Machine Learning in Design Engineering and Manufacturing

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ABSTRACT

Artificial intelligence (AI) has made significant strides in various fields, challenging conventional notions of computer capabilities. However, while data science research primarily concentrates on refining AI models, there are numerous challenges associated with integrating AI into industrial applications.

Knowledge-Based Engineering, with its potential to streamline the production cycle by reusing engineering knowledge and intent, emerges as a promising avenue for AI in the industry. When engineering knowledge is effectively processed and categorized, neural networks naturally emerge as potent tools for automation.

This thesis presents three case studies that demonstrate the practicality of supervised learning, particularly in the domain of neural networks, to address manufacturing automation challenges. These case studies span various stages of the manufacturing system, encompassing engineering design, production planning, and quality control phases. The first application employs supervised learning to automate the generation of engineering drawings, while the third employs optical character recognition to expedite the quality control process for complex engineering drawings. The second application centers on the estimation of fixturing clamps for welding operations in automobile parts.

In summary, this thesis strives to make a meaningful contribution to the field of design engineering and manufacturing by examining the potential of AI in enhancing processes and addressing automation hurdles. By presenting case studies that showcase the utility of machine learning models in production settings, this thesis aims to stimulate further research in this evolving field.
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Appended Publications

Papers I-IV presented below comprise the foundation of this thesis. The papers are referred to with bold capital romans.


Villena Toro has contributed to the main development of the four papers stated above, in terms of synthetic data generation and collection, method development, technical implementation and writing process.
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Introduction

1.1 Motivation

The father of artificial intelligence (AI) is considered to be Alan Turing, a mathematician best known for his significant contributions to intelligence efforts during the Second World War. As a result, this technology has gained recognition for over 80 years. Throughout this period, the field has experienced cycles of hype and interest, followed by periods in which research and industry involvement were minimal, known as the two AI winters. Many speculate that history will repeat itself, and once again, an "AI winter" is approaching. However, there is a notable distinction from previous times: modern AI is now a driving force in the global economic system, accompanied by significant interests.

The so-called tech industry giants are heavily investing in this technology. Companies like Alphabet, Facebook, Amazon, Microsoft, Spotify, and Apple, to name a few, incorporate AI-based algorithms into their platforms to enhance user experiences. According to McKinsey estimations, AI may deliver an additional economic output of around US$13 trillion by 2030 [1]. The most advanced AI technologies rely on data-driven methods that learn patterns to solve specific tasks, also referred to as machine learning (ML). However, the application of data-driven methods in design engineering and manufacturing is still in its early phases [2].

Several additional challenges must be considered in these disciplines. These challenges include the limited availability of publicly accessible data (1), the minimal margin for error in predictions (2), the fact that most data usually is somehow related to 3D models, and the inherent complexity in designing and manufacturing components and assemblies (3). Furthermore, there exists a significant knowledge gap between data scientists and mechanical engineers (4). Typically, one group lacks the necessary foundational understanding of the other field.
1. INTRODUCTION

Presently, trends observed in design conferences highlight a significant focus on research aimed at bridging the gap between disciplines and rendering ML suitable for design engineering. Addressing the challenges mentioned earlier involves the following solutions:

1. Design engineering datasets typically consist of thousands of samples, a far cry from the trillions found in text or image datasets. To overcome the scarcity of data, engineers can generate synthetic data, for instance, through parametric models [3, 4].

2. Manufacturing is extremely susceptible to errors, and it is a rare occurrence for a model in production to operate without supervision. Manual or automated interventions are employed as a firewall against the inaccuracies that may arise from the model’s predictions. In the field of engineering, there is ongoing research focused on areas such as concept generation [5] and AI-supported computer-aided design (CAD) [6]. Here, AI predictions do not lead to critical errors in product development. Conversely, within the manufacturing domain, a strategy often involves the implementation of dual layers in AI-assisted quality control [7].

3. Data processing is just as crucial as data collection. Often, the available data cannot be directly input into a network; therefore, data formatting and dimensionality reduction becomes essential. For instance, 3D CAD models are typically converted into point clouds for classification or segmentation purposes [8].

4. To tackle the knowledge gap between engineering and data science, it is imperative to encourage higher-level education and encourage the integration of these technologies within engineering programs, thereby fostering collaboration between the two domains [9].

