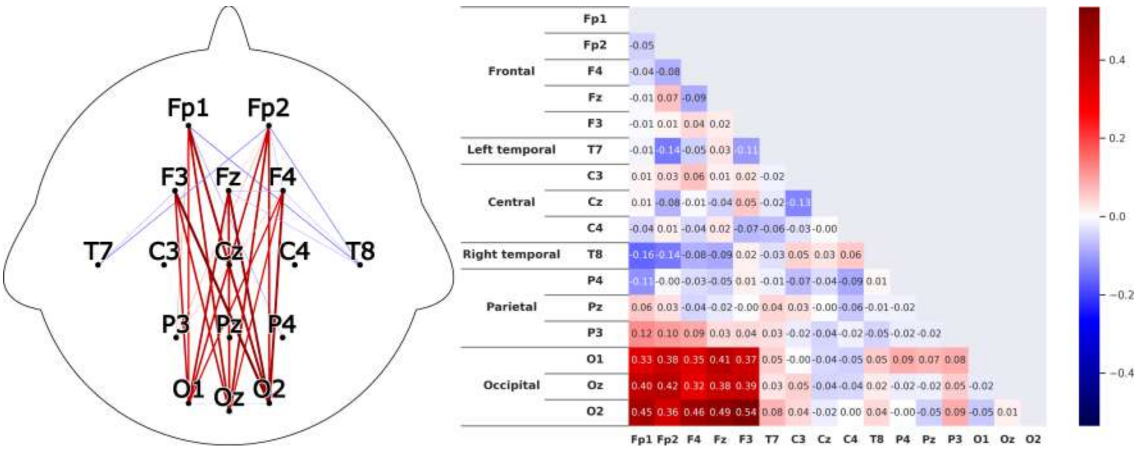

Figure 3.23: Difference of the results between the HKT leader and the HKT process owner as described in Figure 3.17.

groups still reaching 0.6, which can already be considered a strong correlation.

4. Corresponding to *H4*

   To conclude hypothesis 4, it is anticipated that strong correlations can be found between the PFC and the TPJ for *HKT* practitioners.

   In the *EEG* recordings this would be confirmed, if strong correlations between the sensors *Fp1-F3-Fp2-F4-Fz* and *T7-T8*, as well as *P3-P4* can be found.

   This can be seen in Figures 3.17 and 3.18. Values range between 0.52 to 0.72 for the HKT process owner and 0.46 to 0.64 for the HKT leader.

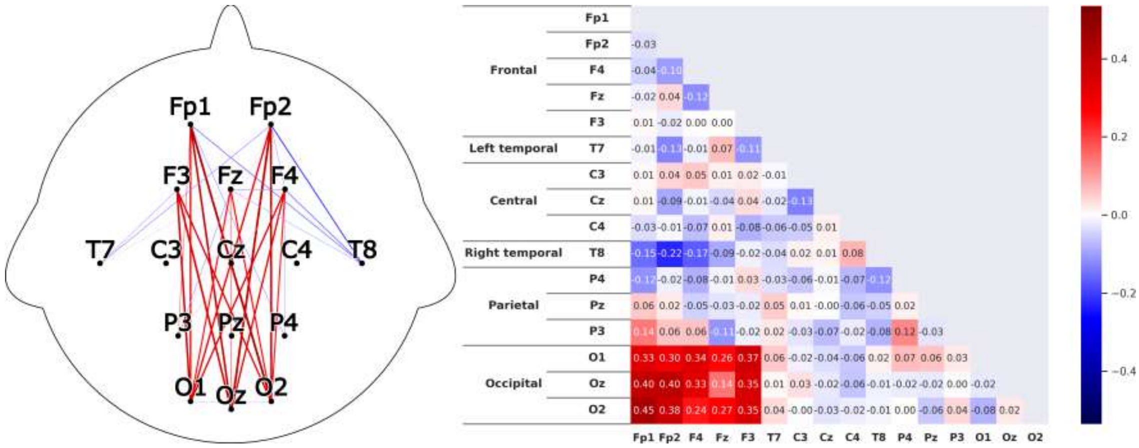

Figure 3.24: Difference of the results between the BSC leader and the BSC process owner as described in Figure 3.17.

5. Corresponding to *H5*

   To conclude hypothesis 5, it is anticipated that only weak correlations can be found between the prefrontal-cortex and the TPJ for *BSC* practitioners.

   In the *EEG* recordings this would be confirmed, if weak correlations between the sensors *Fp1-F3-Fp2-F4-Fz* and *T7-T8* as well as *P3-P4* can be found.

   The results for this hypothesis aren't as clear-cut as the previous. Although clearly lower correlations such as 0.28 for the correlation *Fp1_P3* of the BSC PO can be found, *Fp1_T8* for the same category also shows a correlation of 0.65 in Figure 3.19. What can clearly be seen in the comparison of the BSC PO and the HKT PO in Figure 3.21, is that a handful of the expected correlations of the BSC PO show a significantly lower value compared to the HKT PO. These are the correlations *Fp1_P3*, *Fp2_T8*, *F4_T8*, *Fz_P3*, and *F3_P3*, that on average show a correlation with 0.2 less. This could mean that the right TPJ is less active for the BSC PO. Which in turn would signify that the BSC PO shows weaker activity in the brain region, responsible for empathy or, more general, for the ability to switch between perspectives.

   The difference between the HKT leader and BSC leader in Figure 3.22 shows similar results as between HKT PO and BSC PO. This means that the right TPJ is also more active for the HKT leader than for the BSC leader, which would again mean that also the leader of the BSC shows less activity in the brain region linked to the ability to switch between perspectives.

Results and Discussion of Deep Learning Soft Sensor

With the help of the DL soft sensor, a classification accuracy of 96.5% was able to be achieved. This proves that an automatic classification of the EEG data without the need for any domain knowledge is possible. Furthermore, it reveals that the differences in the neurological activity of the subjects practicing either SM system are significant enough to make this achievable.

To train the Deep Neural Network (DNN), the recorded EEG data was split into three parts. The training, validation, and testing set. By keeping all time slices of a subject pair in one split, it can be assured that the DNN does not learn specifics from the particular pass. Therefore, a split of $10/14 \approx 72\%$, $2/14 \approx 14\%$ and $2/14 \approx 14\%$ was chosen. With 0.5s slices, this equates to 4800 images for the training set, 960 images for the validation set, and 960 images for the test set. Although it would be possible to perform a k-fold cross-validation, this was not chosen, as the data set is big enough for a simple train/test/validation split and it would increase the training time significantly.

The training results in the form of the model loss and accuracy can be seen in Figures 3.25 and 3.26.

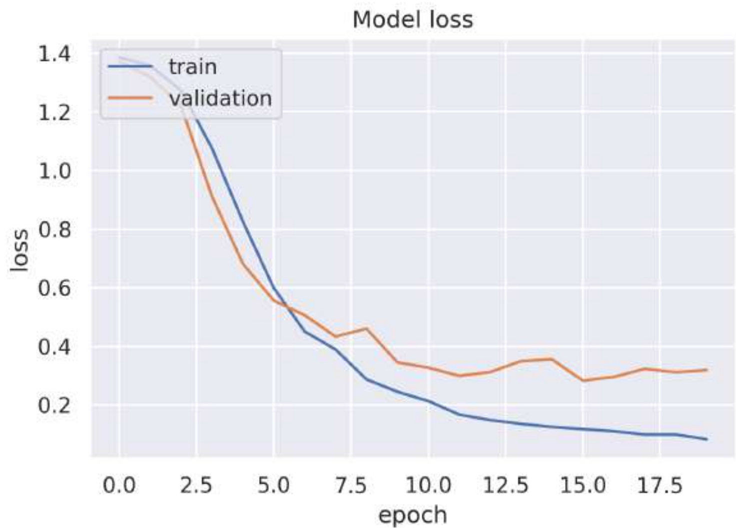

Figure 3.25: Training and validation loss of the trained DL network.

The results from the confusion matrix can be seen in Figure 3.27. In this study, an accuracy of 96.5% has been achieved, which is extremely high, as EEG data usually has a poor signal-to-noise ratio and significant differences between subjects should be expected [235]. Other studies using EEG data and DL for the classification of brain data have also shown positive results. Although it is difficult to compare the applied classification algorithms, as there are few public data sets that are

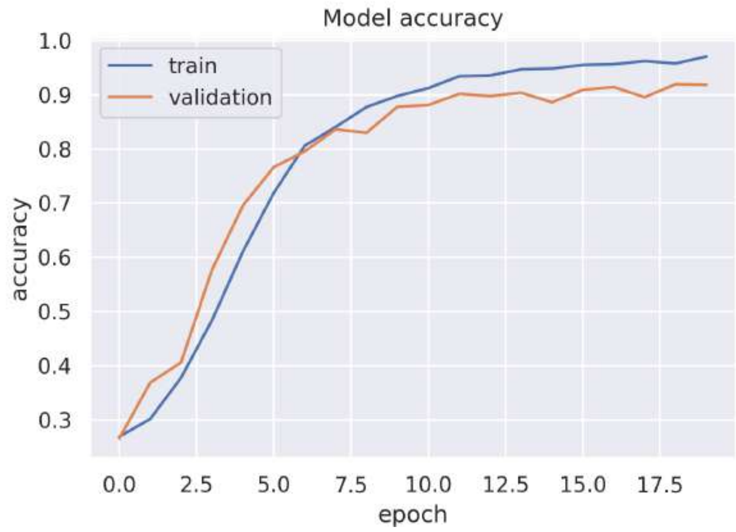

Figure 3.26: Training and validation accuracy of the trained DL network.

consistently used to evaluate the effectiveness of these. Next to Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN)/Long-short-Term Memory (LSTM) implementations have been used extensively. Depending on the classification type, accuracies up to 100% were able to be achieved [236].

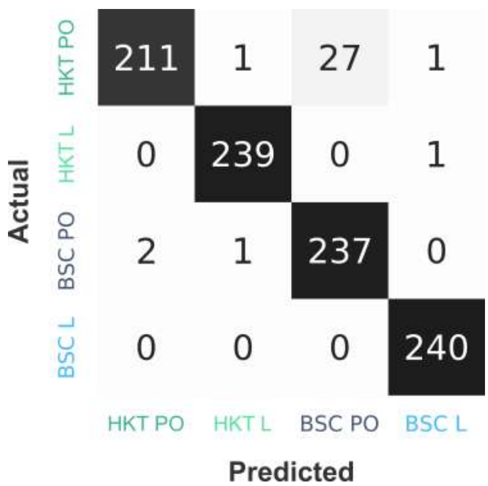

Figure 3.27: Multi-label confusion matrix (n=960) without normalization for the four categories that have been used to train the neural network.

3.6 Conclusions

Research question 1 asks **how algorithms and data can be used to improve the strategic alignment in a business.** As a strategic alignment needs to be found to create value as a collective, a specific focus needs to be laid on it. Through a multidisciplinary approach, this research demonstrates that the the usage of EEG-devices and the analysis of the generated data offers a possible way of receiving information that can be used to improve the strategic alignment of businesses. Through wide-ranging fields such as neuroscience, machine learning, and management science, it has been possible to discover various interesting aspects that support interpreting the thinking processes during the practice of SM systems and with this knowledge, improve the alignment.

It requires to be noted that these are just starting points that need to be confirmed in further studies. The understanding of the brain regions functions is ongoing and the abilities of the regions are not limited to one specific function. The interplay is even more complex and sometimes allows for a wide range of explanations.

Still, the following interpretations can be drawn from the achieved results:

- The studied SM systems both cause large correlations within the PFC for the PO and the leader. This indicates that both systems and both PO and leaders show brain activity that can be considered goal-oriented, which is the core requirement for any kind of improvement and alignment.
- Both BSC and HKT show a solid correlation between the PFC and the left TPJ. The left TPJ, amongst other functions, plays an important role in the strategic planning concerning other people. The difference between BSC and HKT is negligible, but the difference between PO and leader shows interesting patterns. Both correlations *T7_Fp2* and *T7_F3* show noticeable stronger results for the PO. This arises from the different focuses of POs and leaders and demonstrates the different positions in the alignment process.
- The HKT PO shows a substantial correlation with the PFC on the right TPJ. This is especially noticeably compared to the results of the BSC participants. The direction-focused approach seems to enable a wider view, allowing diverse positions to be taken into perspective. This is a crucial characteristic for an Industry 4.0 setting where conflicting information needs to be taken into consideration to find optimal improvements that not only shift the focus but ensure sustainable improvements [57]. This offers first indications that the HKT approach is more suitable for achieving an alignment in a business. The HKT leader shows significantly weaker results in this aspect.

- The SM system BSC on the contrary, demonstrates weak correlations for the right TPJ to the PFC for both PO and leader, while the leader also shows significantly weaker correlations. The reduced correlations of the PFC with the right TPJ indicate that the contemplated perspectives are restricted and the focus on predefined goals limits the aspects that are taken into consideration to receive a goal.

Although the results can be described as preliminary, due in part to the relatively small sample space, if confirmed, the conclusions of this study could have profound implications for the world of western management. The fundamental reason for this assertion lies in the fact that practically the entire corporate culture of operational management is based on the achievement of objectives. In a business environment in which the complexity of processes is constantly increasing, management models that favour a holistic understanding of this reality. Studies such as the one presented, which is clearly multidisciplinary, present, with the help of artificial intelligence, the differences between types of management and the effects that management could have on POs in a quantitative way.

The classification results of the EEG-data emphasize that significant and distinct differences in the brain activity of the examined leadership patterns exist and can be learned by a DNN. Furthermore, the implemented classifier allows for different usages. As the classification can be done in real time, direct feedback can be given. This could, for example, be used during the training of a SM system. An employee with an EEG-device connected to the trained DNN could receive valuable feedback to differentiate the systems and better understand the thinking patterns.

Limitations and further research

A comparison of the subjects would be of high interest to know how far these results are valid for all subjects and which differences can be expected. In this way, possible differences between experience, age, and gender could be examined and it would be possible to see if alterations in group size could change the results. Due to the compliance rules of the organization, this was not possible.

Future research could test the influence of the cultural background and how experience in LM/SM changes the subject's brain patterns. It could also be of interest to examine the influence of the subject speaking during the recording process.

In a broader examination, the **results** of groups using different SM systems with the goal of achieving strategic alignment should be examined. This could confirm if the results found through the brain signals are also seen in the implementation. It requires numerous data points and different metrics to measure this, but could have significant implications in the decision of applying either of these two groups of SM systems.

4. Deep Learning for manufacturing improvement

The goal of this chapter is to find ways to improve a manufacturing line with the help of algorithms and data. More specifically Deep Learning (DL). A soft sensor Deep Neural Network (DNN) is presented that performs a ***classification*** of images from high-resolution cameras towards a fully computer vision based Optical Quality Control (OQC) of the printing cylinder of a global leading player in the Printing Industry 4.0. As shown in detail in Section 4.2, this aims to increase the accuracy of the quality inspection process by first supporting the human expert final decision-making, thereby reducing the cost of quality inspection process through automatization of the visual processing. This ought to be contextualized in a hostile industrial context in which the complexity of error detection is very high due both to the extraordinary variability of possible errors, as well as the changing environmental conditions of light, moisture, dirt, and pollution - all of which can confuse the best algorithms developed thus far. Furthermore, this information can be used to improve the quality and through this, further decrease costs and add value to the production line.

This work can be placed with two points in the Industry 4.0 framework seen in Figure 4.1. A human and the machine, as well as their interaction in the form of the machine and software with the user. In a wider context, the resulting information can be used to change the working of the production line and the connections of the workers. This can be done by not only using the information to detect the defects, but to use this information in the production line to understand where and why this defect originated.

The rest of the chapter is structured to ensure clarity in the presentation, replication of the results obtained, and a proper framing in the ongoing global context of the fourth industrial revolution. Section 4.1 briefly shows the continuous improvement of the manufacturing value stream of an

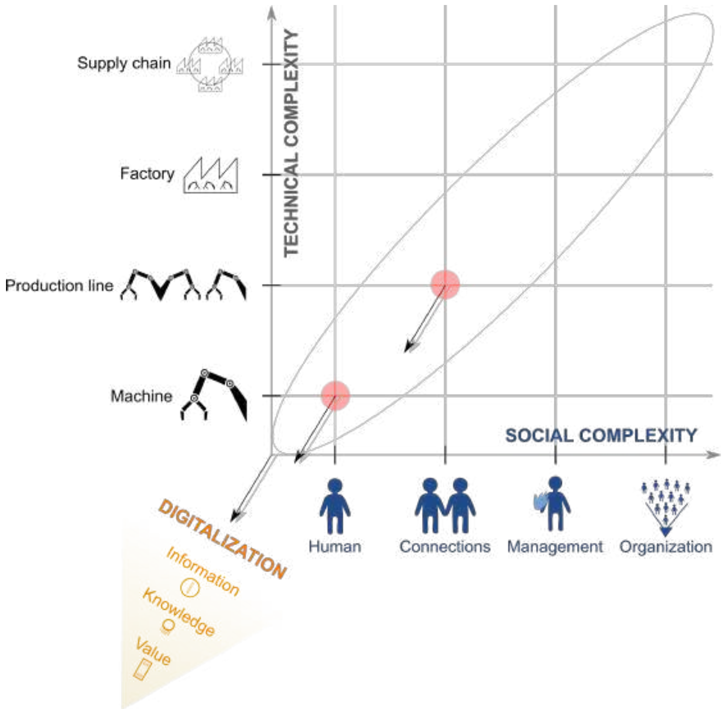

Figure 4.1: Industry 4.0 framework with the main point of this chapter. The graphic is based on the work in [86].

Industry 4.0 leader that made the integration of DL technology possible. Section 4.2 outlines the ***materials and methods*** used to design and implement a better performing OQC integrated DNN soft sensor. Additionally, DNN computer code is made available on an Open Access Repository. Further, Sections 4.3 to 4.6 look at the possibility of using the data gained through the OQC to improve the quality. Finally, Section 4.7 closes this chapter with the conclusions to the research question 2.

4.1 Evolution towards automatic deep learning-based quality control

To frame this research in a more general context and to allow its replication in other value streams, it is important to describe the constant process of continuous improvement [237] that a leading player in the printing industry has followed in recent years to reach the level that has allowed the implementation of the presented DL-based OQC research.

To make it easier for interested readers to recognize the fundamental phases of this OQC evolutional continuous improvement process that paved the road for a fully automatized computer vision OQC process have been summarized in the following and are depicted in Figures 4.2, 4.3,4.4, 4.5.

Figure 4.2: Manual Inspection of Printed Product.

Figure 4.3: Manual Inspection of Monochrome Printed Product.

Figure 4.4: Expert Evaluation with the help of the software cLynx.

Figure 4.5: Machine used to scan the cylinder surface.

- Manual Inspection of Printed Product (Figure 4.2)

  In the first stage, all cylinders of an order were printed together. Due to the processes used producing gravure cylinders, mistakes like holes in the cylinder are almost inevitable. To check the quality of the gravure cylinders, all the cylinders of one order are generally printed together and the resulting print checked manually with the help of a magnifying glass. To do this, the approximate color of each individual cylinder must be mixed and all cylinders are printed one after the other on one substrate. On average, this can be 5-10 cylinders or colours in one job. The big disadvantage is that all cylinders of a job must already be present. Thus, a one-piece flow is not possible. In addition, a lot of time is spent mixing the colours.

As a direct comparison with the expected data was very difficult, the search for errors was focused on the most common errors that can happen during the production of an engraved printing cylinder. The coppering of the cylinder is a galvanic process, therefore it is possible that the cylinder has holes that also print. Another common mistake in the production of engraved printing cylinders is that parts that should print do not print. This can have different causes. Most of them can be traced back to problems during the engraving of the cylinder. To find these errors without a comparison to the expected data, a search for irregularities is then carried out. As there are a lot of issues that had to be checked, it was quite an ergonomically challenging job, where some mistakes were not caught during the check.

- Manual Inspection of Individual Color Printed Product (Figure 4.3)

  In the second stage, the cylinders were all printed individually in the same (green) colour. In an attempt to further improve the quality control of each individual cylinder, the cylinder can also be printed itself. This impression was also checked manually with a magnifying glass by process experts. This has the advantage that there is no need to wait for the other cylinders of a job and no need to mix colours. However, the manual reading of the prints takes longer because there is one print for every cylinder of an order (5-10 cylinders) and not only one print for one order. Although this increased process reliability because process mistakes were directly tested on the product, the ergonomic weaknesses of the OQC process based on human experts could not be eliminated with this new improvement.

- Evaluation of Errors by an Expert with aid of patented Software cLynx (Figure 4.4)

  This was then solved by the third stage: the digital scanning of the cylinder supported by the patented cLynx software (DE102017105704B3) [238]. To improve the quality and automate the process, a software named cLynx was developed to automatically compare the scanned file with the engraving file. The invention relates to a method for checking a printing form, in particular a gravure cylinder, for errors in an engraving printing form. A press proof of a cylinder gets printed and scanned using a high-resolution scanner. To compare the scans with the engraving file, a sequence of registration steps are performed. As a result, the scans are matched with the engraving file. The differences between the two files are subject to a threshold in order to present the operator with a series of possible errors. As a result, the complexity of checking the entire print is reduced to a few possible errors that are checked by the operator. Since most of the work of troubleshooting was done by scanning + software, only the most conspicuous spots found by the software had to be evaluated by an expert.

- Machine scans the cylinder and integrates the software cLynx (Figure 4.5)

In the fourth stage, the entire printing process is omitted, as the cylinder surface is recorded directly with a camera within a cylinder scanning machine. To further reduce the cost of quality inspection, there is a need to check the cylinder without having to print it. To scan the surface of the cylinder, a machine was built with a high-resolution line camera that scans the rotating cylinder at an approximate current speed of 1 meter/second. Because the scanning itself takes a minor portion of the processing time, this speed could actually be increased with a brighter LED lamp. After every movement, a picture is taken, resulting in a flat image of the cylinder (Figure 4.6). The main principles stay the same as with the scanned prints, as two complete recordings of the cylinder are made. These get matched to the engraving file and possible errors are presented to the operator using fixed thresholds (Figure 4.7). This is done by automatically selecting areas around possible errors and calculating the absolute difference between the cylinder scan and the layout engraving file as shown in Figures 4.8, 4.9, 4.10. This significantly shortens the inspection time. However, the most prominent areas still have to be evaluated manually by the employee. For this reason, another fifth step towards a fully automated process is desired.

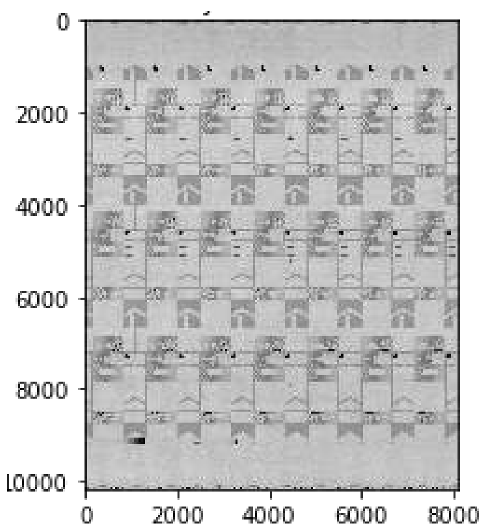

Figure 4.6: Cylinder Scan.

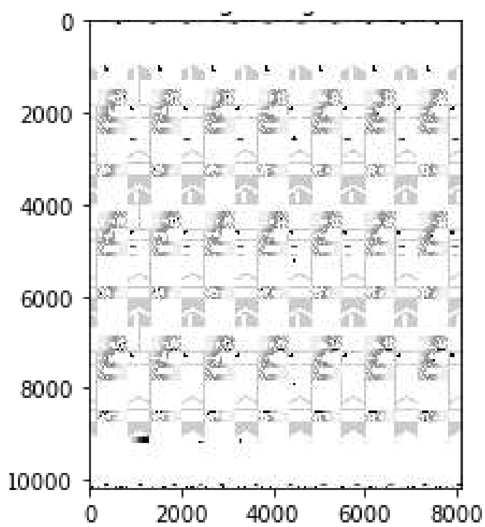

Figure 4.7: Cylinder Engraving File.

4.2 Deep learning for industrial computer vision quality control

To reduce time checking possible mistakes on the cylinder, and further reduce OQC cost and value stream-related lead time, an automatic pre-selection of the errors using artificial intelligence is de-

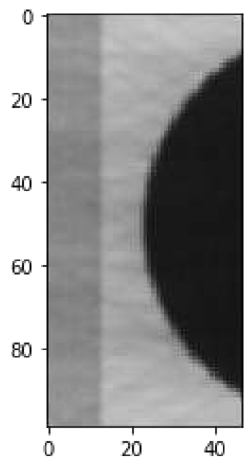

Figure 4.8: Detail Cylinder Scan.

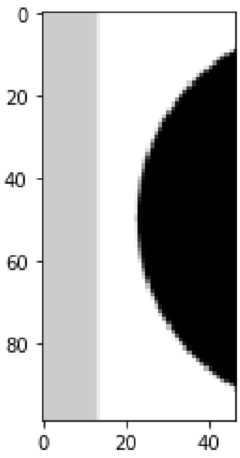

Figure 4.9: Detail Engraving Layout.

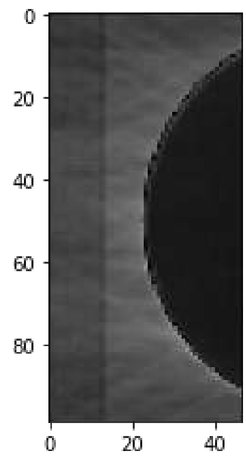

Figure 4.10: Absolute Difference.

sired. Due to intensive research investment and strategic focus on quality control throughout the value stream process, real noisy industrial data has been classified and properly labelled. This is how the idea was born to design a DNN that would learn from the statistical information embedded within the previously classified data to perform a fully automated computer vision quality control.

Due to intensive research investment and strategic focus on quality control throughout the value stream process, there were previously numerous classified and properly labeled data aggregated through the fourth stage. Possible errors were selected using thresholds between the original file and the scanned cylinder. These were then shown to the operator, who judged them as if they were real errors. These judgements were then saved comprising the labeled data-set.

In the fifth stage, the process is taken over by a fully automated DNN architecture. As proposed in this chapter (see Section 4.2), after an intensive experimental program, which has tested different configurations of different filter sizes, abstraction layers, etc., this version was selected [239].

The DNN soft sensor presented achieves an accuracy of 98.4% in fully automatic recognition of production errors. More details are provided in the following subsections. This contribution makes it possible to decide immediately after scanning whether the cylinder can be delivered or whether errors need to be corrected. It was decided not to use specific denoising treatments as specific filters before classification [240], [241]. This is because of the intrinsic capabilities found in the adopted Convolutional Neural Network (CNN) architecture.

Deep Neural Network Architecture for Computer Vision in Industrial Quality Control in the Printing Industry 4.0

Experimental Setup

The experiments in this study were implemented with a computer equipped with an Intel(R) Xeon(R) Gold 6154 3.00GHz CPU and an NVIDIA Quadro P4000 Graphic Process Unit (GPU) with 96 GB of Random-Access Memory (RAM). The operating system was ***Red Hat Linux*** 16.04 64-bit version.

The DL model training and testing were conducted with ***Keras*** which is an interface for ***TensorFlow*** (Version 1.8), and the model was built in ***Python*** (Version 2.7) language [242]. TensorFlow is an interface for expressing machine learning algorithms, and an application for executing such algorithms, including training and inference algorithms for DNN models. More specifically, the TF.Learn module of TensorFlow was adopted for creating, configuring, training, and evaluating the DNN. TF.Learn is a high-level Python module for distributed machine learning inside TensorFlow. It integrates a wide range of state-of-the-art machine learning algorithms built on top of TensorFlow's low-level APIs for small- to large-scale supervised and unsupervised problems. Additional Python interfaces were used: ***OpenCV*** for computer vision algorithms and image processing, ***Numpy*** for scientific computing and array calculation, and ***Matplotlib*** for displaying plots. The details of building the DNN model for OQC with Python are provided online at Open Access Repository and were created with ***Jupyter Notebook***.

Data Pre-processing

In order to train the DNN, standardized, classified input data is needed. For this reason, the Data pre-processing is divided in three steps: (1) decision of which is the size of the image that serves as input for the DNN and what the size of the convolutional window used by the DNN should be, (2) brightness adjustment through a histogram stretching, and (3) automatize the selection and labelling of the file structure to be fed to the DNN.

1. Image Size for DNN Input and Convolutional Window Size

   Due to the need for standardized input data, a decision needs to be made about which dimensions the input images should have. The first decision is the aspect ratio. The following decision should be how many pixels wide and high the input images should be. In order to get a first impression of the existing sizes, a short analysis of the previous manually confirmed errors is made. According to the data, the mean value of the width is slightly higher than that of the height. In the mean aspect ratio, this gets even clearer, with a mean aspect ratio of about 1.5. This is probably a result of some errors that are elongated by the rotation of the cylinder. The median aspect ratio is exactly at 1.0. Because the median describes a higher percentage of errors better, this should also be the aspect ratio of the neural network input. As shown in the representation of the width and height of error in pixel against the LOG of the amount of errors in Figures 4.11 and 4.12.

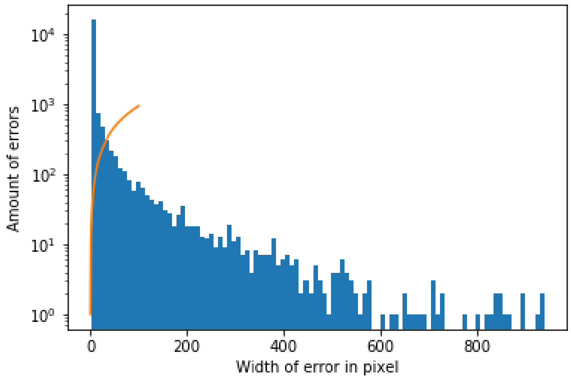

Figure 4.11: Width of errors vs. LOG Number of errors.

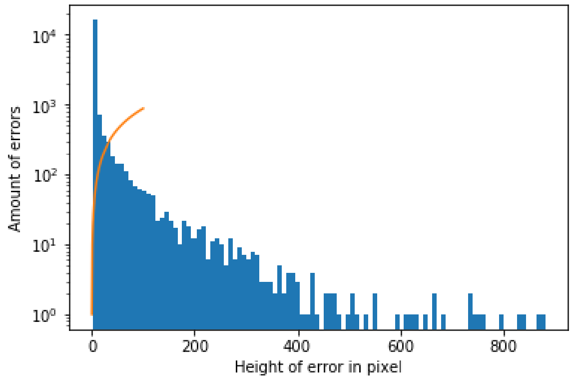

Figure 4.12: Height of errors vs. LOG Number of errors.

As the size of the error also plays a role in the judgment of the errors, scaling operations should be reduced to a minimum. Because of the range of the sizes, this is not always possible. The training time of the neural network would increase dramatically with large input sizes and small errors would mostly consist of *OK*-cylinder surface. Therefore, a middle ground is needed so that most input images can be shown without much scaling or added *OK*-cylinder surface. A size in the middle would be 100 pixels. We therefore calculate the percentage of errors with the width smaller or equal to 100. The results show that about 90% of all errors have both the height and width below or equal to 100 and almost 74% have both the height and width below or equal to 10. One option would be to use an input size of 100x100.

2. Brightness Adjustment

   To get comparable data for all cylinder images, pre-processing is needed and is performed on the complete scan of a cylinder. From this scan, multiple examples are taken. Because there can be slight deviations due to many influences during the recording of the cylinder surface, this can only be achieved by having a similar brightness for the cylinder surface and engraved parts. Another important point is that no essential information gets lost from the images and, that the brightness between the engraved and not engraved parts are comparable for all cylinder scans. Therefore, a brightness stretch is needed, but only a few pixels are allowed to become the darkest or brightest pixels. Notwithstanding, the amount of pixel that become the darkest and brightest pixels cannot be set to a very low value because noise in the image data would result in big differences. In conclusion, a low percentage of the pixels should be set as darkest and brightest. For example, the lowest and the highest percentage should each have a maximum of 0.5%. Figures 4.13 and 4.14 show a stretching example for brightness adjustment for one image so that 0.5% of all pixels will have a value of 0 and 0.5% of all pixels will have the value of 255.

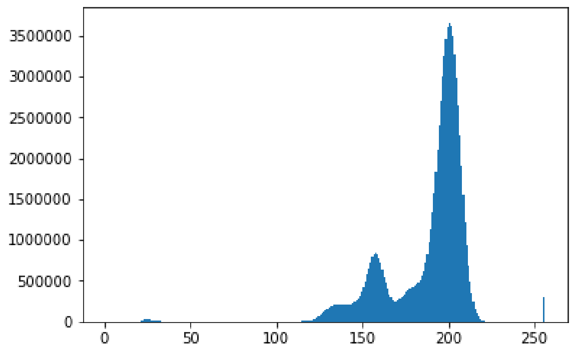

Figure 4.13: Histogram before stretching.

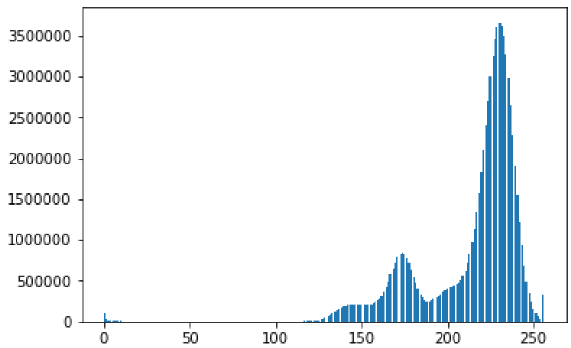

Figure 4.14: Histogram after stretching.

3. Automatic selection and Dataset Labelling

   To simplify the later steps, the images need to be cut from the original file and saved into two folders with examples that are ***OK***-cylinder (Figure 4.15) and examples that are ***not-OK***-cylinder (Figure 4.16). The great variety of patterns presented in the spectrum can be observed in the figures. The very nature of the process implies that each new product represents a new challenge for DNN, as it has probably never before been confronted with these images. For this reason, the errors may be of a very different nature. This implies a high complexity of solving the challenge of training and testing the DNN. Likewise, the different shades of black and grey, very difficult to appreciate with the naked eye when manually sorting the images, represent an added difficulty that must be resolved by DNN architecture.

   If errors are smaller in width or height than 100, the region of interest gets increased to 100. In the rare cases where any side is bigger than 100 pixels, the split subimages are used for the test-data. As shown in the Open Access Repository, there are multiple possible ways to handle the bigger data.

Every example of data contains the actual and target data. There are different ways of using this data as input. One way is just using the actual data. A different option is to use the difference between the actual and expected data. The problem in both cases is that information gets lost. Better results have been achieved by using the differences. These get adjusted, so that the input data is in a range from $[-1,1]$. Once this is performed, and because a balanced dataset is important to train the neural network and the *OK*-cylinder examples far outnumber the ***not-OK***-cylinder examples, an *OK*-cylinder example is only saved if a ***not-OK***-cylinder example has been found previously.

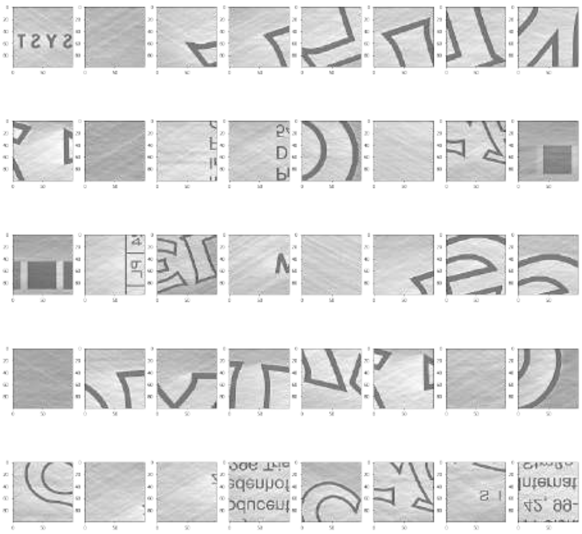

Figure 4.15: OK cylinder Images.

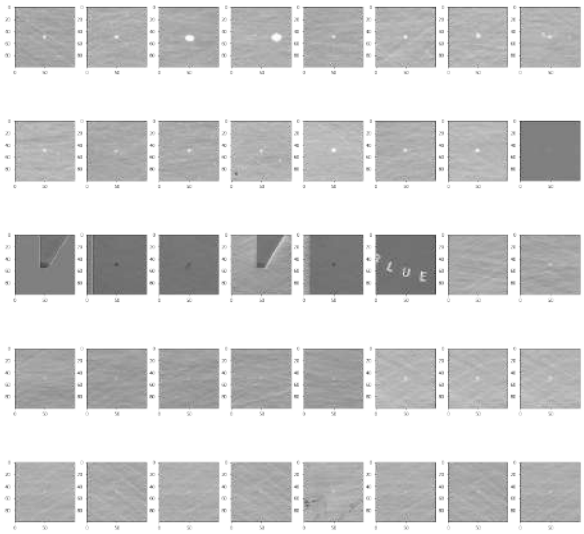

Figure 4.16: not-OK cylinder Images.

Automatic detection of cylinder errors using a DNN soft sensor

The DNN soft sensor architecture design is performed with two main goals in mind: classification and performance:

- *Classification*. The first goal of this architecture is not to identify different objects inside of a part of the image but to separate two classes (***not-OK*** and ***OK*** images), where the main source of noise comes from the illumination factor from the scanner lectures. Therefore, neither the deep architecture nor the identity transference, which is the key for the ResNet [243] is needed in our case, and just a few convolutions shall help identify convenient structural features to rely on.
- *Performance*. The proposed architecture is even more simplistic than the AlexNet [93] one, as not five convolution layers are just but just three. The main reason is to look for a com-

promise between the number of parameters and the available dataset of images. The architecture was always looking to be *frugal* in terms of resources, as it is expected to be a soft sensor, running in real time.

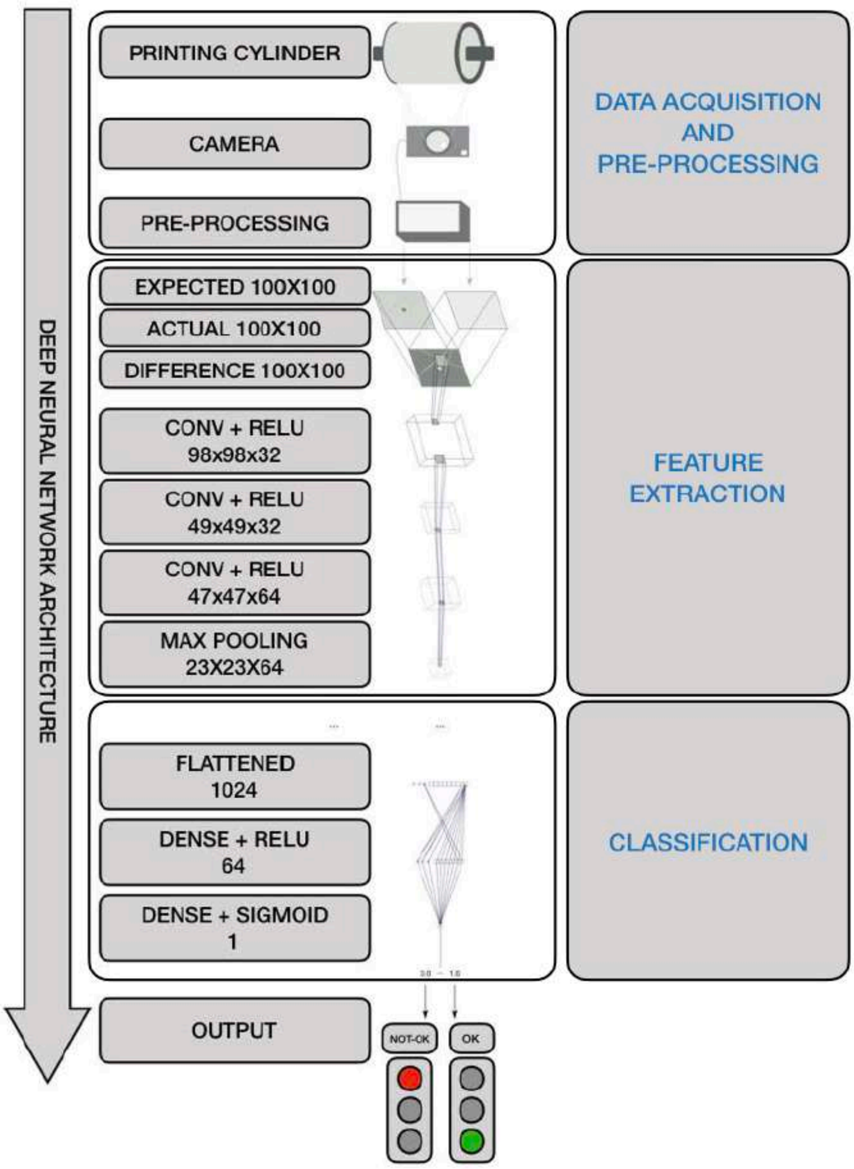

Figure 4.17: Deep Learning Architecture for Industrial Computer Vision OQC in the Printing Industry 4.0.

After data acquisition and preprocessing, the input data of the DNN is represented as a tensor. A type of network that performs well on the classification problem of such data is usually divided in two main parts: feature extractors and classifiers, as shown in Figure 4.17.

As shown in the Open Access Repository, using Keras, Tensorflow backend for the DNN and OpenCV/Numpy for image manipulation, a balanced dataset of 13335 ***not-OK***- and 13335 ***OK***-cylinder examples is used, giving a total of 26670. These were collected over a period of 14 months from almost 4000 cylinder scans. The training images are mirrored vertically and horizontally, resulting in 85344 training samples in total. All ***not-OK***- cylinder examples are labeled ***0*** and all Ok examples are labeled ***1***. As the standard procedure, the data is split into ***training dataset*** (80%), ***testing dataset*** (10%) and ***validation dataset*** (10%). The ***training dataset*** is used to train the DNN throughout a number of epochs as shown in Figures 4.18 and 4.19. It can be observed that both accuracy and loss do not increase or decrease significantly after epoch number 10.

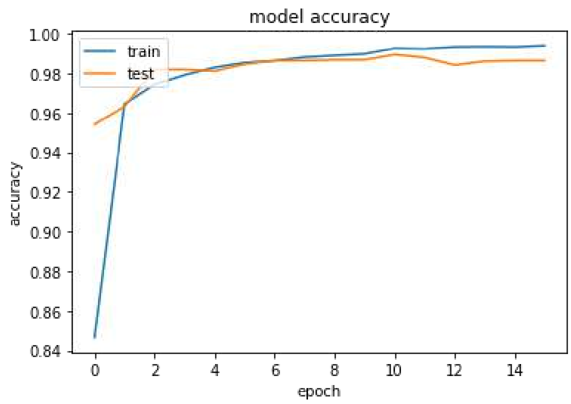

Figure 4.18: DNN Model Training Accuracy.

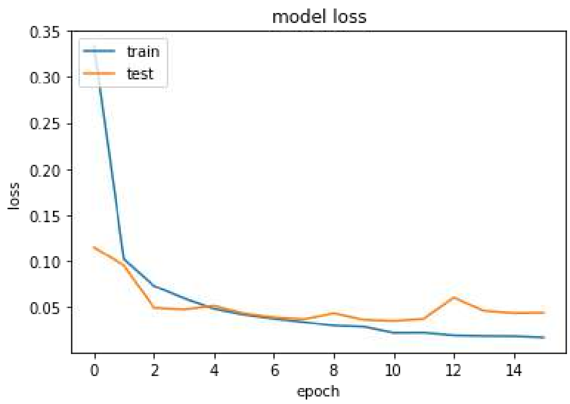

Figure 4.19: DNN Model Training Loss.

The ***testing dataset*** is subsequently used to test DNN performance. Specifically, given the balanced dataset chosen, the accuracy delivered by the DNN soft sensor is 98.4%. The *TN* rate is 97.85%, the *TP* rate is 99.01%, the *FN* rate is 2.15% and the *FP* rate is 0.99%. These levels of accuracy can be considered acceptable for such a complicated industrial classification problem. The results are summarized in Figure 4.20.