Nevertheless, a large portion of research is conducted within a tightly controlled framework, which limits its practical applicability in the industry. These often termed "toy problems" fail to capture the complexity of real-world scenarios. In this thesis, the aim is to take mature ML algorithms and apply them to authentic industry issues. This involves seeking innovative ways to adapt well-established algorithms to produce the desired final output in practical situations.

Knowledge-Based Engineering (KBE) acts as the bridge that unites engineering applications with ML models. KBE embodies the integration of various software-oriented disciplines with the aim of minimizing time and expenses in product development [10]. The integration of ML into the realm of KBE extends the boundaries of design automation (DA), particularly in scenarios where capturing engineering knowledge through a rule-based approach proves exceedingly challenging.
1.2 Terminology

Consistently throughout this thesis, the focus has been on neural networks. One type of neural network implemented recursively is the Convolutional Neural Network (CNN), a specialized network designed for extracting information from visual inputs. While initial experiments began about forty years ago, the standardization of image labeling in the early 2000s and the introduction of ImageNet, a dataset with millions of annotated images, form the foundation for the models used today. Despite minor progress, these models have not seen significant performance improvements since 2016 [11]. The CNN has matured into a technology that is now widely accessible and relatively cost-effective in terms of computational resources.

1.2 Terminology

This section provides clarification regarding the author’s intent when referring to specific terms and domains, as they may hold different meanings for various readers and may be described differently in the literature.

- **Product Development Process.** This thesis adopts the term "Product Development Process (PDP)" as defined by Ulrich and Eppinger [12]. The PDP encompasses the stages from ideation to the sale of an engineering product. Marketing, Design, and Manufacturing, among other functions, are integral at various stages of the product development journey.

- **Manufacturing System.** The conceptualization of the manufacturing system, as articulated by Black [13], places a significant emphasis on the manufacturing function within the PDP and investigates the interdependencies between various stages. In alignment with this perspective, the design function outlined in the PDP is encapsulated within the manufacturing system and identified as "Design Engineering". Figure 2.1 presents a simplified diagram, drawing from Black’s framework, which illustrates influences specifically on the Design Engineering stage.

- **Design Engineering and Manufacturing.** In this thesis, the term "Design Engineering and Manufacturing" encompasses the functions of the PDP that are characterized by strong engineering intent, specifically, the Design and Manufacturing functions. Therefore, it has been employed interchangeably with the term "Manufacturing system". This term does not relate to functions such as marketing, legal, or management.

- **Knowledge-based Engineering.** La Rocca [10] defines "Knowledge-based Engineering" (KBE) as an engineering method to extract knowledge, integrating various disciplines, including but not limited to ar-
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Artificial intelligence, object-oriented programming, and computer-aided design.

• Design Automation. Although "Design Automation" can be considered a distinct discipline, this thesis adopts the perspective of Pinfold and Chapman [14], viewing it as the outcome or goal of a successful implementation of KBE.

1.3 Aim

The central focus of this thesis has been to investigate alternative ML approaches within the context of manufacturing systems as potential solutions to achieve DA where rule based approaches are impractical. Throughout this research, neural networks have showcased remarkable versatility in addressing a wide array of tasks. The consistent objective across the presented papers has been the development, integration, and utilization of readily applicable algorithms, enabling companies to seamlessly integrate them into their workflows through either partial or complete automation. Additionally, a significant aim has been to help bridge the knowledge gap existing between two distinct disciplines: design engineering and manufacturing, and data science. These overarching goals are encapsulated in the following pair of research questions.

RQ1 How can data-driven methods, particularly neural networks, improve design automation and integrate seamlessly into manufacturing systems?

RQ2 What are the current limitations of machine learning in design engineering and manufacturing?

RQ1 addresses the intricate technical facets encompassing the development and integration of diverse algorithms employed within the scope of this thesis. On the other hand, RQ2 addresses the existing limitations observed in the appended papers and anticipates potential limitations in future applications. This investigation proves indispensable in the process of selecting the optimal approach for each distinct challenge encountered.