In Table 4.1, the DNN architecture shown in Figure 4.17 is described layer by layer by outlining the rationale behind the choice of a layer rather than another. Going even further, to compare the performance of the proposed soft DNN sensor, it has been compared to three similar architectures. The result of this comparison is shown in Open Access Repository and summarized in Figure 4.21 in which it is clearly shown that the proposed DNN soft sensor has superior performance to other alternative architectures.

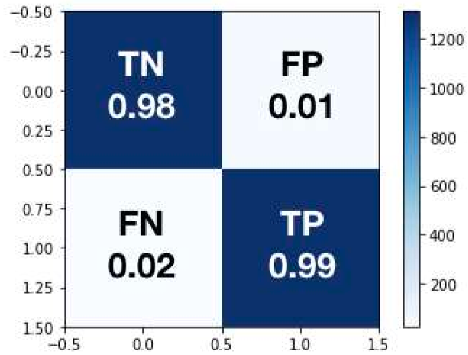

Figure 4.20: DNN Model Testing Confusion Matrix

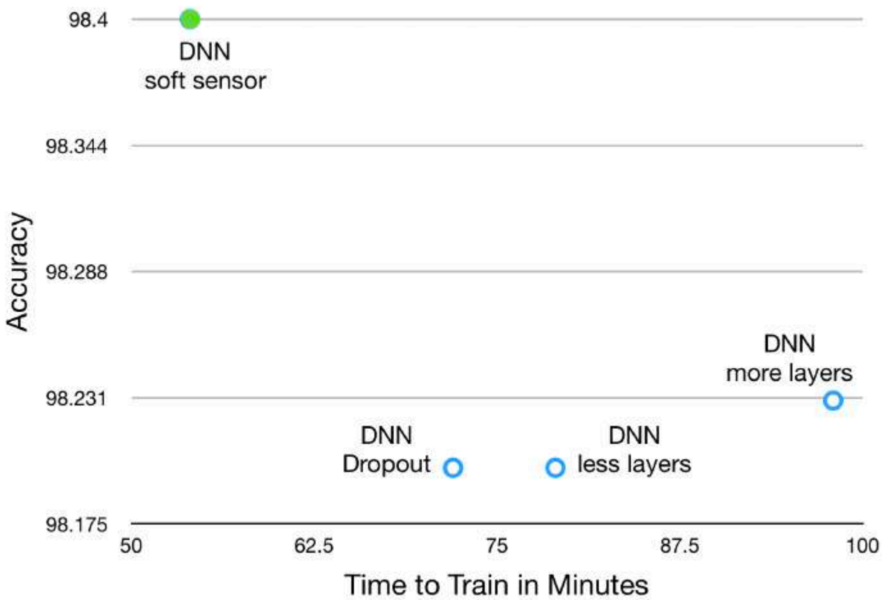

Figure 4.21: Deep Learning Architecture Comparison. Time to Train vs. Accuracy.

Two parameters, accuracy and computational time, have been measured consistently on the same training and test set, and then compared. First, it has been tested with an identical architecture by adding a dropout, then it has been tested with a deeper architecture and finally with a more shallow DNN with fewer layers. The accuracy should be as high as possible to generate the lowest possible error in data characterization, and the computation time should be as low as possible to ensure that the soft DNN sensor can be effectively integrated into an Industry 4.0 environment, thus ensuring maximum effectiveness and efficiency, respectively. A DNN sensor must be not only accurate but also fast to ensure, among other things, a minimum Lead Time impact on the process and low CO_2 emissions derived from the energy consumption associated with the computation.

Table 4.1: Detailed description of the DNN architecture

Layer Size	Layer Name	Layer description and rationale behind the choice.
(98, 98, 32)	conv2d 1 + activation 1 (relu)	This is the first convolutional layer of the network. As observed in Figure 4.26, this layer mainly finds edges in the input image. To keep the values in check, an activation function is needed after each convolutional layer which sets the negative values to zero (Figure 4.27).
(49, 49, 32)	max pooling2d 1	To reduce the complexity of the convoluted result a max pooling layer is used. Only the maximum in this case of a 2*2 pixel window is chosen.
(47, 47, 64)	conv2d 2 + activation 2 (relu)	In the second convolutional layer the results describe more complex forms as is visible in Figure. 4.26. To keep the values in check, an activation function is needed after each convolutional layer.
(23, 23, 64)	max pooling2d 2	As with the previous max pooling layer this layer is used to reduce the complexity of the convoluted result.
(21, 21, 64)	conv2d 3 + activation 3 (relu)	In the third convolutional layer resulting features are even more complex. To keep the values in check, an activation function is needed after each convolutional layer.
(10, 10, 64)	max pooling2d 3	As with the previous max pooling layer this layer is used to reduce the complexity of the convoluted result.
(8, 8, 32)	conv2d 4 + activation 4 (relu)	This is the final convolutional layer with the most complex features. To keep the values in check, an activation function is needed after each convolutional layer.
(4, 4, 32)	max pooling2d 4	As with the previous max pooling layer this layer is used to reduce the complexity of the convoluted result.
(512)	flatten 1	The flatten layer is used to flatten the previous 3 dimensional tensor to 1 dimension.
(64)	dense 1 + activation 5 (relu)	To further reduce the complexity a fully connected layer is used. Before the final connection takes place the relu function is used to zero out the negative results.
(1)	dense 2 + activation 6 (sigmoid)	As the probability of the input image being an error is wanted, the sigmoid function is needed to transform the input value into a probability [0-1].

Visualizing the learned features

Experience has shown that visualizing what each of the DNN layers learns can help deep architecture designers improve their understanding of the learning of the DNN hidden layers and thus support an appropriate fine tuning of their design for improvement purposes. This is because visualizing what the DNN has learned can help in the understanding of the decision making process. There are different ways of visualizing what has been learned by showing different parts. These can make it easier to understand why some things do not work as expected. For example, why some pictures with errors were not categorized as errors (FP).

This visualization can be performed in different ways. For instance, given an example image of a ***not-OK*** cylinder shown in Figure 4.22, an option is to visualize what the DNN captures using class activation heatmaps. A class activation heatmap is a 2D grid of scores associated with a specific output class, computed for every location in any input image, indicating how important each location is with respect to the class under consideration. An example is shown in Figure 4.23.

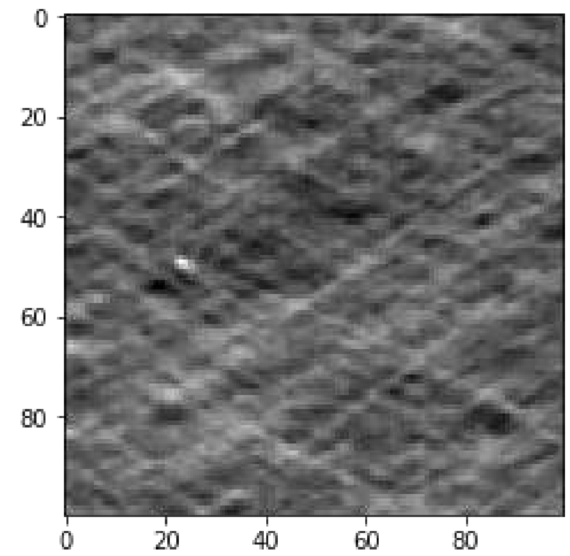

Figure 4.22: Example Image of Error in ***not-OK*** cylinder.

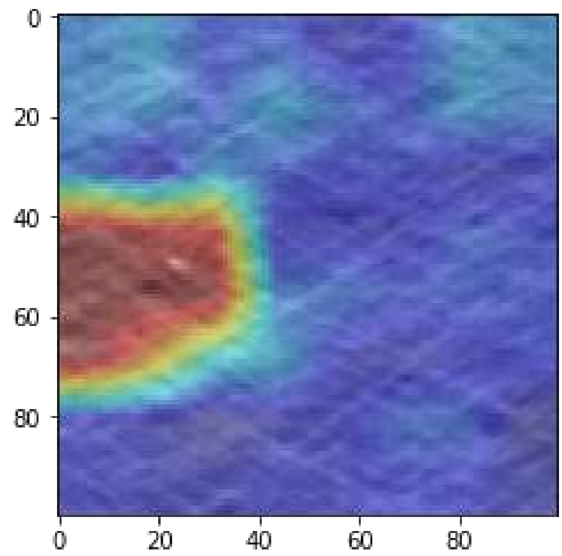

Figure 4.23: Activation Heatmap of Error in ***not-OK*** cylinder.

Another option is to calculate an input image that gets the highest response from a layer. This is done by displaying the visual pattern that each filter is meant to respond to. This can be done with gradient ascent in the input space: applying gradient descent to the value of the input image of a convolutional network to maximize the response of a specific filter, starting from a blank input image. The resulting input image will be one that the chosen filter is maximally responsive to. Examples are shown in Figures 4.24 and 4.25.

Finally, an alternative approach would be to show the outputs of all DNN layers as color-coded images. Visualizing intermediate activations consists of displaying the feature maps that are output by various convolution and pooling layers in a network, given a certain input (the output of a layer is often called its activation, the output of the activation function). This gives a view of how an input is decomposed into the different filters learned by the network. We want to visualize feature maps with three dimensions: width, height, and depth (channels). Each channel

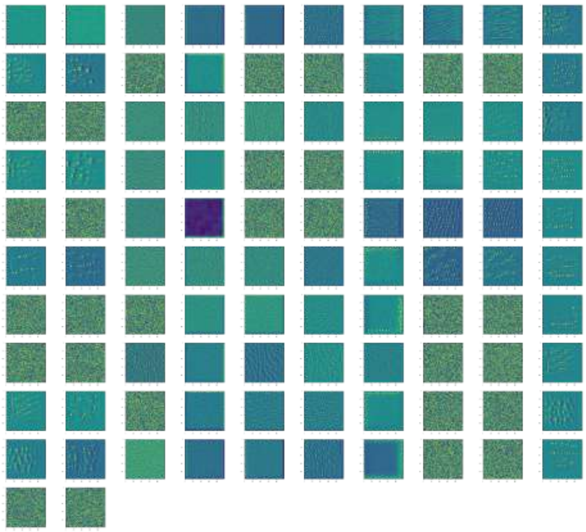

Figure 4.24: Most Responding Input.

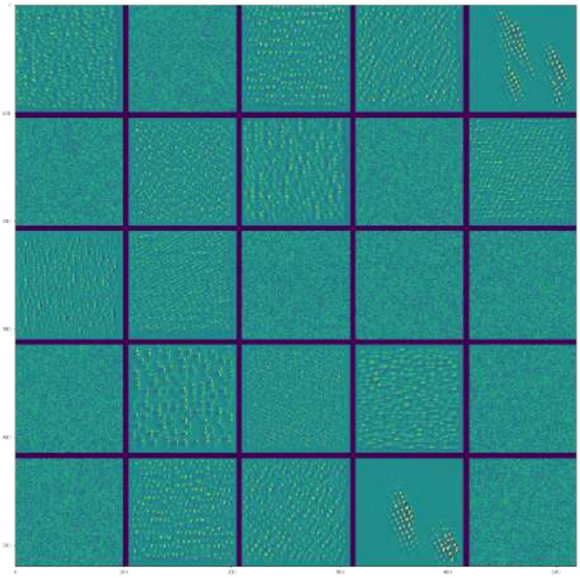

Figure 4.25: Most Responding Input Detail.

encodes relatively independent features, so the proper way to visualize these feature maps is by independently plotting the contents of every channel as a 2D image. For explanatory purposes, on the Open Access Repository, four different examples, *TP-TN-FP-FN*, of such feature maps are depicted. These shall help the reader better understand what the DNN *sees* and how it *responds* in different circumstances. One of these examples, *TN*, is visualized in Figures 4.26 to 4.36.

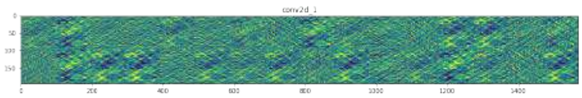

Figure 4.26: 1st Layer Conv 2D-1.

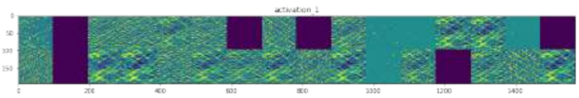

Figure 4.27: 2nd Layer Activation-1.

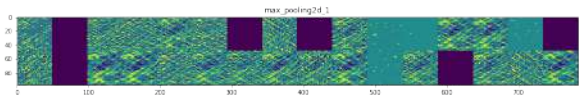

Figure 4.28: 3rd Layer Max Pooling-1.

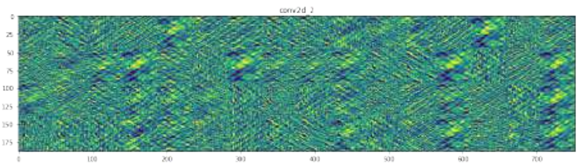

Figure 4.29: 4th Layer Conv 2D-2.

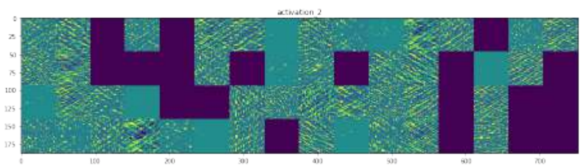

Figure 4.30: 5th Layer Activation-2.

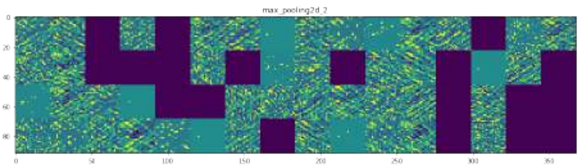

Figure 4.31: 6th Layer Max Pooling-2.

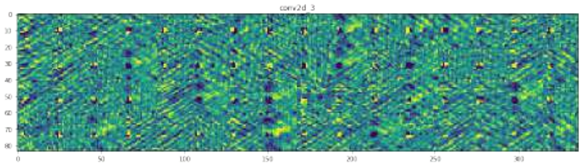

Figure 4.32: 7th Layer Conv 2D-3.

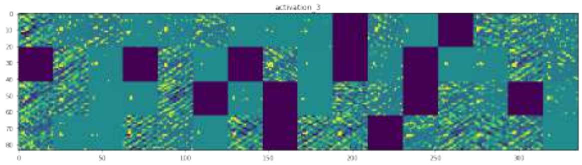

Figure 4.33: 8th Activation-3.

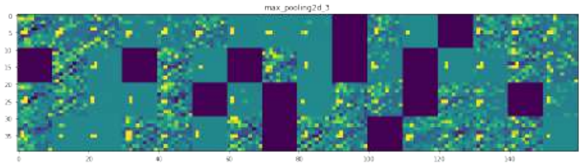

Figure 4.34: 9th Max Pooling-3.

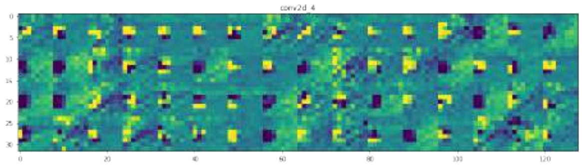

Figure 4.35: 11th Conv 2D-4.

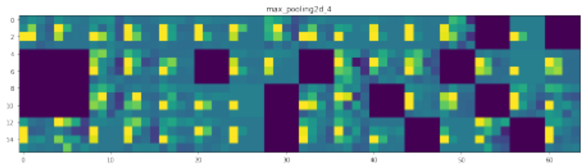

Figure 4.36: 12th Max Pooling-4.

4.3 Deciding on production steps to improve quality

The achieved results can also be a useful tool to improve the quality of the process with the help of the classification data and further algorithms. It could be used in the way that the underlaying effects for the creation of the defect are found and further eliminated. The first step in the assessment of possible starting points in the production is the analysis of the production steps and the impact a defect in this step would have.

The potential savings of energy, resources, and time depend on multiple factors. The two major factors for the environmental consequences are the impact of a defect and how often it occurs. The cost of the defect can be measured by the impact on the various forms of environmental waste, but also on further kinds of drain used from a management point of view. To a specific degree, most include environmental waste. Perhaps every kind of waste found in Lean Management (LM) to a certain extent impacts the environmental waste, as prior lean experience can be an important predecessor for environmental management practices [244]. Still, both environmental waste and lean waste can sometimes even stand in conflict [245]. Therefore, in the following, the view on the waste is through the lens of environmental waste.

The environmental waste of a defect needs to be measured by examining the impact it has on the production compared to a defect-free item. Only viewing the environmental waste, it is composed of the material and energy that is needed to fix the defect. For some types of defects, it's possible to fix a mistake by correcting the current production step. For other defects, it can be necessary that also earlier steps have to be repeated as the defect can not be fixed.

To get a complete picture, it can be an interesting challenge to estimate a realistic potential of how much a production step could be improved. As this can usually just be an educated guess and could lead to falsely dismissed production steps that have a high potential, the basis of deciding which production step has the highest potential to be improved should only be based on the resulting waste of a production step.

4.4 Potential savings of the production steps

In the following, the results using the discussed methods for determining the potential savings of every manufacturing step are examined. Defects are usually found at the end. Therefore, the root cause for the defect can't always be determined. This raises the difficulty of finding the source of a defect, and in which production step it occurs. In addition, it increases the difficulty of determining the exact potential waste savings for every production step. Because of this and to show generic data, in the following relative figures in the form of a proportion of the total waste of each production step between 0-1 are given.

During mechanical dechroming and decoppering, the risks for the resulting defects are very low. Although imperfections in the resulting copper layer can exist, these neither significantly interfere with the next production steps nor directly lead to defects on the cylinder surface, as long as these are not extreme. A rare defect could be that the decoppering has not been deep enough, and cells of the earlier engraving are still visible. Although a rare case, this would cause immense waste, as all production steps would have to be repeated to produce a defect-free object. Therefore, the proportion of defective items through this production step are rated with 0.1 in the following evaluation.

The degreasing step is also a low-risk production step. Nevertheless, a big contamination could lead to dramatic consequences, as the copper would not be able to form a solid layer. The degreasing step still only contributes to 0.1 of the added waste.

The coopering phase has the highest associated risk for resulting defects. During this production step, the major risks are holes in the cylinder surface. This is also confirmed in [246] as the highest waste producing category for rotogravure manufacturing. Sizeable holes in the surface could print. Even if these are smaller or the copper hardness is not consistent, this could lead to defects in the next production phase. Hence, this production step adds a proportion of 0.45 to the total.

For the engraving phase, the complexity of defects is the highest, as the cells need to be placed with a very high accuracy and with a consistent depth across the complete cylinder surface. As a result, the range of unique types of defects is very high, whereas the most common is the fracture of the stylus [247]. However, also other defects, such as distortions of the engraved image in any direction or pin holes, are possible. As a result, this production step comprises 0.25 of the total waste.

In the last step, the chroming can also add defects to the item. These could be small holes or incomplete chrome plating. Due to it being the last step and as most of the defects resulting from this production step can be fixed, be chemical dechroming and rechroming the cylinder, the total waste is manageable. This step is responsible for 0.1 of the total waste.

Because of the analysis, the highest waste saving potential can be seen in the copper plating phase. This is the production step responsible for the highest amount of waste. Moreover, if defects are found at this stage, repairing the item has a much lower cost than in later stages. As an added benefit, it can help in analyzing the origin of a defect.

4.5 Methods for improving quality control

The previous analysis shows the best next target point for the future work. The implementation allows for various strategies. In this section, three alternatives are described and rated based on the costs and saving potentials.

The different alternatives are visualized in Figure 4.37. On the left (I), the quality check deployed at the investigated manufacturing plant can be seen, where only one visual inspection at the end is used, that uses algorithms from computer vision and Artificial Intelligence (AI) to detect defects [133]. This kind of quality check has its equivalents in other manufacturing areas, such as for laser welding [244] or metal additive manufacturing [248]. Although visual inspection systems show outstanding results for the final quality check, as discussed, this still doesn't prevent internal waste to accumulate, as defects are usually only found at the end.

The first alternative to the current workflow (Figure 4.37-II) uses multiple instances of the visual inspection system. Although it is possible to use a visual inspection system after every production

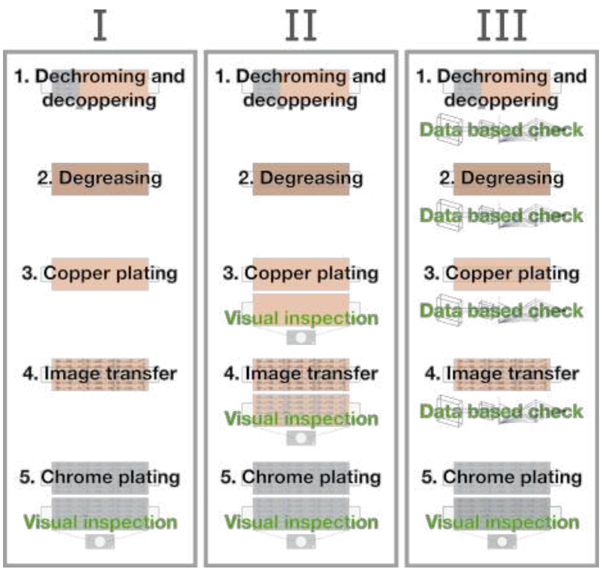

Figure 4.37: Three different possible quality checks for rotogravure manufacturing. The currently deployed quality check on the left. An alternative with more visual inspections in the middle and a data based method on the right.

step, only three steps with high waste were chosen for this alternative. Nevertheless, a visual inspection system could be used for each step. The visual inspection system could ensure that only items with no defects are passed on to the next production step. This would make it possible to fix or discard an item without producing waste by adding the next production steps to the already broken item. A downside to this approach is the strong cost point of the visual inspection system and that only the symptoms in the form of defective items are considered and not the root cause in the form of a not optimized production step that only produces defect-free items.

The second alternative (Figure 4.37-III) doesn't use any further visual inspection systems. Quality checks are data based. Details on feasible ways how this can be achieved are discussed in Section 4.6. Depending on the achievements of the data-based checks, it would also be possible to replace the final visual inspection system. This alternative would reduce the costs for the needed hardware and could help analyze the core problems in each process step.

In the long term, the correlation between the defects found by the inspection system and the operational parameters will make it possible to address 4.37-III, following the LM culture.

4.6 Deep Learning for rotogravure manufacturing

Data based alternatives

DL appears to be a promising tool to improve the manufacturing quality. Still, other data-based strategies should be taken into consideration. Through the rise of data generation and collection, many types have been developed over the years. All coming with advantages and disadvantages. Although in general terms this includes LM focused systems such as Six Sigma or Kaizen [249], the further focus lies on automated techniques that process data and give an output which is used to improve the quality.

A solution to a problem should never be more complex than it needs to be. Therefore, a first step should almost always be the visualization of the data and, if possible, simple models could be developed and the correlations of the factors checked. Through this, big influencing factors can already be determined. Domain-knowledge can be a considerable plus in this stage. Unfortunately, this approach is not sufficient for most cases as a manufacturing system is usually dynamic, uncertain, and complex [250]. With the help of machine learning, it is possible to model more complex systems. This gives an enormous advantage as most processing steps have many influencing parameters that result in a high dimensional relation.

Most Machine Learning (ML) algorithms can be grouped into two major categories. Supervised and unsupervised learning. Unsupervised learning is used to detect patterns in unlabeled data sets and generally needs little supervision by a human. Supervised learning, however, depends on a labeled dataset and learns to find the connecting patterns between input and labels. It learns from the examples provided. If the data and the use case make it possible, supervised learning usually achieves better results.

Through the data won from the vision-based systems, it is possible to label the data with the information of existing defects. This makes it possible to use supervised learning if the use case allows it.

The more concrete groups that are promising for the planned results are classification and regression. Although the exact use case depends on the planned achievements, which will be further discussed in Section 4.6. Classification algorithms could be used to detect defective states. This would be the best choice if the factors resulting in a defect are only temporary. Through regression, prediction and forecasting could be implemented. This would be more useful if the influencing parameters are more continuous and need to be kept in check.

Since the 2000s, DL, which belongs to ML, has seen a substantial surge in popularity. Although more traditional ML approaches such as Support Vector Machine (SVM)s have also shown successes in manufacturing [251] [252], DL are most often superior. The more traditional approaches require manual feature extraction, while DL networks are able to learn more complex features in each layer, which reduces the difficulty significantly [132]. The advantages of deep neural networks have been proven mathematically [253]. This is one of the reasons why it has seen many successful implementations in manufacturing in the last years [254] [255] and why it is chosen as the prime candidate for future work.

Roadmap to improve rotogravure manufacturing using DL

To test which algorithm is most suitable for a problem, the required results and the data that can be used to train the neural network need to be examined.

The eventual goal is to find ways that reduce the waste in production, which allows for distinct strategies. These can range from detecting, with a high probability, that a defective item was produced to further inspect the item for faults, to improving the production step by adjusting controllable variables that have an influence during the production through an automatic system. While the latter would be the ideal end state, where every production step would adjust itself to only produce defect-free items.

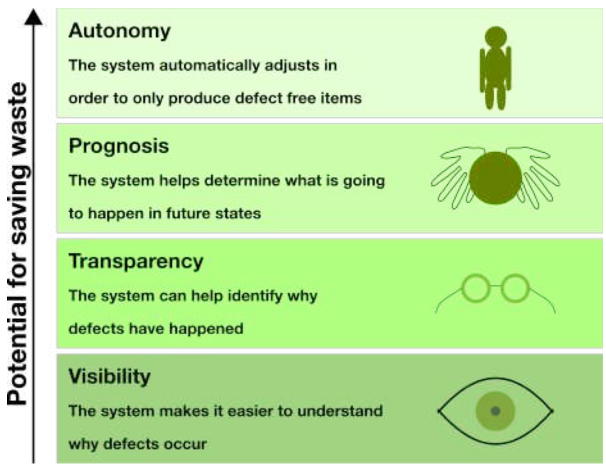

Figure 4.38: Potential steps in order to improve waste saving through quality improvement aided by the possibilities of DL.

According to the Industry 4.0 maturity index from Schuh et al. [256], the steps visibility, transparency, prognosis, and autonomy can be described as a path towards Industry 4.0 or in more general terms as an improvement to the manufacturing. This can also be adapted to this case of quality improvement with the help of DL as seen in Figure 4.38.

The first step increases the visibility of the system. Here, this could, for example, be done by visualizing the interacting parameters through feature reduction with the help of auto-encoders [257].

Creating transparency can achieve further potential. For example, showing which parameters have a negative influence on quality or how these parameters interact. Making a prognosis can increase the potential. For example, the staff could see the influence of the current state on the system. With this knowledge, it's possible to know which parameters have the biggest influence on the quality and should be adjusted. As the last step, a fully autonomous system can be imagined that adjusts its own parameters to produce defect-free items.

Because the goal is to detect defects, it is necessary to know when a defect has occurred. After the copper plating, the cylinder is checked by scanning the cylinder surface with the help of a line-scan camera and an LED-light. Any holes or other anomalies can be detected through a deviation towards the cylinder surface. The check after the image transfer and the chrome plating is more difficult, but also starts by scanning the cylinder surface. Now it needs to be compared with the engraving file through transformation and brightness adaptations, as described in the beginning of this chapter. These results are the target for all supervised ML/DL algorithms in the training phase.

For the input data, it is necessary that it, in more or less hidden form, contains the information that a defect exists. It is desirable that no further delays or costs are added. These properties to the current knowledge should be able to be achieved by the data already produced by the machines in every production step. These are usually a mix of different outputs from sensors and parameters from the machine. In the case of copper (Figure 4.37.3) and chrome plating (4.37.5) these would apply to the galvanization process such as the temperature, the amount of additives or the current. For the image transfer step (4.37.4) these would be related to the speed of the machine, the pressure of the stylus, and any fluctuations in the electricity used. If it is not possible to achieve the desired results, added sensors could be installed that contribute further information.

4.7 Conclusions

Research question 2 asks **how data and algorithms can be used to reduce costs and add value to a manufacturing line**. An important point in these advancements is that these can build on the previous developments and therefore allow a constant improvement. This research shows the possibility through the use of data and algorithms with the goal of adding value through better quality and automated steps in the workflow.

Quality Control

The costs associated with the quality control can be drastically reduced through the automation demonstrated in Chapter 4. In addition, the accuracy of error detection increased considerably. The results can be therefore considered *very promising* and allow for different ways to increase the performance and add value to a manufacturing line. However, these results have to be interpreted in a broad context of Industry 4.0. This section provides some essential aspects that will help to understand and contextualize the contributed results through a meta-discussion at various organizational levels. This will help to present a possible future strategic development of these ***deep technologies*** in the short, medium, and long term.

There are different steps that have to be taken until the full potential can be used in the production without taking a too high risk of missing an error.

1. Using the DNN fully automates the OQC classification to predict the amount of errors a cylinder has.

   The DNN *only* provides a successful result 98.4% of the time. To be sure that the wrongly classified images are not big mistakes, human experts will review all possible errors. DNN has already had a positive influence on the workflow, as we know how many errors are very likely an error: DNN helps significantly in the planning of the next workflow step because it is known with a high probability if the cylinder needs to go to the correction department or if it is very likely that the product is an *OK*-cylinder.

2. Showing the error probability to the operator that is currently deciding if it is an error or if it is not.

   This gives a hint to the operator, who can give feedback if there are relevant mistakes that were not predicted as mistakes. This can also help the operator to reduce the likelihood of missing an error.

3. Only showing possible errors that have been predicted by the DNN.

   In the last step, the DNN could completely filter out errors that are not relevant. This can also be used in multiple steps because it is possible to increase the threshold error probability for the possible error to be shown. At some point, a threshold will have to be chosen, taking into consideration the cost of checking a possible error and the cost of missing an error. This would completely eliminate the step of checking the errors, and the confirmed errors would only be checked by the correction department.

Quality Improvement

This chapter proposes steps that should make it possible to improve the quality in manufacturing and especially in rotogravure manufacturing based on the results of the developed optical quality control system. To verify the results, the aim is to extend this work by applying these concepts to real-life data of a rotogravure cylinder manufacturer. This should help to show that a general systematic quality improvement and waste reduction strategy is possible by using data and DL algorithms.

A roadmap of the planned next steps is shown in Figure 4.39. It is not a simple transformation from 4.37-I to 4.37-III, but consists of multiple steps that build upon each other. The first step will be to have a visual inspection system after the copper plating. This gives the information if a cylinder has defects and will be the target data for the DL system in this part. The second step will be to record the data from the used machines for copper plating. This will be the input for the DL system, from which it will learn which parameters influence the emergence of defects. In the next step, the DL system will add visibility to the copper plating by showing which parameters have the biggest influence on the emergence of defects. Adding to this, the next step will allow transparency by identifying why defects have occurred. Through integrating the prognosis in the next step, the ability will be added to determine the future outcome and given the ability to take preventive countermeasures. These steps will be repeated for all production steps until, in the last step, full automation of the quality control can be achieved.

Limitations and further research

Although there has been an immediate performance increase in OQC error detection accuracy and cost effectiveness, the larger scope for improvement is down to the managerial dimension of such a sensor. This is because it can be expanded to not only detect defects but also to classify them

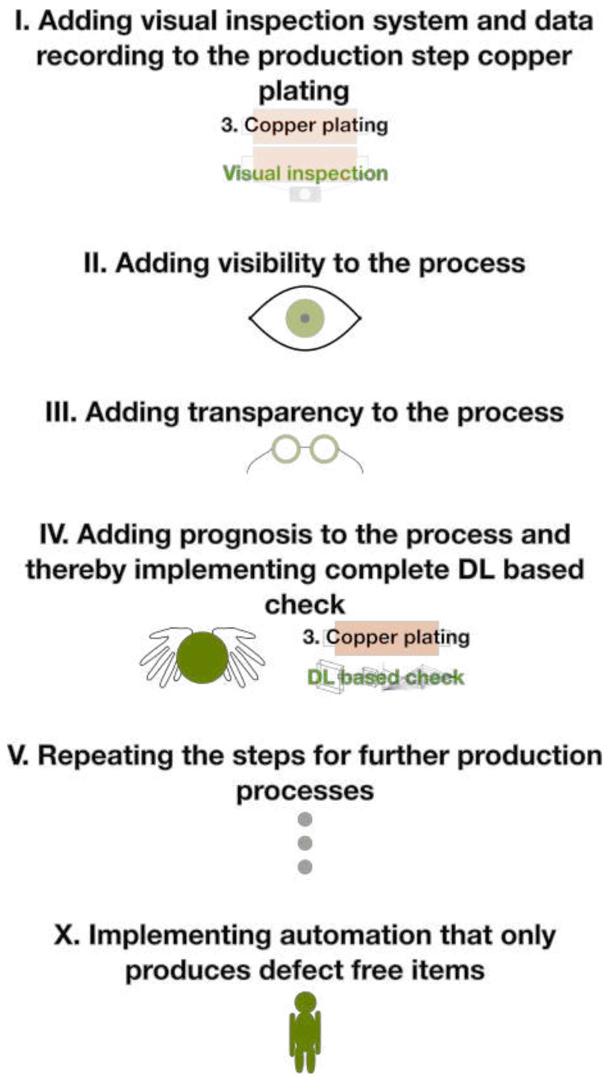

Figure 4.39: The planned next steps for the DL based quality improvement in rotogravure manufacturing.

into categories. Although this requires additional effort, it will enable the cause-effect analysis regarding manufacturing conditions and defect frequencies.

Some of these efforts can be specifically targeted to achieve an improvement in the accuracy of the model. For example, learning from false predictions: to further improve the correct prediction rate, it is important to take a look at the examples that have not been predicted correctly. This could potentially improve the understanding why the wrong prediction was made by the DNN.:

- *Not-OK examples that have been predicted as OK*. Looking at the actual errors in the test data that have not been predicted as errors, as in Figure 4.40, a few issues could be the cause of the wrong predictions. Some of the examples actually do not look like they are really ***not-OK***. The cause of this could either be that the input data was not labeled correctly or that the error really is not highly visible in the image.

- *OK examples that have been predicted as* ***not-OK***. After looking at the visualization of the DNN, it gets clear that the main focus for finding mistakes is looking for extreme edges. These can be seen in a lot of wrongly classified examples. Especially the first two examples seen in Figure 4.41 have some extreme edges that are a result of a slight misalignment of the images in the preprocessing. Therefore, the image registration in the preprocessing part between the original and the recording of the cylinder surface needs to be improved.

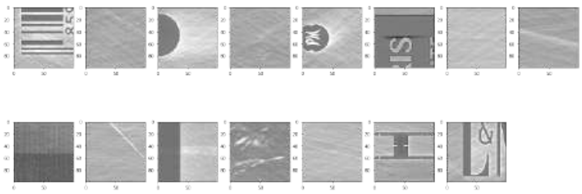

Figure 4.40: *FP*. Is an error but has been predicted as ***OK***

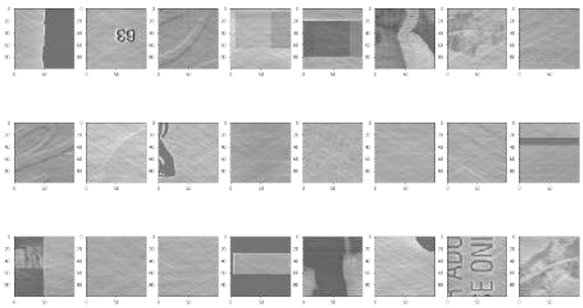

Figure 4.41: *FN*. Is not an error but has been predicted as such.

This technology could also be implemented at the customer side to increase the defect detection accuracy in the printed product itself. This strategic step is currently being discussed internally. Such analyses will provide sensitivity about operations and operational conditions, which will also impact the value stream related efficiency and effectiveness.

These aspects will probably be the next steps in further research actions to be developed within an Industry 4.0 context. For instance, DL applied to manufacturing Industry 4.0 technology will have an impact at various levels of aggregation in the printing manufacturing value chain:

1. DL at a shopfloor level shall impact quality, reliability and cost.

   At the shopfloor level, this thesis has shown an example of how DL increases the effectiveness and efficiency of process control aimed at achieving better quality (e.g., with OQC) and lower costs, allowing self-correction of processes by means of shorter and more accurate quality feedback loops. This intelligence integrated in the value streams will allow many humans and machines to co-exist in a way in which artificial intelligence will complement in many aspects. In the future, significant challenges will still be encountered in the generation and collection of data from the shopfloor.

2. DL at a supply chain level shall impact lead time and on-time delivery.

   At a higher level of supply chain, producing only what the customer needs, when it needs it, in the required quality, the integration of DL technology will allow not only the systematic improvement of complex value chains, but a better use and exploitation of resources, thus reducing the environmental impact of industrial processes 4.0.

3. DL at a strategic level shall impact sustainable growth.

   At a more strategic level, customers and suppliers will be able to reach new levels of transparency and traceability on the quality and efficiency of the processes, which will generate new business opportunities for both, generating new products and services and cooperation opportunities in a cyber–physical environment. In a world of limited resources, increasing business volume can only be achieved by increasing the depth of integrated intelligence capable of successfully handling the emerging complexity in value streams.

To summarize, despite the ”black box problem” and the challenge to have enough information and labeled data available for learning, DL will probably conquer in the field of machine vision, one country after another, and will act in the background without the user being aware of it. The role that DL will play in the creation of cyber–physical systems will be adopted from a strategic point of view, in which business leaders will tend to think of deep architectures as possible solutions to problems.

5. Order entry in the printing industry 4.0

The goal of this chapter is to demonstrate how algorithms and data can be used to reduce the complexity of the customer-manufacturer interaction. This is done by implementing a novel semi–automized job entry application for the printing industry. This tool has been developed for rotogravure manufacturing, but can easily be adapted to other printing tools. It should turn a tedious and complex process into an easy–to–use process, by combining the insights of domain knowledge and data with the intent of turning these into usable algorithms.

Within the Industry 4.0 framework (Figure 5.1), this deals with two points. On the program level, this needs to take the technical level of the implementation, as well as the human using it, and the interaction between those two, into account. On a broader level, this has a substantial influence on the organization and supply chain of the business, by opening up completely new paths for business models. Through this implementation, the digitalization and processing from information to knowledge to value can be generated.

An algorithmization of knowledge offers many benefits. With no further cost, it can be made available worldwide. This opens a wide area for commercialising the software, as wide parts are applicable for the whole printing industry and not only for rotogravure printing. Through this implementation, the wide opportunities that exist through digitalization in all industries today are demonstrated. Even though the printing industry is considered more conservative towards change and disadvantaged by digitalization, there also exist ways to benefit from the upcoming developments. A negligent focus can hinder growth and create a dependence on the forerunners of this revolution that can even come from outside the industry.

Although in some cases solutions for parts of the substeps exist in the literature, no complete

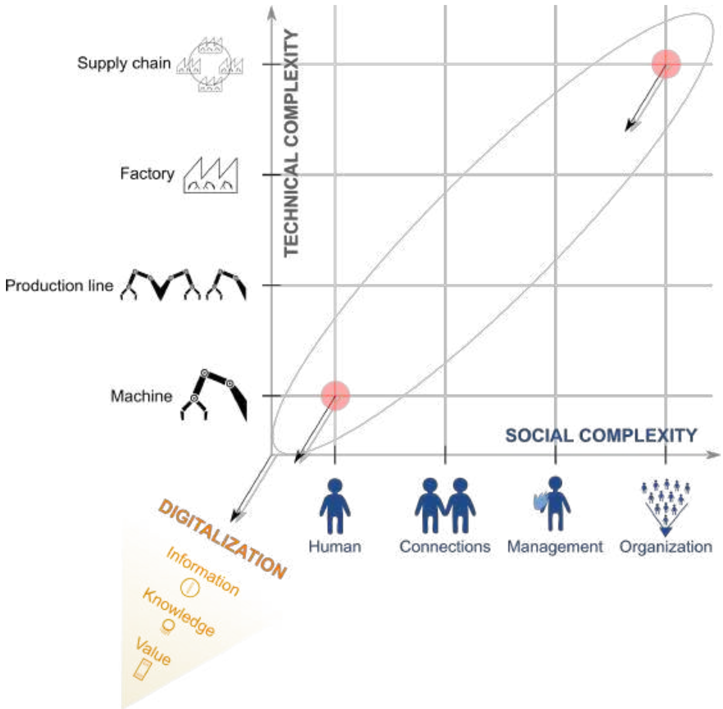

Figure 5.1: Industry 4.0 framework with the main points of this chapter. The graphic is based on the work in [86].

concept nor a published tool in the industry exists to tackle this challenge. Through the whole process, different knowledge from multiple areas is needed. With machine learning, information can be extracted from the available data. Color science opens up ways to manipulate and optimize the colors during the printing process, while the domain knowledge of the printing and prepress process is necessary to understand the context and to mimic the manual processes that are done today.

All steps needed for a job entry are described in Section 5.1. In the following sections, the solutions are developed and explained. For the steps where solutions in the literature have been mentioned, these are described and put into the context of the developed solution. Where possible, a validation of the data is included. This is further highlighted in chapter 6, where a conclusion is drawn and an outlook is given, how these results can be used from a business perspective. Furthermore, additional features are discussed that can further improve the usefulness of this application.

5.1 Overview of the required steps

To set up an order in an automatic way, a series of steps are needed. These build on each other, as some information from the previous steps is needed to complete the next. An automation of these steps is desired. Due to the sometimes hidden nature of reasoning in some aspects, some steps can only give results that are good enough but do not completely align with the needs of the user. Therefore, optimal results can only be achieved if the optimal choice in each step is confirmed or adapted by the user.

In the following, the needed steps are listed. These were captured by assessing the steps taken in the manual process. Adjusting these for the automatic process, and in the final step, sorting these by analyzing the dependencies of the information that is necessary for each step. A short description of the step is given in the following summary. A graphical representation of the steps can be seen in Figure 5.2. The solutions for the steps are described in the next sections.

0. Check format
   - It needs to be ensured that the file is readable and in the correct format for the processing in the following steps
   - Problems can arise when an incompatible or too old version of the software was used to prepare the file
1. Find and set the Region Of Interest (ROI)
   - The files aren't designed for automated processing and hold further information intended to be read by an operator
   - For further processing, the region of the actual object intended to print is needed and all other information can be ignored
2. Detect and set optimal ink sequence
   - The order of the printing colors has a huge influence on the printed outcome
   - Different colors can form and printing errors can get hidden by a later printing color
   - The expected outcome is heavily dependent on the needs and preferences of the printer
3. Detect print risks
   - Even though modern printing machines have a very high accuracy and technical support systems, a misalignment of colors can happen

  - This affects elements that are created by multiple colors or border a different color
  - These areas need to be identified, as a data adaptation in these areas can diminish the effects

4. Optimize print elements
  - The areas detected in the previous step are analyzed for an optimal solution
  - As a misalignment of the separate colors printing is a common problem since the invention of printing, multiple techniques have been developed to minimize the impact on the final print result by changing the image data
  - The choices are dependent on the elements affected, but can also be dependent on the personal preferences

5. Determine the optimal production parameters
  - Through different printing parameters, different results can be achieved
  - The required results depend on the image data and the interplay between all colors used for a print
  - A general rule is to prevent a Moiré pattern of halftone colors printing on top of each other by choosing suitable parameters that have a very low chance of producing a Moiré pattern

5.2 Detecting the region of interest

The incoming file not only holds the information from the packaging but also additional information. An example of the complete file and the region of interest can be seen in Figure 5.3. Only the part in the region of interest is later used for printing. The additional information can be useful for an operator or to understand the context, but is unhelpful in the automatic analysis of the print. If elements are considered that will not be in the final print, this would change the results and lead to an undesirable outcome. Therefore, it is important to identify this area.