Overall, this thesis seeks to increase efficiency in companies through automation by integrating ML pipelines in their work flow, freeing engineers of repetitive tasks that generates very few added value for the company.
1.4 Approach

This thesis encompasses contributions to two distinct projects: i-PROD\textsuperscript{1} and AutoFix\textsuperscript{2}. Both projects share a common goal of enhancing automation levels within Swedish companies by harnessing DA and KBE. While the methodologies are shared between these projects, there’s a shift in their application with respect to the specific products offered by the project partners and the stages of the process they target. For example, the contribution to the i-Prod project focuses on mechanical engineering drawings (EDs). This thesis explores two aspects within this project: the automatic generation of EDs from CAD files during the later stages of the design phase, and information retrieval from raster EDs for quality control. The manufacturing phase, which lies between the design and quality control phases addressed in i-PROD (see Figure 2.1), is also considered here, particularly in the context of automobile construction within the AutoFix project. The latter project’s primary emphasis is on fixture placement and design for body-in-white assemblies.

Both projects adopt a comprehensive approach to automating their respective application domains, encompassing configuration and optimization. However, the research conducted here primarily centers around the ML exploration phase. Similar technologies were employed to tackle the challenges posed by the application cases in both projects.

1.5 Research Methodology

The methodology employed in the three application cases can be categorized into two levels. At a higher level, the methodology aligns with action research in the field of software engineering, as proposed by Staron [15]. On a more specific level, the implementations discussed in this thesis adhere to a quantitative general ML approach [16].

1.5.1 Action Research in Software Engineering

Action Research is a methodology centered on enhancing the efforts of individuals by taking tangible actions. Reason and Bradbury [17] provide a comprehensive definition, describing it as a participatory, democratic process concerned with developing practical knowing in the pursuit of worthwhile human purposes, grounded in a participatory worldview which we believe is emerging at this historical moment. It seeks to bring together action and reflection, theory and practice, in participation with others, in the pursuit of practical solutions to issues of

\textsuperscript{1}i-PROD (DNR 2021-02481) is a research project funded by Sweden’s innovation agency Vinnova under the Advanced and Innovative Digitization program.

\textsuperscript{2}AutoFix (DNR 2020-02974) is funded by Vinnova through the Strategic Vehicle Research and Innovation (FFI) program.
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pressing concern to people, and more generally the flourishing of individual persons and their communities.

In practice, Action Research entails a close partnership between industry and researchers, with the aim of generating novel practices or products. Within the field of software engineering, Action Research is specifically geared towards crafting new empirical methods. These methods not only yield fresh processes but also contribute to the accumulation of knowledge and the learning experience throughout the endeavor.

![Action Research Project](image)

**Figure 1.1:** Action research methodology as presented by Staron [15].

The canonical Action Research cycle comprises five iterative stages [15]. Figure 1.1 illustrates this cycle, taking into account inputs and outputs. Here are the key steps:

1. **Diagnosing.** This initial phase involves identifying the problem to be addressed. The industrial context serves as a guiding factor in selecting which problem to focus on. For example, in Paper II and Paper III, the scope was determined through multiple visits to the respective companies and interviews with engineers.

2. **Action planning.** During this stage, the research team collaborates with the industrial partner to plan the proposed solution in detail and secure management approval. This is where the tools and data collection methods are agreed upon. Paper IV primarily explores the devel-
opment of new tools in the context of the AutoFix project during this phase.

3. Action taking. The research group implements the planned changes and observes their effects. In the cases covered in this thesis, these actions often involve the interaction of one or more ML models. Regular feedback meetings with the industrial partner are scheduled to ensure progress and adjust the course if needed. In Paper I-III the action taking stage corresponds to each developed solution.

4. Evaluation. In this phase, the results are presented to management. If the presented results are inconclusive or do not meet the desired objectives, the research group must collaborate on defining new actions or adjustments.

5. Learning. Practical guidelines and insights gained from the research process are disseminated, both internally within the organization and to the broader research community.

Although not explicitly addressed in the papers, the evaluation and learning stages have played a crucial role in shaping the final outcomes presented within them.

1.5.2 General Machine Learning Approach

The majority of research papers in the field of ML follow a sequential approach, encompassing well-defined stages. These stages generally include Data Collection, Data Pre-processing, Model Training, Model Testing, and Model Evaluation [16]. A graphical representation within the action research methodology of these stages is depicted in Figure 1.2.