Although the task of finding the region of interest in the incoming file can be placed in the same realm as object boundary detection[258], there are some points that differentiate it from the general usage. Most object boundary detection algorithms in the literature are used to detect objects in photographs or other complex images. This makes the detection of boundaries very challenging. For the incoming files, the conditions are a lot easier. A certain level of distinction is always

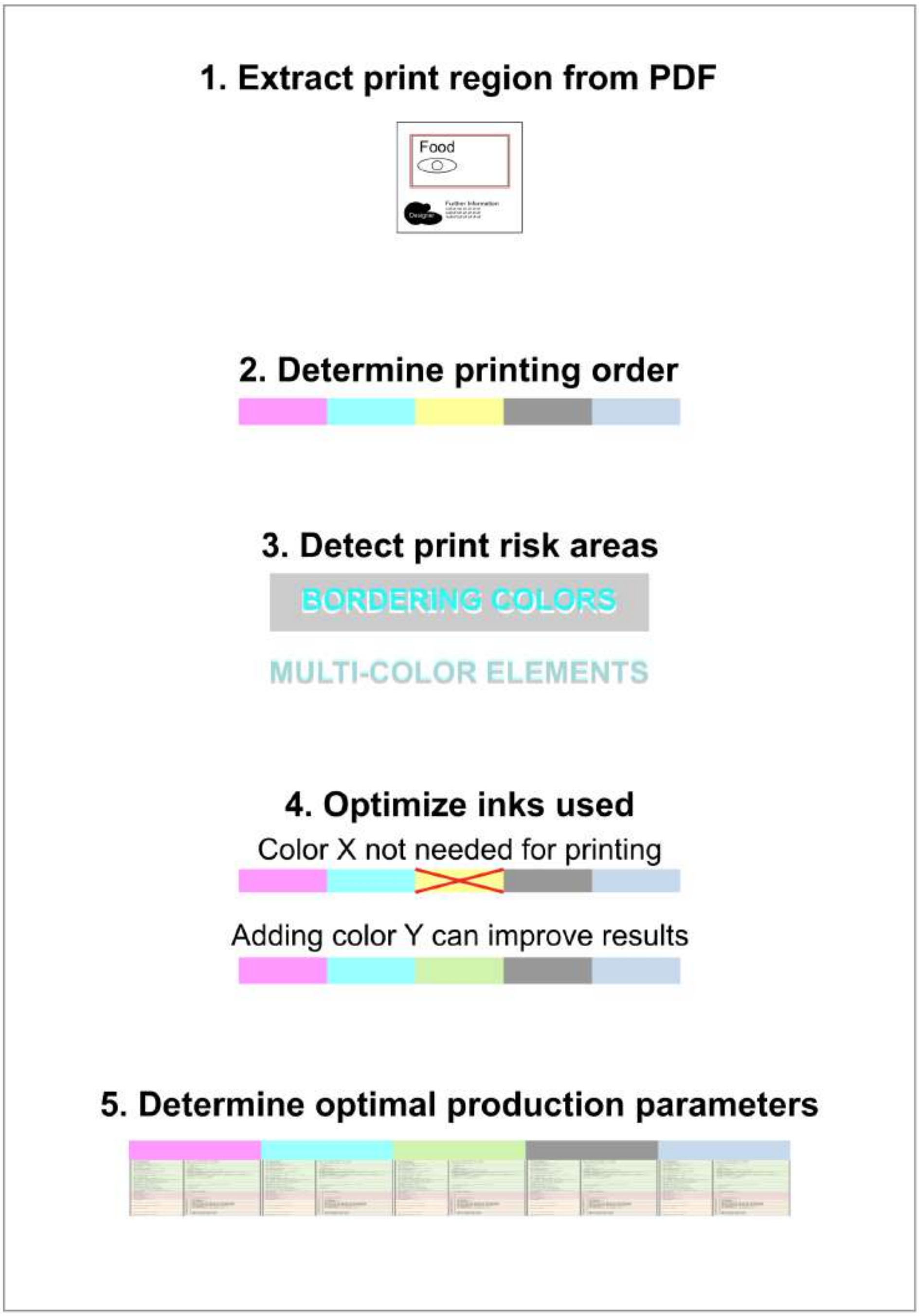

Figure 5.2: Proposed workflow for a semi-automized job entry process.

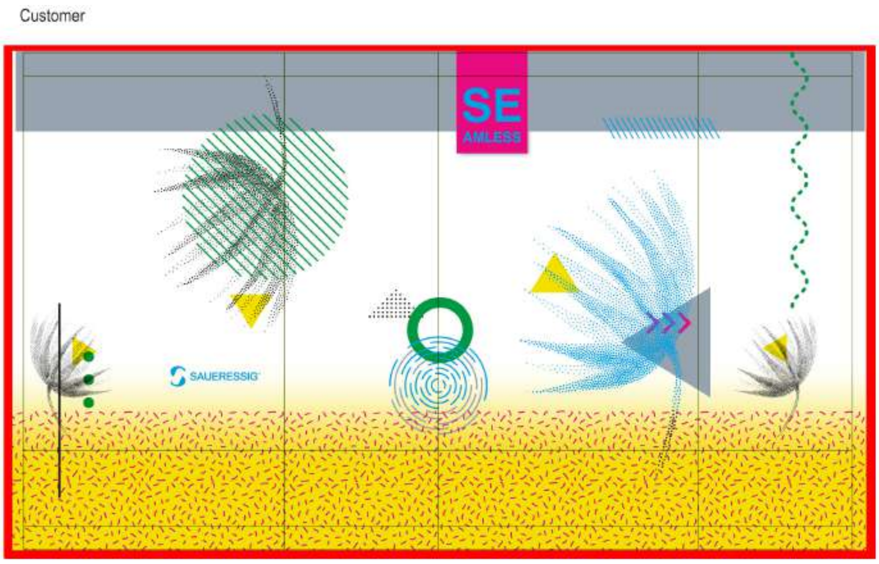

Figure 5.3: Example packaging with the ROI marked in red.

given and the borders are defined in a clearer way. As it is necessary to use the boundaries in the manual processing of the file, also certain standards have developed to help this process.

As with many following points, the difficulty lays in the fact that no standard exists, that is followed by all. Different technical options exist to mark the actual print in the file. These often are not used or sometimes used in a way that it was not intended for. For this reason, better results can be achieved by analyzing the image data. Depending on the data, two variants exist that are further analyzed in the next part.

These have some advantages towards the neural-network-based approach. As no training needs to occur, a lot of computational resources can be saved. It also does not require a clean, labeled dataset. Furthermore, by using simple rules, these can be communicated and understood by the user. This prevents many unexpected results that could be shown. Still, it requires that a high enough accuracy can be achieved with this method.

ROI detection using technical drawing

The most standardized way to identify the region of interest is through a separation which is often named *cutter*, *technical drawing* or simply *td*. This doesn't always exist, but is often used to show the outline of the print. An example can be seen in Figure 5.4.

The separation does not just hold the outline, but often further elements from the legend that are

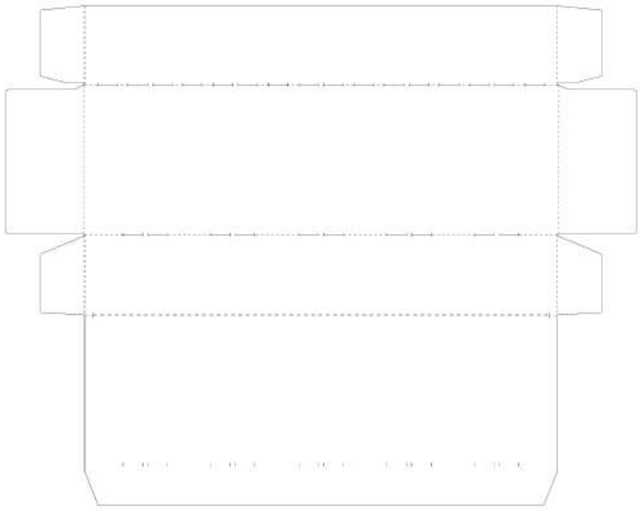

Figure 5.4: A technical drawing separation containing the outlines of a packaging.

far smaller. By identifying the biggest outline, the area can be identified that holds the print. In the example case where two big elements exist that have similar dimensions, both outlines need to be combined. This offers a high chance of selecting the correct ROI, but can be combined with the following general detection to further increase the accuracy.

General ROI detection

The possibility of using the technical drawing separation to identify the ROI is not always given, as this separation does not always exist. In these cases, it is necessary to find a set of general rules that can help the process. As each customer has different standards, it is important to find those that apply to all.

In this context, it is important to identify the properties that are expected to have the biggest contrast. To a large extent, legends contain text and an outline. The print, on the other hand, can be expected to have a continuous area with multiple layers and varying colors. By combining the features that can be calculated from these properties, a high chance can be assured that the correct ROI is identified.

The most promising feature is that the values of the elements printed in general have a wide range of colors that will be printed. This can, for example, be measured by first adding all separations, as seen in Figure 5.5. Although these do not contain any color, most information is still pertained. A

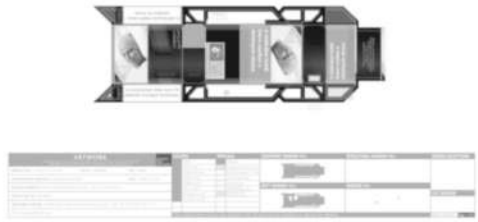

Figure 5.5: The values of all separations added up and scaled to the maximum viewing range.

high variation of values should be expected for the print, whereas the legends have less variation through the main use of full tones. For every found contour, the number of unique values can be measured.

A second possible feature is the amount of ink used. This can be calculated by summing the values for every separation and for every contour found in the file. High values should be found in the actual print, whereas the other elements in general should have less surface covered by the different inks.

The area of the contour can also play a role in determining the ROI. The contour area is the number of pixels found within the contour. In general, the area of the print should be bigger than that of the legend.

It is also possible to combine the values calculated to get a fuller picture of the contours. The received values can have a wide range, depending on the category. To combine the values, the range needs to be reduced. This can be done through a normalization of the values. By dividing the value through the maximum possible value in the image, a value in a range from 0 to 1 is achieved. Different ways of combining the values and different factors for each category are possible. A multiplication of the values would make a very low value have a big influence on the outcome, whereas a sum of the values could offer a more balanced result.

Verification of the results

To verify the results, these need to be compared with the ground truth. As no clean labeled dataset exists, a random sample set of 50 jobs was rated by an expert. To check the accuracy of the features, the results of each and the combination were calculated. For the combination, all three values were multiplied with the same priority. The results can be seen in Table 5.1.

Table 5.1: Overview of the results from the ROI detection features for 50 random samples.

ROI detection accuracy	
Feature	Accuracy
Variation	0.86
Sum	0.92
Area	0.78
Combined	0.88

For all variations, the correct ROI was found for at least three quarters of the jobs. The lowest accuracy of 78% is achieved for the detection only based on the area of the single contours. Using the variation of pixel values as an indicator, a noticeably higher accuracy of 86% could be achieved. The highest accuracy of 92% is achieved with the sum of all pixel values. Not always is it possible to use the found contours as a basis, as the parts of a packaging can in rare cases be separated. The used combination achieves a slightly lower accuracy of 88%.

In a closer analysis of the individual results, the optimal combination of values depends on the customer. During the creation of the data, they follow different norms affecting the outcome. If one customer expects a wide range of information, the legend is created in a larger area. This can be used by adapting the factors for calculating the optimal ROI detection and therefore achieving an even higher accuracy. Still, already with these results, a high enough accuracy can be achieved to process the next steps.

5.3 Detecting the optimal ink sequence

The ink sequence influences the outcome of the final print in multiple ways. Different requirements assume different ink sequence orders. There is no optimal ink sequence that fits all the needs [259]. It has been shown that the later printing color is more dominant in the end result, which can also be simulated with the known spectra of the paper and the inks [260]. With this, the color gamut changes depending on the selected printing order and Moiré-like patterns can be amplified or attenuated [261]. Therefore, the optimal sequence needs to be learned from previous jobs, to offer the correct ink order to each customer.

Identifying identical colors

As the knowledge of the optimal ink sequence can only be gained from previous jobs, it is necessary to identify identical colors. The challenge lays in the fact that the names given are not taken from

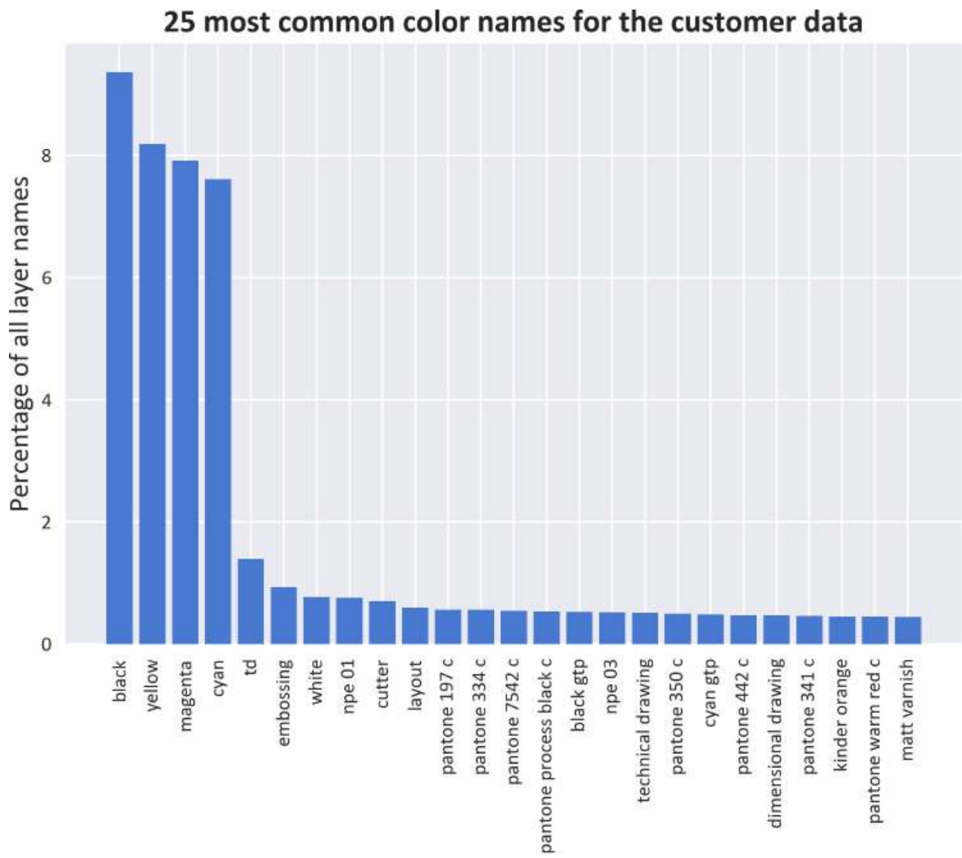

Figure 5.6: Overview of the used color names

a predefined list. The entry is a free-text field and the same color can have different names from different languages or spelling mistakes. Still, it can be expected that a high repetition of color names exists. This allows two entry points in the form of the color name and color information as Red Green Blue (RGB)-values.

To verify if this approach can work, it is necessary to analyze the distribution of color names. For this, 17.500 color names from a random selection of jobs received from the customer were collected. Of these, 2.108 are unique color names. The distribution of the 25 most common color names is displayed in Figure 5.6. The four primary colors for printing with Cyan, Magenta, Yellow, Black (CMYK) already combine 33% of the total color names. The displayed 25 most common color names combine 45% of the total color names and the 100 most common color names combine 63% of the total.

This shows that a certain standardization is present, but also a high chance exists that an unknown color name can be used. For this reason, it is advisable to expand these results through the use of the RGB-value of the color. Although there is also no clear standard for giving specific values for a defined color, the format limits the possible colors to $256 * 256 * 256 = 16.777.216$ possible color values. As this is also still a too extensive list, it needs to be reduced.

This could be done by binning multiple values to one. A binning of 4 separate values to one would reduce the scope to $64 * 64 * 64 = 262.144$ possible color values. Even with this, it is unlikely that sufficient information can be collected for all query values. Therefore, it is possible to use a selection of predefined colors, such as the Pantone colors.

To ensure these colors are close enough to all possible values, an examination is necessary. For the test, 10.000 random RGB values were used. The closest color from the list of CMYK and Pantone colors was searched for each RGB value. From this match, the Delta E value was calculated.

The distribution of these values is visible in Figure 5.7. The mean distance between these values is 3.2, which is above the just noticeable difference, but still a very close match.

To visualize this difference, one example of an RGB value (Figure 5.8) with a Delta E of 9.71 to the found color (Figure 5.9) are shown. By analyzing the outliers with a high Delta E value, it appears that the majority have a very high green or blue tone. This can be explained by the fact that the extreme green and blue tones are outside of the possible color space that can be printed. Therefore, there are no standardized print colors close to the RGB values. Taking this into consideration, it should be possible to use the closest CMYK or Pantone color to put the given RGB values into the context of a color name.

Calculating the optimal ink sequence

To learn the optimal ink sequence, different algorithms can be applied. A neural-network based approach could be possible. Similar to the other tasks, this has some disadvantages in the traceability of the decision-making process. Therefore, in the following, three algorithms are tested that use the information of the color names.

The simplest algorithm identifies the average relative position the color has in the training data with a value from 0 to 1. 0 means it always had the first position when it occurred in the sequence and 1 the last. With the information from all included colors, a sorted sequence can be generated by the relative positions of each color in the training set. It plays on the fact that the previous positions are a good indicator of the new order. In addition, every color that has been used before has this information and can be placed within the order. If, for example, a job with black, red, and white is the starting point, the average positions of black, red, and white in previous jobs are taken. Through the received values, an ordering of the inks can occur. There are also disadvantages, as

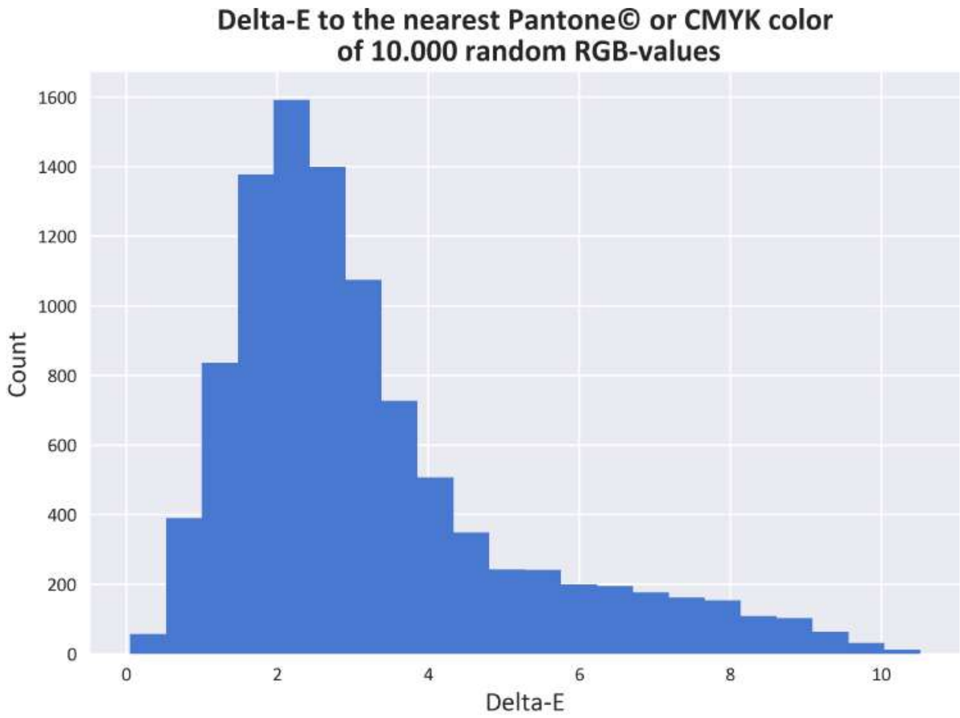

Figure 5.7: Plot of the distribution from Delta E values of 10.000 random RGB-values to its closest CMYK or Pantone color.

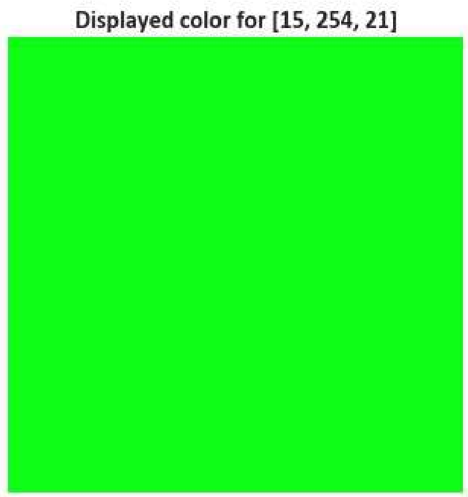

Figure 5.8: Random color that has a Delta E of 9.71 to the closest Pantone/CMYK color.

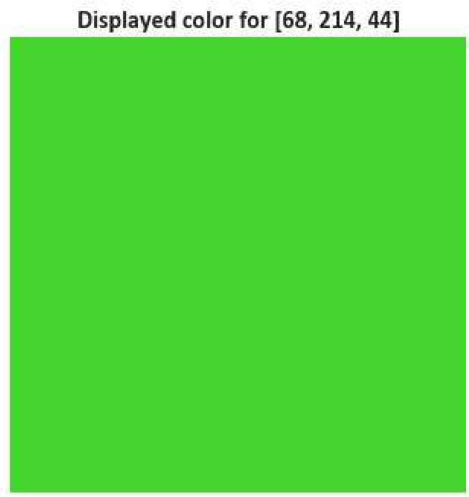

Figure 5.9: Nearest color found for Figure 5.8 in the form of the Pantone 802 C.

the relative position of a color can vary depending on the other colors present in the job.

A more complex version uses the order of two colors. By learning these, the focus is on the relation between two colors and not the general position of a color. This limits the possible results to color combinations that have been used before, but could improve the results. There are different ways how to interpret the results from this. The simplest checks the first position, where the following color is usually printed after the color that is being placed. If, for example, a job with black, red, and white is the starting point, the simplest check would first check the ordering of black and red, and after this, the order between white and black, as well as white and red.

For the full interaction of all included colors, it is also possible to find the information from previous jobs that used the same set of colors. If, for example, a job with black, red, and white is the starting point, all jobs that also have these colors can be searched. If one or more previous orders are found with this selection of colors, the one found in the majority of cases is used. This further limits the possible rate of finding any information but can give a higher accuracy, as the interactions of all colors were taken into account. Even though the same set of colors was used, it does not guarantee the correct sequence, as differences can exist.

Verification of the results

The rating of the result depends on the desired outcome. All will try to optimize for a perfect sort, but all deviations from the optimal can be more or less worse for further processing. For an expected outcome of 1.Cyan, 2.Magenta, 3.Yellow, 4.Black, the optimal result is the same. However, if a result of 1.Black, 2.Cyan, 3.Magenta, 4.Yellow is preferred to 1.Magenta, 2.Cyan, 3.Black, 4.Yellow, depends on the cost of the resulting outcome. If the deviations from the optimal are all bad without differentiation, every job that deviates from the optimal is considered an error, and these can be counted. If the sequence can be changed manually afterwards, it is advisable to count the minimum steps that would be needed to get the optimal sequence. A more general approach, which measures the distance from the original, sums up the difference between the actual and expected position.

$$\sum_{n=1}^{x} |positionexpected_n - positionactual_n| \tag{5.1}$$

For the examples, the results were calculated with different versions. For the single separation identification, the two-color comparison (if not possible for every layer, information from the single separation is used), the full sequence comparison (if not possible for every layer, information from the two-color comparison is used) and a random shuffle for comparison were calculated. As error rates, the general approach and a binary approach, where the correctness for every set and for single separations are checked, were chosen.

To train and test the optimal algorithm for the ink sequence, the information from 69.000 jobs with a total of 475.000 separations was used. It contains the position used in the final ink sequence, the color name, and further production parameters. An important categorization can be done through a so-called proof profile id that exists for every job. Through these, specific preferences like the CMYK sequence and further information, for example, if it is a fine print or reverse print, are defined. This data set was split into a training set containing 80% and a test set containing the remaining 20% of the data. The results were rated by different evaluation methods.

Table 5.2: Overview of the results from the automatic ink sequence detection algorithms

Automatic ink sequence accuracy and error rate			
Algorithm / Evaluation	Average share everything correct	Average share separations correct	Average position distances
Shuffle	0.020	0.181	16.008
Relative previous position (General)	0.245	0.562	6.228
Relative previous position (Grouped)	0.476	0.729	3.611
Two color comparison (General)	0.046	0.231	14.788
Two color comparison (Grouped)	0.047	0.231	14.825
Full sequence (General)	0.832	0.905	1.132
Full sequence (Grouped)	0.886	0.936	0.791

The results are shown in Table 5.2. As expected, the accuracy of the shuffle is very low and serves as a reference for the other algorithms. Only 2% of the orders had the correct ink sequence and 18% of the separations were matched to the right position. The average position distance lays at 16. These results depend on the average number of separations in an order and would be better if fewer separations in a job exist and worse if more separations in a job exist.

The relative previous position, which is not grouped, already shows a substantial improvement. Already 24% of the sets have a correct ordering of the separations and 56% of the separations hold the right position. The decrease of the average position distance is also extensive, as it drops to around 6. This is a lot better than the random shuffle but also hints that a lot of the sequences are far away from the optimal based on the still relatively high average position distance. The cause can be that the results of fine and reverse print are mixed up in the average. This is confirmed by looking at some often used colors and its distribution of values. White has an average value of 0.52. However, most values are either very low or very high. A std of 0.4 strengthens this suspicion. This should improve a lot through the grouping based on the proof profile id, as fine and reverse print do not use the same id.

As expected, the results based on a grouping of the proof profile id, improve by a lot. The relative previous position reaches an accuracy of 47%, where the ink sequence for the job was predicted correctly. Furthermore, the average share of correct separations increases to 72%. These results show that a large portion of this gain can be traced back to the categorization of the fine and reverse print. However, also the different preferences of the printers play into this. All in all, these results show that a relatively stable average position within a sequence exists for colors, but further context is needed to improve these results.

The two-color comparison algorithm, on the contrary, only shows slightly better results than a random ordering. This can probably be traced back to the naive implementation of the algorithm. The positions are set in an iterative way, where the position of the new color is set by finding the first position, where the following color has been set afterwards to average in the training set. An increase in accuracy can be expected if the relationships between them are analysed in more detail to create a better balance between the results. Still, this algorithm does not show promising results for the requirements and is not further analyzed.

In contrast, the full sequence search shows remarkable results. The general implementation reaches 83% of correctly identified sequences. In total, 90% of the separations had the correct position and the average position difference dropped to 1.132. These results also show that specific sets of colors are probably used just for fine or reverse print, as the results for the general implementation would have been much lower if the same set of colors is normally printed in either way. A portion of the results can also be expected to be examples where the found sequence belongs to the same job that has been printed before. As different possible results exist for a set of colors, a further increase in accuracy can be expected for the grouped version of this search.

As expected, the grouped implementation of the full sequence search further improves on the results of the full sequence search. A total of 88% of all sequences from the test jobs were identified correctly. Of the separations, 93% received the correct positions and the average position distance dropped to 0.791. This means that on average, for every job, less than one separation would have to be moved by one position to achieve the optimal sequence.

The only downside to the full sequence search is that this method could not be used for all data. In the general implementation 82.5% and for the grouped implementation, 79% of the tests jobs had the corresponding color set available in the training set. This share of jobs can be increased further by using longer periods of data as training. For the rest, the results from other methods need to be used. To gain the highest accuracy, a first check is done in the grouped full sequence archive. If it does not exist there, the general archive can be searched. For the rest, the grouped relative previous position can be used to get the sequence. Taking this into account, the final accuracy of the order being correct for all separations can be calculated at $0.79*0.886+0.035*0.832+0.175*0.476 = 0.81236$ or 81%.

5.4 Detecting print risks

As discussed in Section 2.2, the possible misregistration can have unfavourable effects in some parts of the image and should therefore be found. These identified areas can be changed in the image data. If possible, these changes can be made with no visible differences to the intended outcome. In many cases, this is not possible, and a decision needs to be made which outcome is preferred. This decision-making process is further analyzed in section 5.5.

Image processing based risk area detection

To find these areas, it is important to understand how these develop, and which forms can exist. As discussed in Section 2.2, these effects occur when the printing tools do not align completely. This movement can occur in all directions and the effects are seen at the edge of elements printed with more than one color or if two colors border each other.

In image processing terms, all possible movements can be mapped by the difference of a dilation and erosion of the image. For a single separation, this can be seen in Figure 5.10. The size of the erosion and dilation depend on the expected strength of misregistration during printing. Larger possible misregistrations need larger erosion and dilation than those with a smaller misregistration.

Not all of these visible areas have the same negative effect for the human viewing the print. For bigger elements, the misregistration does not have such a large impact, as a big share of the elements are still being printed as expected. Smaller elements, on the other hand, can already lose its

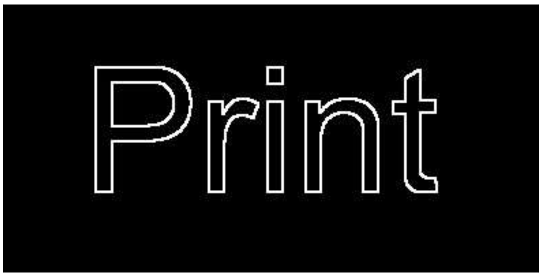

Figure 5.10: Difference between erosion and dilation from single separation.

Figure 5.11: Blurred version of Figure 5.10, highlighting areas with a bigger impact.

outline if a smaller misregistration affects these elements. In that case, it would be very hard to identify or read those elements, which lowers the quality in a significant way.

In addition, not all movements and resulting misregistrations have the same probability. The chances of a small movement are much higher. To combine and apply these conditions to the initial image, a simple blurring of the area is possible, as seen in Figure 5.11. If the elements are smaller and closer to each other, the results are higher than for bigger elements. This is also the case for regions showing smaller misregistration movements. Still, this area itself is not prone to errors because of misregistration.

Negative effects can only occur if this area overlaps with the same area of another separation, as it is the case in the example of the cyan and yellow separations. If no overlapping occurs, such as is the case for a single color separation not sharing a border with any other separation, no risk exists. Through image processing, this behavior can, for example, be generated by using the minimum of two separations. Borders with half-tones create less negative results than those with a full-tone. Some separations can also diminish these risks.

If a very dark or opaque color is printed on top of that area, this can overprint any area affected by misregistration. Moreover, the misregistration needs to be taken into account, so only an eroded version of this dark separation can delete the area where it is printed on top. By applying this, a map is produced that shows all areas of the print that are at risk of producing undesirable results during misregistration. An example of this can be seen in Figure 5.12, where these areas are marked in red.

Verification of the risk area detection

The verification of the results can be done in multiple ways. The main goal is to verify that the detected areas actually are at risk of producing unwanted results in the case of misregistration. A

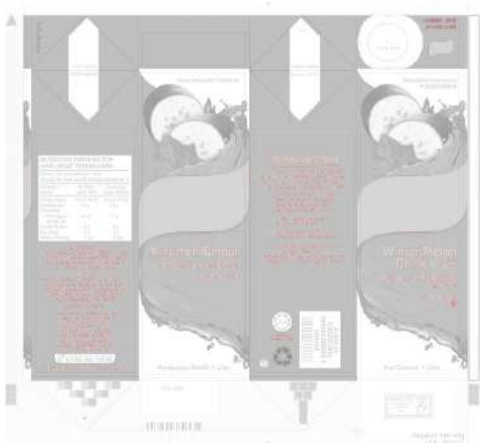

Figure 5.12: All areas in the print are marked in red that can produce undesirable results, if a misregistration takes place.

direct way would be to create a large sample of prints with the analyzed data and compare the areas with the printed results. This is a very cost-intensive process and would require a lot of samples to receive representative results. Therefore, other alternatives are needed.

An alternative is the comparison between the customer and reproduction data. As a part of the job of the reproduction employee is to reduce the risks through misregistration, a noticeable difference should be expected for both, if the procedure is correct. This can show that the detected areas were specifically changed. It should be noted that the quality and outcome can vary depending on the supplier of the data. Printable data can already be available from the customer. Still, in a large enough sample, a large difference should be detectable.

For this verification process, a random selection of the customer and the reproduction data of 100 jobs were chosen. For each job, a rating was calculated. This rating is based on the severity and spread of the area under risk of the misregistration. A higher score would mean a higher risk during printing.

The results show a noticeable difference between the customer and reproduction data. They are visualized in Figure 5.13. For the customer data, the mean data affected by the misregistration is 1%. The reproduction data shows less than a quarter of this value with an average of only 0.26%. This is a clear indicator that is not only produced by a few outliers, as can be seen in the chart, but a larger average difference. Although there are also some customer jobs with no or a very low area at risk of misregistration, which can be explained by the jobs that have already been prepared to be print-ready.

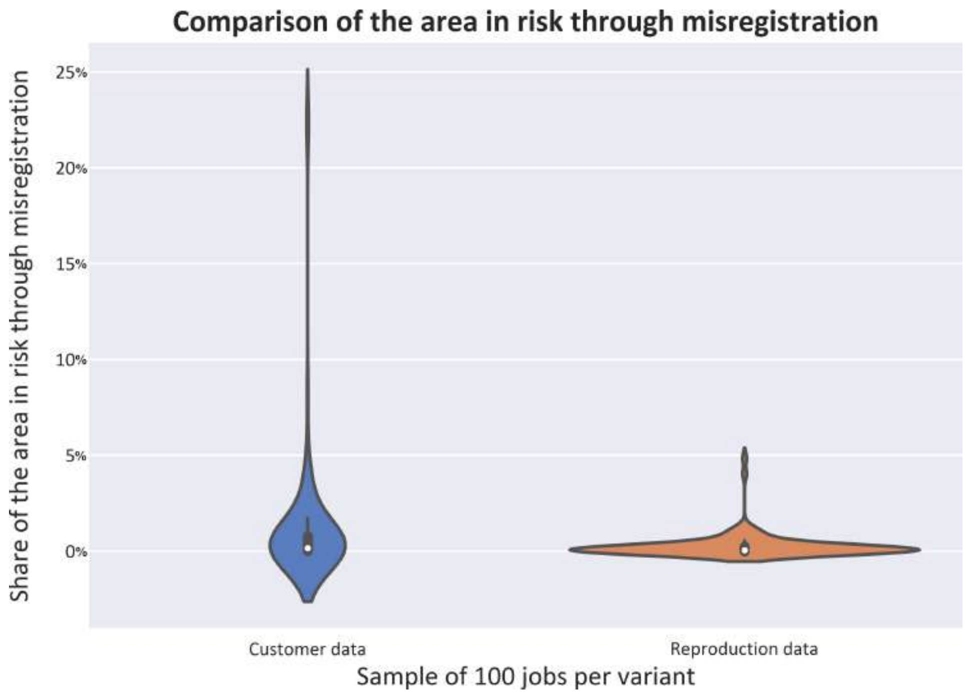

Figure 5.13: The extended area that could be affected by a misregistration was analyzed for 100 examples of each the customer data and the reproduction data.

5.5 Optimizing the print elements

Over the years, different techniques have been developed to lessen the impact of misregistration on the final outcome. For the job entry, it is important to know if more or fewer separations are used for printing. If applied correctly, both can reduce the impact of misregistration and still keep the intended output as close as possible.

To calculate this, certain prerequisites must be met. First, it must be possible to simulate a print with the given data. Otherwise, the results cannot be rated. Second, based on these possibilities, the advantages and disadvantages of the different methods need to be calculated. Finally, the best separation selection can be determined.

Simulating a print outcome of multiple colors

From the entry data, only approximated RGB values for the separations are available during the job entry process. The separation data is only available as a greyscale image. Exact results of the colored version are difficult to simulate, as these depend on many parameters. This would require color management with the used inks.

Therefore, the available RGB values for every separation need to be utilized. These are set to give a visual impression of the color used. It is representative for the full tone color, but does not define the color values of the half-tones in the image. Therefore, these first need to be calculated.

Given the RGB-value, different ways exist to calculate the half-tone RGB-values. These different algorithms can also be seen in the different output of PDF viewers. Even though the same data is used, this can be represented in different ways. As not all parameters are defined, no ground truth can be used to compare the results, but the visual perception should be close enough to deliver meaningful results.

For the calculation of the halftone values, a linear calculation was chosen. Based on the greyscale images of the separations, the luminance value l of the halftone and the RGB-values of the defined color are interpolated. First, the brightness values are inverted for it to color the darkest values the most. These values are multiplied with the adapted and inverted future R, G, or B value of the fulltone. Finally, the image is inverted again to receive the original intensity:

$$r_{halftonevalue} = 255 - (255 - l_{halftonevalue}) * (1 - r_{fulltone}/255)), 0 \leq r \leq 255 \quad (5.2)$$

$$g_{halftonevalue} = 255 - (255 - l_{halftonevalue}) * (1 - g_{fulltone}/255)), 0 \leq g \leq 255 \quad (5.3)$$

$$b_{halftonevalue} = 255 - (255 - l_{halftonevalue}) * (1 - b_{fulltone}/255)), 0 \leq b \leq 255 \quad (5.4)$$

The combination of the colored separations can be done through a multiplication of the RGB-values [262]:

$$r_{new} = \frac{r_1 * r_2}{255}, 0 \leq r \leq 255 \quad (5.5)$$

$$g_{new} = \frac{g_1 * g_2}{255}, 0 \leq g \leq 255 \quad (5.6)$$

$$b_{new} = \frac{b_1 * b_2}{255}, 0 \leq b \leq 255 \quad (5.7)$$

Verification of the simulated print outcome

Although smaller differences cannot be prevented and will not limit the effectiveness of the algorithm, the restrictions need to be known. To test the applicability of this approach, different color combinations were printed with a cyan, magenta, yellow, and black separation and a digital

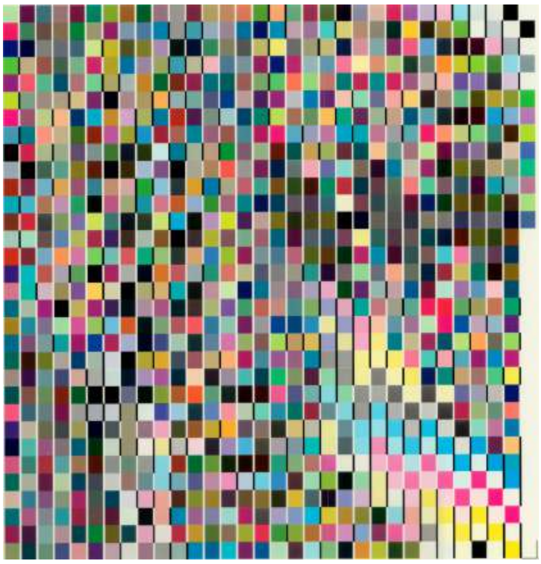

Figure 5.14: Printed color chart with the four separations Cyan, Magenta, Yellow and Black.

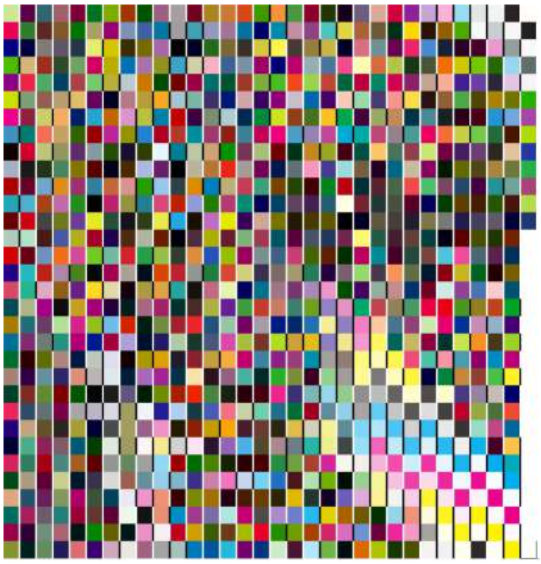

Figure 5.15: Digital composite created with the CMYK separations used to print Figure 5.14.

composite was created. The results of the scanned print are visible in Figure 5.14. It should be noted that the process of scanning already changes the color values in a significant way, as the values from the print are converted to RGB. For comparison, the digital composite was also created using the color separations and the mentioned procedure. It is shown in Figure 5.15.

The first impression is that the digital composite has more vivid colors, which in part is due to the fact that the RGB space can create more extreme colors than through a mix of cyan, magenta, yellow and black. To highlight the differences, the absolute difference of both print and digital can be seen in Figure 5.16. Noticeable differences to the print can be found in some green and brown tones. These are, on average, brighter in the print. This might be caused by the effects of half-toning. Still, the results on average are close and can be used to determine the influence of the options for trapping, which has been described in Section 2.2.

With a closer inspection through the Delta E values between the simulation and print, a better understanding of these differences can be gained. It should be noted that these results are limited by the fact that the RGB values can only be approximated towards the L*a*b values, but it still gives a better understanding of the differences. The histogram of the Delta E values can be seen in Figure 5.17. With a mean value of 7.8, small but noticeable differences between the colors can be seen on average. Only a few values go higher than 15, with the maximum reaching 20.

Based on the limits of the available information, the results are satisfying for the further process.

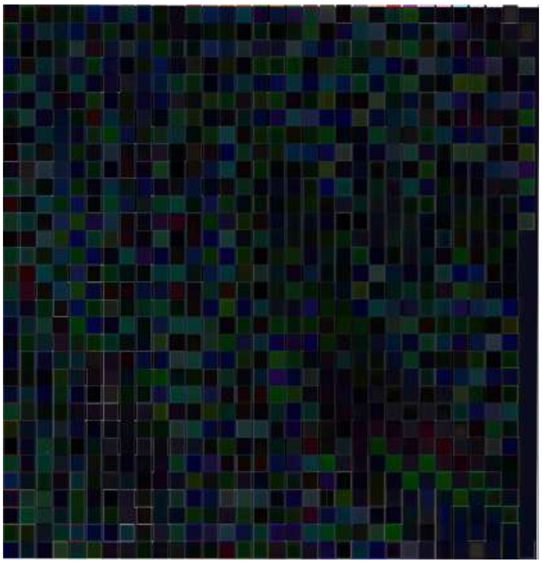

Figure 5.16: Difference between the print (5.14) and the digital composite (5.15) of the four CMYK separations.

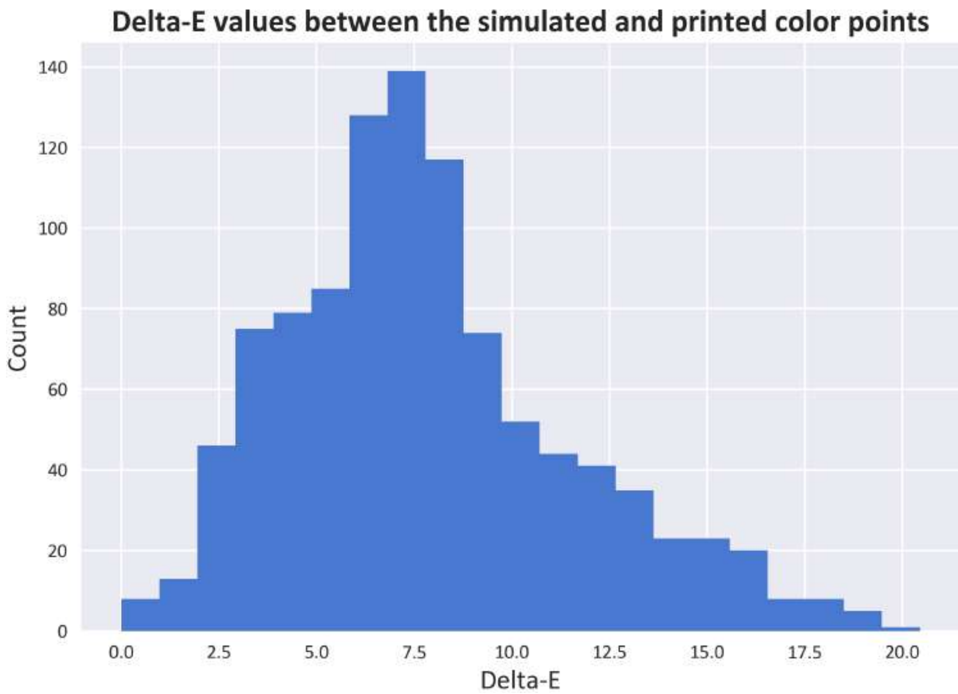

Figure 5.17: For every color in Figure 5.15, the Delta E value towards the color value in Figure 5.14 was calculated.

It does not have the claim of being an appropriate solution for color proofing [263], but it does not have to for the task. The distribution is close to a Rayleigh distribution, which suggests that outliers should not be expected within smaller areas of the color space, but in a broader space. This is also seen in the images, where specific tones such as green and brown show the biggest differences. Therefore, these results can be used as the basis for further calculations.

Reducing separations used

The first step should be the reduction of the amount of different inks used to print the elements. In the best case, this makes the use of one or more printing tools redundant. In all cases where it can be applied, it reduces the risk of unwanted effects caused by misregistration. Granted, the color is not substituted by more colors, such as replacing a black through the three colors cyan, magenta, and yellow. As a downside, the modification can only be done by changing the color to some degree. However, these differences do not have to be noticeable.

To find close colors that can be used as a substitute, a method needs to be developed for the search. The first step is to define the search space. In theory, this could be a N-dimensional space created by the number of inks used (N) holding all possible combinations of the different tones of the inks. In practice, most cases are limited to the color space created by the CMYK colors. This is due to the fact that the overprinting effects are even more complex than the mixing of colors. Printing tests to determine the exact interaction under specific conditions are only done for the basic colors cyan, magenta, yellow, and black. For these, the possible colors created by the combinations need to be known.

Based on the methods derived in Section 5.5, the possible colors can be generated. To reduce the amount of possible colors, 5% steps for the colors were chosen. This still offers a high enough accuracy to determine if a color can be substituted by a different color combination, but lowers the amount of possible color points from $256^4 = 4,294,967,296$ combinations to $21^4 = 194,481$. This is a factor of roughly $22,000$ less, which is very noticeable in time and resource use. The colors create a space of possible alternative colors.

Using all CMYK colors, this is a four-dimensional space. The color space created through the combination of cyan and magenta can be seen in Figure 5.18. The results of a combination of cyan and yellow are visible in Figure 5.19. All possible colors are displayed in Figure 5.34. This is each time the search space.

The search needs to be divided into two steps. A first global search should determine if the print

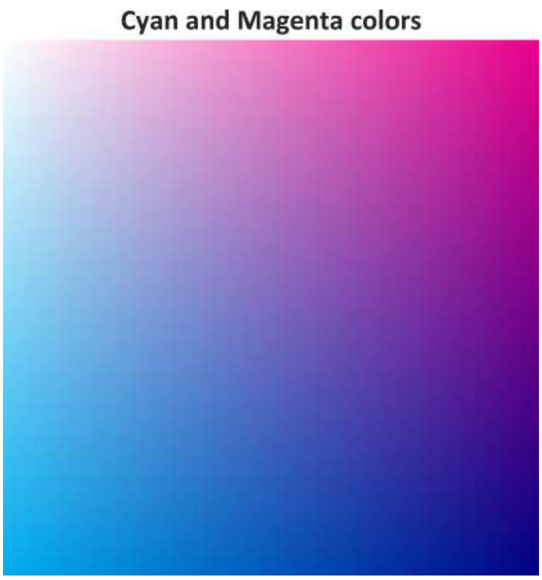

Figure 5.18: All possible colors that can be generated with the combination of cyan and magenta.

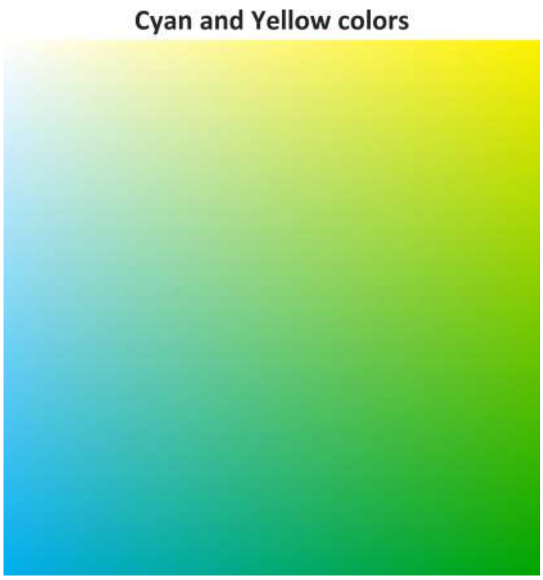

Figure 5.19: All possible colors that can be generated with the combination of cyan and yellow.

can be produced with fewer inks. If this is possible, this is going to be the first rule for the local search for the elements. If it is not possible, the local search is only based on the usage of fewer colors and a low Delta E value to the intended color.

All variants carry out the search by finding the nearest neighbor in the selected search space. If the closest representation using CMY is searched, only the values with no black can be part of the library. The search for the Euclidean distance is based on the 1976 version of the Delta E calculation. Slight differences can be expected towards the more accurate 2000 version when the values are further apart, but these differences are not relevant to the result and offer an improved speed.

In the first global step, all combinations are selected where one separation is removed. On the basis of applying this to the CMYK separations, four possible combinations are possible. CMY, CMK, CYK and MYK. A special evaluation of the CMY combination needs to be taken into account.

In theory, no print would need an extra black channel if cyan, magenta, and yellow are already available, as it would also be possible to create a black color through the mixture of cyan, magenta, and yellow, but in practice, this results in difficulties. For comparison, the same gradient and gray-wedge was printed by the color black (Figure 5.20 and through the combination of cyan, magenta, and yellow (Figure 5.21) on the same substrate. Already, a visual difference can be seen. Through the measurement with a colorimeter, this is confirmed. The 100% tone created by the color black

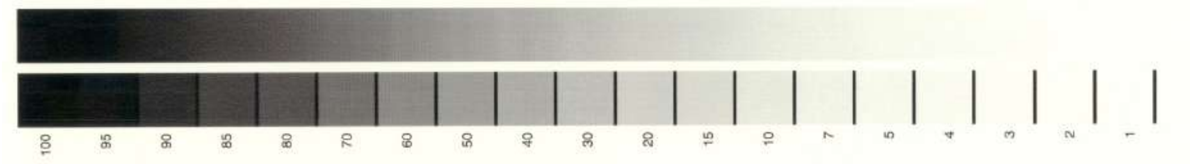

Figure 5.20: Gradient and graywedge printed with a black ink.

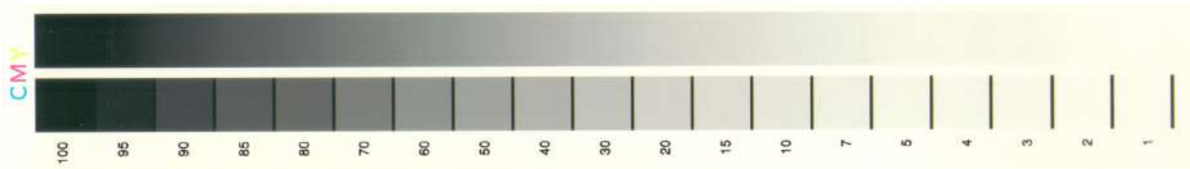

Figure 5.21: Gradient and graywedge printed with a combination of cyan, magenta and yellow in the same ratio.

has a L*a*b value of (L=16.46, a=0.95, b=-1.28). The same tone in the CMY combination, on the other hand, has a L*a*b value of (L=17.40, a=-1.45, b=-1.60), which signifies that the combination of CMY is brighter and further from neutral than the black color. This can be traced back to the spectral results of the color.

To receive an optimal black through the combination of cyan, magenta, and yellow, it would be necessary to have the exact spectral components of which the combination is black. The actual spectrum is a bit off from the optimal. This can, for example, be seen in the spectrum of the yellow ink in Figure 2.4. The combination of the CMYK spectra results in a black that shows higher reflectance in certain parts of the spectrum. Furthermore, the ink usage can be reduced to a third in the black areas by only using the black ink instead of the combination of cyan, magenta, and yellow. For these reasons, the reduction of the black separation should only be considered if no noticeable areas exist that neither have neutral grey tones nor very dark tones.

The results have been calculated on an example image. The original RGB image can be seen in Figure 5.22. By using all available CMYK values, the colors can all be simulated, as seen in Figure 5.23. Only some quantization effects in the sky are visible, due to the limited steps chosen for the colors. This leads to a mean Delta E value of 1.09 for the image and a maximum difference of 5. Bigger differences are seen when fewer separations are used.

As the example image has many noticeable areas with very dark tones, only the CMK, CYK, and MYK combinations need to be checked. The result of only using cyan, magenta, and black can be seen in Figure 5.25. Large parts of the image look very similar, but the differences in the leaves are very noticeable. These differences are further confirmed by the Delta E values towards the original image. Only the areas with leaves are visible in Figure 5.26. The average Delta E value is

Figure 5.22: Original RGB-image. No quantization effects are visible in the sky.

Figure 5.23: Generated CMYK image based on Figure 5.22.

Figure 5.24: CMYK channels used to create the best CMYK fit in Figure 5.23.

8.5, with a standard deviation of 9.4. The maximum value even reaches 71. This makes the CMK combination a nonviable option.

A much closer result can be achieved by using only cyan, yellow, and black and leaving out the magenta separation. The result in Figure 5.28 comes very close to the original. In the Delta E image, seen in Figure 5.29, only small differences are seen in the sky. The average Delta E value for the complete image only lays by 3.8 and a standard deviation of 2.7, while the maximum reaches a value of 16. Meaning that color differences towards the original are visible, but in general only through a direct comparison. All in all, this would be an example, where it would be possible to print the image without the magenta separation.

If one or more combinations exist, where the results are still very close to the original, a reduction of the separations used is possible. In the case of two or more combinations, a next level search

Figure 5.25: CMK image based on Figure 5.22. Large parts of the image can be simulated, but the green from the trees can't be displayed.

Figure 5.26: Delta E values between Figure 5.22 and the CMK based simulation (Figure 5.25) colorized by the viridis color map [264].

Figure 5.27: CMYK channels used to create the best CMK fit in Figure 5.25.

can be started. If, for example, both combinations of CMK and CYK show only small deviations from the original image, it is also advisable to check if the image can already be created by only cyan and black. In this way, only the necessary calculations need to be done.

This could be repeated up until a single separation, if again, two or more combinations were found. For the example selected, only the CMK combination gives acceptable results. Therefore, no further checks need to be done. Still, to visualize the possible results, the original image was simulated with the closest yellow color in Figure 5.31, which can only be used to guess the outline of the original image and in no way can be used as a replacement. This is further exemplified through the Delta E map seen in Figure 5.32, where only the brightest spots in the sky show lower Delta E values. The mean Delta E value reaches 133, with a standard deviation of 60 and a maximum value

Figure 5.28: CYK image based on Figure 5.22. No bigger visual differences can be found towards the original picture.

Figure 5.29: Delta E values between Figure 5.22 and the CYK based simulation (Figure 5.28) colorized by the viridis color map.

Figure 5.30: CMYK channels used to create the best CYK fit in Figure 5.28.

of 250.

The decision, which reduction is possible, cannot always just be based on the Delta E values. If these are all below a certain threshold, such as the just-noticeable difference or even slightly higher, the decision can be made in an automatic way. If it is higher than a certain threshold, it is certain that it is not a possible replacement. In the cases in between, it is necessary to do a further analysis.

This decision needs to take more of the global visual impression into account. The easiest way would be to let this difference be analyzed by an operator. Although differences between the operators should be expected, this is also the case in the current operation. A more complex approach could do an automatic analysis of the differences by taking the known effects of the human visual system into account. As an alternative, these could also be learned by a neural network, by offering a wide class of rated examples.

Figure 5.31: Yellow image based on Figure 5.22. No color except for yellow can be simulated and the darker parts are the furthest from the ground truth.

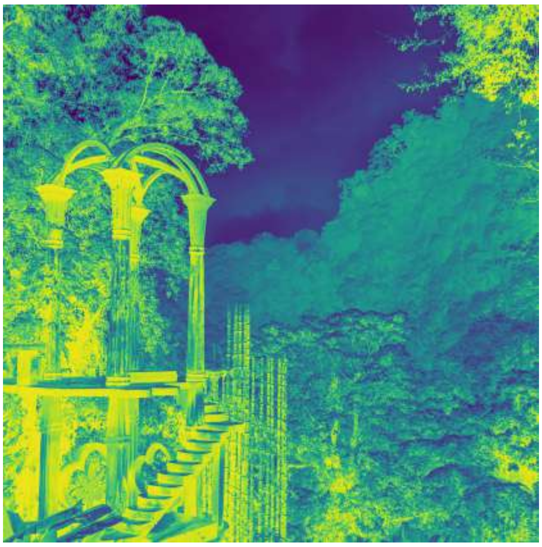

Figure 5.32: Delta E values between Figure 5.22 and the yellow based simulation (Figure 5.31) colorized by the viridis color map.

Figure 5.33: CMYK channels used to create the best Y fit in Figure 5.31.

Reducing separations used for the elements

The local search for the best color combination of the elements needs to take the results from the global search into account. If a combination was found that uses fewer colors, only colors out of these combinations can be used. This includes combinations with even fewer colors. The function can be demonstrated with an example.

The search is based on the algorithm developed in Section 5.5, but offers a higher accuracy. This is done by further expanding the search space to all available values. Moreover, the CIE2000 version is calculated to achieve a higher accuracy. These factors slow down the search but offer a more comparable search.

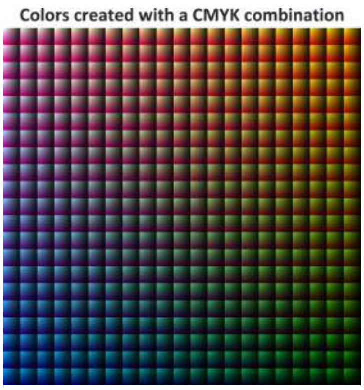

Figure 5.34: All simulated possible colors that can be created with a combination of cyan, magenta, yellow and black.

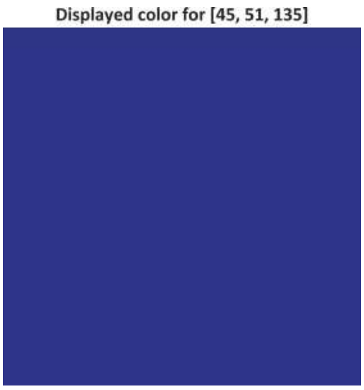

Figure 5.35: Query color and the same color that can be printed with 78% cyan, 69% magenta, 7% yellow and 13% black.

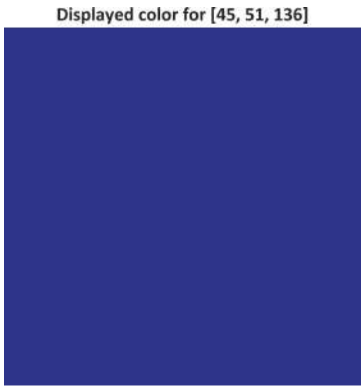

Figure 5.36: Closest color to Figure 5.35 that can be printed with only CMY through 81% cyan, 72% magenta, 16% yellow.

The search with a maximum Delta E value of 10 for the RGB-value $(45, 51, 135)$ gives four different CMYK variations. The exact color can be reproduced with the usage of all four colors and can be seen in Figure 5.34. Both CMK (Figure 5.37) and CMY (Figure 5.36) can also be used to create the same color with a Delta E value below 0.2. Only in the combination of CM is a small color difference, with a Delta E of 4.68 noticeably. Although not a direct goal, it is also possible to find a combination with the lowest ink application within the selected range of colors (Figure 5.39). The ink application is calculated by adding all values of the applied inks. If, for example, two fulltone inks are printed on top of each other, a 200% ink application is achieved. These results all allow a possible color reduction and open up a wide range of possible further applications outside of the job entry.

Calculating the applicability of using trapping

The optimal trapping is not necessary for job entry, but the knowledge, if an acceptable trapping is possible, is needed to determine whether a new separation should be created. If the trapping of all elements can be done with no visual artefacts, adding a new color to the printing process is not needed. If the results are not sufficient, the advantages of using another ink in the production of the print are heightened. Therefore, a rating of the applicability of the trapping is needed.

For the calculation, a distinction needs to be made between the two different types of trapping applied. The elements that are created with more than one color and elements that border each other. Elements that border each other, such as in Figure 5.40 and 5.41 do not lead to the usage of a separate color. These can only be improved through trapping. Elements created with more

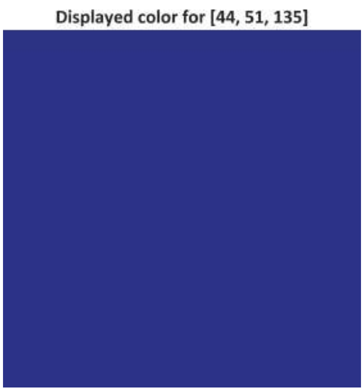

Figure 5.37: Closest color to Figure 5.35 that can be printed with only CMK through 77% cyan, 66% magenta and 22% black.

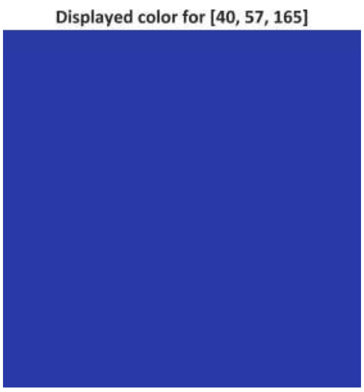

Figure 5.38: Closest color to Figure 5.35 that can be printed with only CM through 83% cyan and 69% magenta.

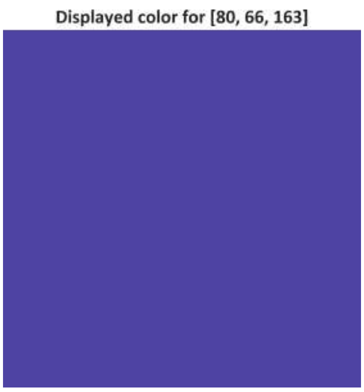

Figure 5.39: Color with the lowest ink application of 135% in a close range to Figure 5.35. The Delta E value is below 10.

Figure 5.40: For bordering colors, a similar brightness but very different colors can significantly reduce the applicability of trapping.

Figure 5.41: As the inside elements are brighter, the inside elements are enlarged and a outer boundary is created.

than one color, on the other hand, can be improved with the usage of a single color, especially if the trapping results would be very noticeable.

The fact if a trapping result is noticeable or not is driven by two main factors. The created color difference and the share of the element affected. The lower the created color difference and the share of the element affected are, the higher the applicability of the trapping is. The interplay between those factors can be investigated with a rating of examples.

In the experimental setting, a wide range of color combinations and strengths of trapping were applied to a lettering. These were rated in the categories ”acceptable trapping” or ”unacceptable trapping”. This line can be a bit blurry, as there are many examples that may be acceptable. In Figure 5.42 and Figure 5.43, low Delta E values make the results acceptable. These are rather improbable real-life examples, as it is rare that one of the colors already comes so close to the intended color, but it sets the boundaries of which the applied trappings are acceptable.

Figure 5.42: Only 12% of the area from the elements are affected by the trapping and the difference of the visible color to the composite is quite low, with a Delta E of 10.

Figure 5.43: Though 54% of the area is changed through the trapping, the Delta E value of 7 of the intended color to the new outline is low enough to not make it visible.

Figure 5.44: Only 12% of the area is changed by the trapping, but the Delta E value is quite high with 30, which still makes the changes noticeable.

Figure 5.45: With 60% of the area affected by the trapping and a big Delta E value of 23, a big visual effect is noticeable at the border of the two colorss.

An increase in the share of the element affected and the Delta E of the color visible towards the intended color both decrease the acceptance of the trapping. Even the small trapping visible in Figure 5.44 is noticeable enough that it is not acceptable, as the Delta E of 30 is very high. A slightly lower Delta E, but a much larger share of the elements affected in Figure 5.45 further increase the non-acceptability. This can also be seen in the data of the test.

The results of the ratings visualized in Figure 5.46, show that these factors are consistent with the classification of the trappings on the example image. Only rare outliers can be found in between the two groups. A straight line starting from $(0, 45)$ to $(45, 0)$ can be drawn to reach a high accuracy. This makes it necessary to incorporate both the share of the elements affected and the Delta E value of the new visible color towards the intended color part in the calculation, if a trapping can be applied in an acceptable manner.

Calculating the advantage of using a new color

Through the previous steps, all possible improvements were analyzed. Changes with a small difference that are not noticeable can be applied with no disadvantages. For the rest, there is a trade-off through changes in the visual outcome. In the case of elements printed with multiple colors, printing certain elements in a new separation with a new color can be an alternative.

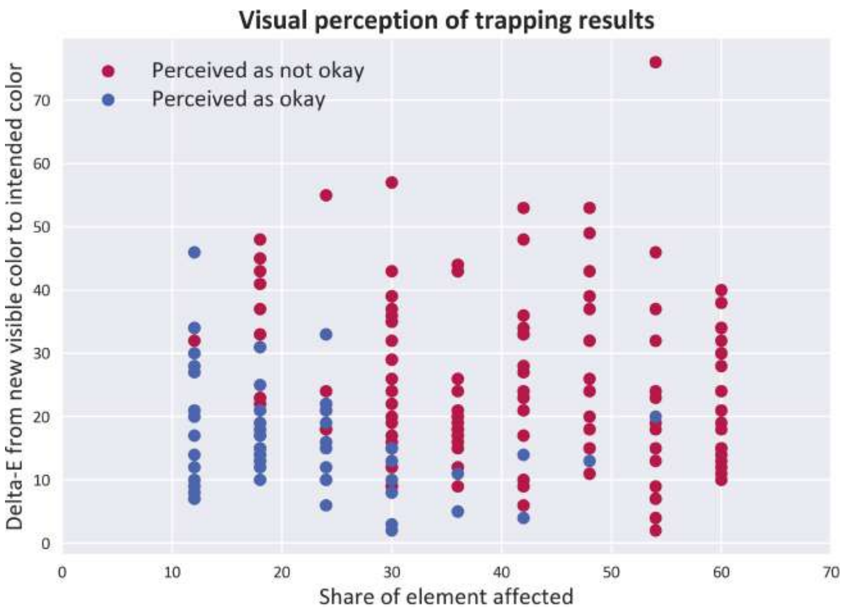

Figure 5.46: Examples with random changes in the severity of the trapping and the colors used were rated by an expert, if these would be acceptable trapping results. Samples are found in Figure 5.42, 5.43, 5.44 and 5.44.

This also has disadvantages through added costs, but these can be outweighed by the improved quality. The costs are mainly based on the printing process and the logistics. First, the additional printing tool has production costs. Furthermore, the specific ink needs to be present, the interaction of other colors and the paper needs to be known and the printing machine must handle the load. However, the ink can also be saved when less total ink is used to create a specific color.

The starting point for the analysis is the risk area for the overlapping elements calculated in the previous section. Only the exact colors present inside this area can be at risk through misregistration. The higher the number of pixels with that color, the higher is the advantage of using the separate color. If only low numbers of pixels are found with that color, no advantage can be gained from printing it through a separate printing tool. Therefore, only the colors with a high number of misregistration pixels need to be further analyzed.

These colors are further analyzed. A mask can be created containing all relevant pixels for this color. For the decision-making process, it is important to know if a trapping can be applied with no noticeable visual artefacts. If this is not the case, a higher chance exists that a separate color is chosen.

Only those with a large benefit need to be shown to the user. Based on the calculated values and a visual inspection, the decision can be made. If no new color is chosen, the trapping needs to be applied. If a new color is chosen, this is not necessary anymore and an optimal outcome can be achieved with the finalized reproduction images.

5.6 Determining the optimal production parameters

Many parameters need to be set for each printing tool. The most influential parameters change how the color will be printed. These parameters are necessary, as all images are screened. Screening creates a pattern of high frequency points that cannot be discerned anymore on the final print from a standard viewing distance. For rotogravure cylinders, these are cells that in general are created on a copper surface. Through the screening, it is possible to better control the amount of color that will be printed and allow a combination of colors to be printed together.

A variety of parameters define the outcome of the screening. An example of a screening can be seen in Figure 5.47. This was created with a 0 degree screen angle, which is the angle of the lines created by the cells that are direct neighbors. As two lines with a 90 degree difference are created, symmetric cells can only have screen angles in the range of 0 to 90 degrees, where the results from 0 and 90 degrees are equal. Different densities of the color have been created through varying sizes. Depending on the production method, this can also be done by varying the depth of the cells.

In Figure 5.48, a 13 degree angle has been simulated. In addition, the frequency of the cells has been increased. This can be created by decreasing the possible size of the cells or by decreasing the cell wall. The cell wall is the space between the cells where no ink will be printed. They are necessary to release the ink from the cells in a reproducible manner. It is possible to use different combinations of these parameters.

Different production parameters of the printing tool affect the outcome of the final print. Many sets of parameters are possible to achieve good results. Certain combinations can be useful to achieve specific requests for the final image. Others can create unwanted effects in the print. For this reason, the first step is to learn parameter sets that have been used with similar color combinations before. In the second step, these possible parameter sets are checked based on the image data of the separations and known rules for parameters that should be avoided.

To ensure that the image data can be produced with the found parameters, it needs to be analyzed. This can be done with rules that are based on the domain knowledge. In general, the printed outcome should be as close as possible to the digital file. Therefore, only parameters should be

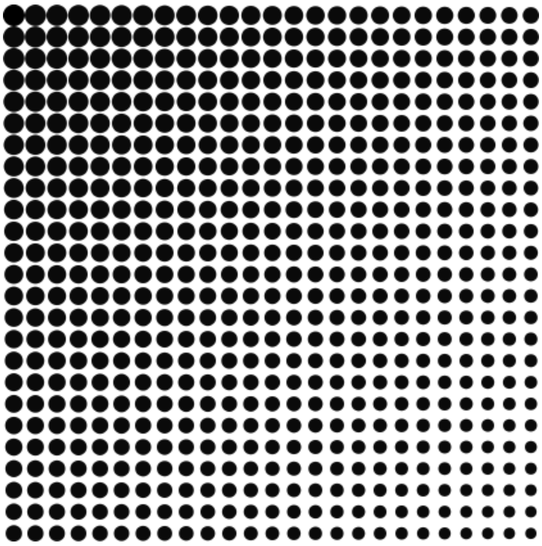

Figure 5.47: Simulated screening of a color black with a 0° screen angle. Lighter tones are created through a reduction of the cell size towards the bottom right.

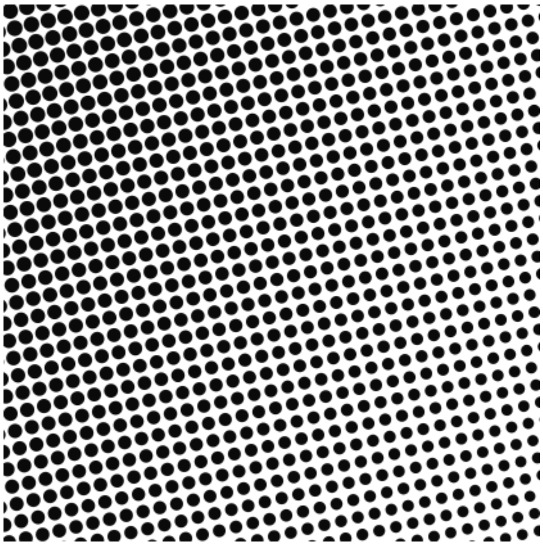

Figure 5.48: Simulated screening of a color black with a 13° screen angle. Also, a higher frequency or screen ruling is used than in Figure 5.47.

chosen that can be used to create this outcome.

The rules can be categorized into two main groups. The first ensures that all elements print as expected. This depends on the production method and the parameters selected, as certain properties of the ink printed are anticipated or depend on the image data. In the second group, the interaction between the single printing tools is taken into account. If the printing tools print as expected when they are printed alone, this does not yet guarantee a good result for a composite created by all printing tools.

Single printing tool rules

The biggest influence is given by the production method. For the rotogravure cylinder creation, multiple possible methods exist. Electro-mechanical engraving uses a graver to scrape out the cells. Laser-engraving directly uses a laser to create the cells [265]. Autotypical etching first uses the laser to create a mask with a protective cover and after that, the cells are etched into the cylinder. Depending on the elements, different methods should be preferred.

The preference is influenced by the limits and possibilities of the method. Autotypical etching should not be used to create half-tones, as it is very difficult to create reliable results for varying sizes of the etching process. Laser-engraving can reduce the screening effect of the half-tones, as

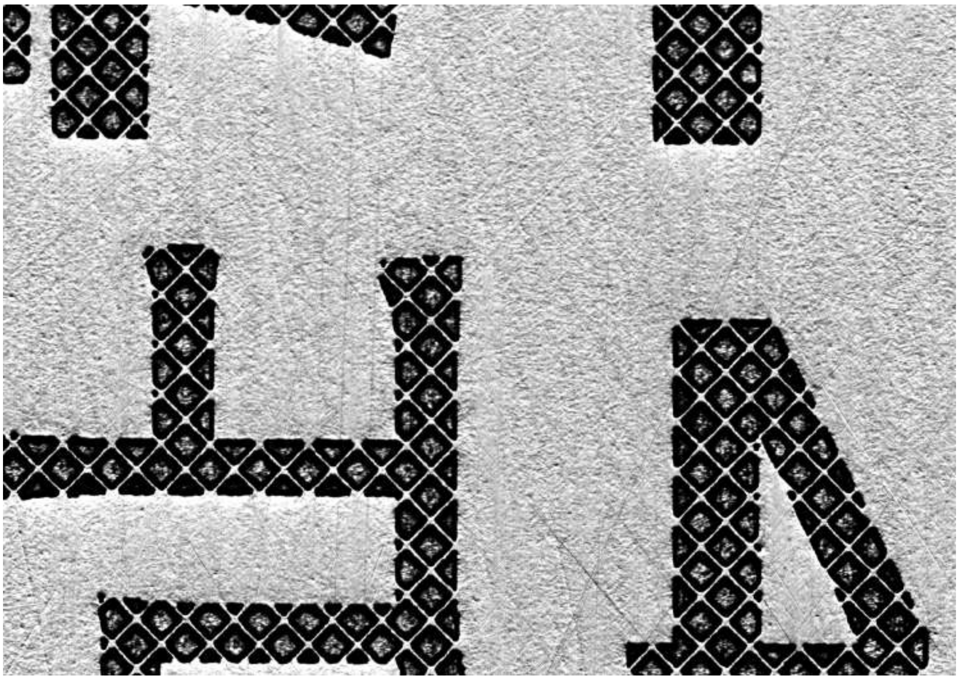

Figure 5.49: Thin elements with many cells that are below a minimum volume to print and will result in a non-optimal print.

it is possible to change the ink density by reducing the depth of the created cells. These can ensure an acceptable outcome for the separate printing tools.

One property limiting the parameters that can be used is the existence of thin elements in the image data. The challenge can be understood through the thin elements visible in Figure 5.49. In the chosen screening, there are many cells at the edges of the elements that are only a fraction of the size of a complete cell. If this falls below a certain threshold, which is depending on the cell size about 50%, the cells can neither take in nor release the ink in an expected way. This leads to a low-quality output that should be prevented.

Different approaches have been developed to optimize the outcome. A higher raster frequency would reduce the share of broken cells. For most production methods, this would implicate a longer production time. It would also reduce the total possible ink coverage, as the cell depth also often needs to be decreased. Another approach is sold under the name *HQH*. This works with the image data before it is engraved. By increasing the thin positive or negative elements, the end result is closer to the expected output. If a production method is chosen that allows the free placement of all cells, this can be used to set the cells in an optimal position. Historically, this has only been used for special purpose printing tools, as the manual placement of cells is a time-consuming and costly process. Recently, the author developed the software *AI screening*, which

Figure 5.50: Optimized cell placement calculated with the *AI screening* software, which has been created by the author.

Figure 5.51: Example of a region of a production file containing both thin and wider elements.

Figure 5.52: A closing operation is applied on Figure 5.51 through a dilation followed by an erosion.

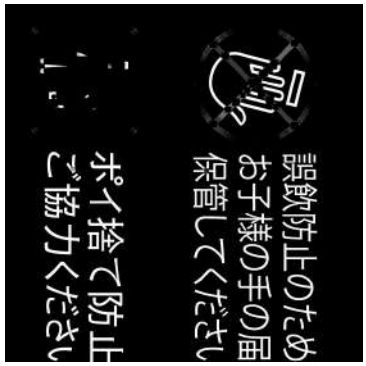

Figure 5.53: Difference of Figure 5.51 and Figure 5.52 highlighting the small printing elements.

mimics this approach to achieve optimized results, as demonstrated in Figure 5.50.

To detect if a special processing is necessary, the presence of thin elements needs to be determined. A solution is the usage of morphological image operators [266]. In particular, a closing operator. As an illustration, Figure 5.51 was chosen. Through dilation, followed by erosion, all thin elements are removed. This can be seen in Figure 5.52. In the difference between those images shown in Figure 5.53, the thin elements are clearly visible. Depending on the limit set for the thinness of the elements, the kernel size of the morphological operator can be adapted. This makes a flexible detection of thin elements possible.

Combined printing tools rules

There are also combinations of parameters that should be avoided. Two possible ways exist to detect the risk of a Moiré pattern. The first is a simulation of the printing results with the image data and the possible screening parameters. The second option is to use a fixed set of rules that need to be fulfilled to reduce the chance of a Moiré pattern. Both have advantages and disadvantages.

By knowing the screening parameters and the approximated ink properties, a print of all colors can be simulated. If any visible, low frequency artifacts arise that should not exist, this shows an increased risk of a Moiré pattern. To provide accurate results, it needs to be ensured that all possible variations that can affect the results are taken into account. These are not always easy to calculate, as even small differences can have a big influence. Due to the varying hardware used by different engraving machine manufacturers, the set frequencies have slight differences. Variations can also come from differences between the printing presses. This makes a simulation difficult.

As to date there is no available software to rate the risk of a Moiré pattern through a simulation with the applied parameters, specific combinations of parameters have been identified that come with an increased risk of a Moiré pattern. Due to the varying influences, an increased risk does not have to result in an unwanted result. The same parameter set, together with the same image data in the production process, can sometimes lead to a noticeable Moiré pattern and sometimes to an acceptable result. This results in a more distinct reduction of possible parameter sets, but guarantees good results through the positive experiences that have been made with these rules. The rules only need to be valid for all pairs of images that both have halftones that print together, as no Moiré pattern can occure with fulltone print.

The following two rules have been identified and can automatically be checked with the knowledge of the overprinting half-tones from the image data:

1. The screen width needs to be the same.
2. The same machines need to have been used for the production of the printing tools.

5.7 Conclusions

Research questions 3 asks, **how data and algorithms can be used to reduce the complexity of the customer-manufacturer interaction**. This has been demonstrated in this research on the example of the printing industry. By combining the domain knowledge of the printing industry with computer vision algorithms, new algorithms were developed to automate parts of the steps in the customer-manufacturer interaction and reduce the complexity of the decision-making process to a minimum. By using previous data, it is also possible to learn customer-specific preferences, even if the underlaying logic for this decision-making process is not known. Through this, a guided system for the customer-manufacturer interaction was able to be set up.

To a certain degree, it can be guaranteed that a good printing quality can be achieved with the developed system. This does not necessarily result in a perfect outcome. The reasons why a different option is chosen cannot always be fully understood, as not all information is known that can influence the decision and it is not even always clear which information influences the decision.

In this case, the easiest option is to offer the information to the customer in an easy-to-understand way. Showing the advantages and disadvantages of the choices. From this, the customer is able to make an informed decision, factoring in the points that are not known to the system.

These algorithms form the building block of a software-based ordering system that reduces the complexity of the customer-manufacturer interaction significantly. Through it, many further extensions are possible. It can be used to offer further services and quality assurance to give more value. Two main paths exist for this.

Limitations and further research

Where possible, the results of the steps of the developed system have been verified with existing data and expert knowledge. To verify the complete workflow, extensive tests with the customer will be necessary. These can point out any potential pitfalls that exist within the developed system. Where necessary, the algorithms and the used data need to be improved in an agile approach.

Difficulties may arise when new data shows strong deviations towards the previously known data. These cannot all be taken into consideration and need to be compensated by a smart user interface design [267].

Different further research paths exist:

Extension towards the design phase

The first possible way is to tackle the previous steps in the printing process. Through the strategic point in the middle of the printing process, where the customer is already using this platform, this can be a good entry point. This can include the design creation and overall decision-making process for the optimal color selection.

Through a large database of measurement points and the right algorithms, a visual simulation of the end-result under the specified parameters can be done. This can influence the parameters that are chosen for the production but also reinfluence the design phase. Through the direct feedback loop, this can be made possible. Normally, it would take multiple days and a lot of work to show the influence on the printing result without this kind of system. It also opens up the possibility of collaborating with ink suppliers and offers a time-efficient way of showing the customer how a different ink could influence the outcome. This can lower the barrier of adapting new technologies such as more sustainable water-based inks.

A bolder approach would be to take over the complete design process. The basis could be a blank slate or a previous package, where a redesign is wanted. Technologies like a Generative Adversarial Network (GAN) can offer a multitude of new possible designs with a minimum cost. Although a technology such as GAN is still in its infancy, the current developments make this an achievable goal in the next years.

Extension for reproduction automation

The second possible way of development goes in the opposite direction towards the production of printing tools. At least a part of the reproduction work that is done today can be automated. This has already been proven in this research. It can also be used to reduce any quality issues that can arise in the steps before producing the printing tool, as all differences can be checked and confirmed, and issues that could arise during printing have already been detected through the resulting software of this chapter.

The low-cost usage of the digital algorithm-based architecture offers different business perspectives for the developed tools. It can be offered as a stand-alone service that offers this service for a specific cost and outputs the data to be used by any printing tool developer. The other strategy is to use it as an incentive. The customer orders more printing tools, as the whole process is much easier and a faster lead-time can be offered, which also increases the customer satisfaction. As all decisions are explained during the job entry process, the customer does not need people with domain knowledge doing the ordering process and can trust on the decisions made by the system. This increases customer loyalty, as the quality can be guaranteed and the overall costs of ordering from the customer side are lower, as no specially trained worker is needed.

An even more ambitious point of view is to use the in-grained knowledge to switch the dependence on the printer. The opportunity arises to offer the functionality as a platform in the ordering process for the business needing prints and not the printer. Currently, the printer is the customer of the business needing the prints. The printing tool manufacturer is the customer of the printer. By gaining further knowledge about the printing tool and its influence on the printing process, an optimal instruction can be offered to the printer. This would offer the opportunity to be the direct contact and reverse the dependencies.

Overall, this demonstrates the possibilities that exist through digitalization. These opportunities do not just exist for the from-the-ground digital companies. In the last years, old industry leaders have increased their focus on digital transformation and are seeing the benefits [268]. This opportunity also exists for the printing industry.

6. Conclusions and future work

The results of this thesis demonstrate the importance of algorithms and data for value creation and as important tools on the path towards an Industry 4.0, or in the vision of the European Commission towards an Industry 5.0 [73] that has a strong focus on the well-being of its workers and the environment. The answers to the research questions are found in the corresponding chapters. This chapter examines the findings in the context of the recognised gap and which further research needs to be done to continue filling this gap, as the achieved results can only be seen as a piece in a much wider puzzle.

6.1 Conclusions

This thesis demonstrates possible ways of reducing the gap that exists in the successful implementation of the Industry 4.0. A main challenge has been found in the current technical focus of current transformation processes. The focus needs to be placed more on the human side and the integration with the technical aspects. Algorithms and data have been shown to be helpful tools for this case in this thesis.

By placing the results in the context of the Industry 4.0 framework (Figure 1.1), the focus has been set on the interaction of both the human and technical sides in the approaches. This forces taking both most important aspects into account, which is not possible with most Industry 4.0 frameworks that are built on many more dimensions [269]. Furthermore, focussing on the complexity of both parts, the inherent complexity is made explicit and the focus is set on the context of reducing it [74].

By answering research question 1, ways have been investigated to aid in the use of shopfloor management systems. The usage of a specific shopfloor management system can have a substantial impact on the shopfloor, as it is a core tool for creating a strategic alignment. This has been identified as a research question relevant to the gap, as finding a strategic alignment is a big challenge for a company on the path towards Industry 4.0 and demonstrates the link between the social complexity found in management and the technical complexity found in the factory. As a first point, through a comparison of current research findings of the brain with Electroencephalography (EEG)-data of workers performing shopfloor management systems, indications have been found that those Lean Shopfloor Management (SM) systems with a focus on predefined goals can have a detrimental effect on the brain patterns of the workers, by limiting the possible approaches that are taken into consideration. A continuous improvement by giving directions, on the other hand, does not show these negative effects, as it seems to allow a wider view and diverse positions to be taken into perspective. As a second point, it has been demonstrated that a trained Deep Neural Network (DNN) is able to categorize EEG-data with an accuracy of 96.5%. This functionality could be integrated into the work process to help workers understand the own thinking patterns or be used during the training of a SM system. As this is *only* a case-study, the results should only be used as a first indication.

By answering research question 2, possible directions for reducing costs and increasing the value of the production line have been researched. This is only possible if the strengths of both the workers and technology are taken into account. Through a strategic development in software, the experience of the workers can be generalized with the help of Deep Learning (DL). This reduces the burden of repeating tasks through an automatic classification of defects with an accuracy rate of 98.4% and opens completely new ways of using this knowledge. Through another DNN and the information of the production line, the possibility exists for reducing the costs and adding value by increasing the quality.

By answering research question 3, the focus has been on the reduction of the complexity in the customer-manufacturer interaction. This accentuates the integration of the users and technology in this process. A reduction of the complexity can be achieved by reducing the complexity of decision-making processes in the interaction of the customer with the manufacturer through algorithms and data. Only realistic suggestions are offered during the ordering process and the most probable solution is recommended. This reduces the necessity of owning an often needed detailed knowledge and makes it possible to focus on relevant decision-making processes. By continuously implementing these processes, it will be made possible to keep up with the increasing complexity in manufacturing.

6.2 Future work

Due to the gap touching many different areas, it cannot be filled with just one thesis. Further developments will need a multitude of different disciplines and viewpoints to *catch up* with the technical developments that have been made in the past years. Algorithms and data will be able to support this endeavour if these are also implemented with the human side in mind. It has the potential to help empower workers but can also have negative impacts if not implemented with sufficient foresight [270].

Based on the Industry 4.0 framework used in this thesis, a multitude of different challenges can already be identified. This thesis attempts to solve the connection points found on the linear growth line in Figure 1.1. These are just a selection of all possible connection points, as seen in Figure 6.1. Even a single point can bring various difficulties that cannot all be detected through single projects. Many more projects will be needed to even get an overview of the difficulties.

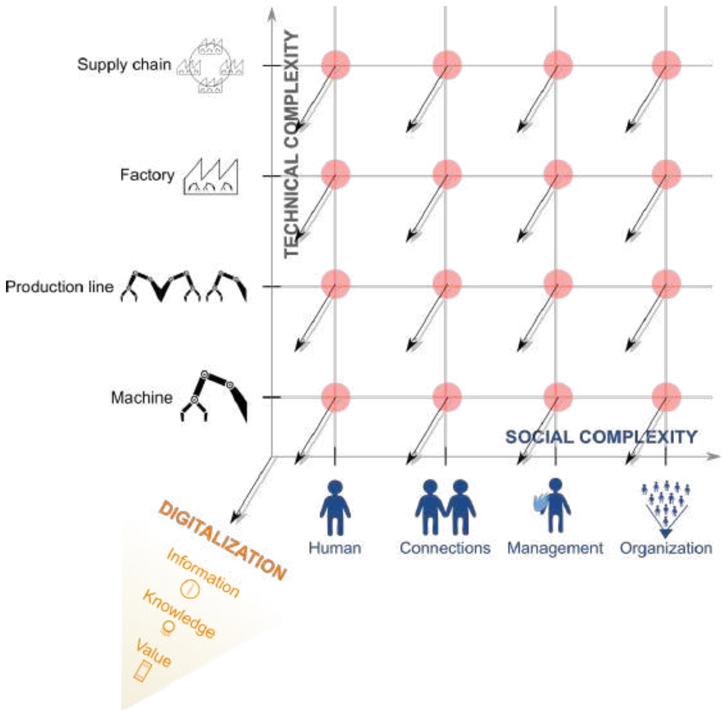

Figure 6.1: Industry 4.0 framework with all possible challenges. The graphic is based on the work in [86].

Further work within this gap is not only possible through algorithms and data. Many different approaches need to be taken into account to reach a large enough leap to incorporate the human side in the advancements of the Industry 4.0.

A large step towards a true Industry 5.0 direction can be taken, if projects are always viewed in the framework formed by the dimensions of humans and technology. This forces the perspective of seeing both involved parts as equal so that both need to be taken into consideration for the implementation.

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