The technical implementations described in Paper I, II, and III adhere to these steps for each model developed and deployed.

Data Collection

In this initial stage, data scientists are presented with three alternatives. The first involves the availability of a readily accessible dataset, either from private or public sources. While this is the ideal scenario, it is unfortunately uncommon in the engineering field. In the context of Paper II, labeled data was provided by a project partner.

In the second scenario, researchers encounter unlabeled data, which necessitates significant effort to manually annotate each sample or potentially engage labeling services. However, in the case of intricate engineering or medical challenges, labeling services might not be readily accessible.
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Figure 1.2: A general ML approach fits between the action planning and action taking phases in an action research project. An iterative process is presented to achieve the desired model performance. Further actions (e.g., model integration) might be required to evaluate the whole solution.

Engineers often resort to the third option: generating synthetic data. In Paper I and III, data was generated using a CAD generator and an image generator, respectively.

**Data Pre-Processing**

In this phase, the dataset undergoes analysis and transformation to fit the format acceptable as input for the model. It is during this step that labeled data can be expanded using data augmentation methods.

It is important for a dataset to maintain balance, indicating an equitable distribution of data points across the design space. An instance of an imbalanced dataset can be observed in quality control scenarios for defective products, where the defective samples might be less prevalent than the correct ones.

Ultimately, the dataset is partitioned into training, validation, and test sets, ensuring a comprehensive evaluation of the model’s performance. A principal contribution in Paper II is the novel pre-processing technique adopted.
1.5. Research Methodology

Model Training
The model employs the training and validation sets to calculate performance metrics at the completion of each epoch. Out-of-the-box architectures were used in Paper I - III. However, Paper I and II also include custom architectures developed for their specific application.

Predicting the performance of a model’s architecture is notably challenging, and the number of hyperparameters grows exponentially with the model’s complexity. Manual hyperparameter tuning (as done in Paper I) or techniques like grid search, random search, or Bayesian optimization (as in Paper II) can be employed to optimize these parameters.

Model Testing
Model testing yields crucial metrics for evaluation purposes. During this phase, the model is assessed against the final portion of the dataset, referred to as the testing dataset. The testing dataset contains samples that the model has not encountered before, mimicking the performance it would exhibit during the actual inference phase.

In this stage, data scientists can diagnose potential underfitting, indicating inadequate learning of the data’s features. Conversely, overfitting can occur if the model’s performance on unseen samples deviates from the expected metrics observed during training. Overfitting can occur when the model essentially “memorizes” the training dataset, impairing its generalization capabilities.

Model Evaluation
The prevailing approach tends to be primarily quantitative, except in cases of applications such as Natural Language Processing (NLP) and generative algorithms. In these contexts, relying solely on quantitative metrics may prove inadequate for thorough model evaluation [16]. Within this thesis, typical quantitative metrics used have been mean-average precision, accuracy or loss. More specific metrics for the three implementations will be elucidated in greater detail in Chapter 3.

This overarching approach forms an iterative loop that continues until the model’s evaluation aligns with the quantitative objectives established by the researcher at a higher level. Typically, a model is deemed satisfactory when its performance meets a predefined threshold, often set by a baseline model derived from prior research or human performance. For instance, in Paper III, the outcomes are evaluated against a previous publication’s performance metrics. Given the novelty of the applications in Paper I and II other approaches are followed. The baseline reference is drawn from the ini-
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tial iteration in Paper II. In the case of Paper I, the metrics are complemented by a qualitative analysis of the results.

1.6 Outline

The organization of this thesis is as follows. Chapter 2 offers a frame of reference, encompassing pertinent areas for the thesis, including DA, the manufacturing system, and neural networks. In Chapter 3, a concise overview of the engineering applications in the two research projects is presented through a summary of the appended papers and their application cases. This sets the stage for Chapter 4, which engages in a comprehensive discussion of the work. Finally, Chapter 5 provides answers to the research questions and a general view of the future of AI for design engineering.
Frame of Reference

The frame of reference provides an overview on the field and techniques employed during this thesis, namely Design automation, Design Automation in the Manufacturing System, and Neural Networks.

2.1 Design Automation

Design automation refers to the strategic use of information and knowledge to enhance the design process. It involves the systematic incorporation of data, tools, and systems for planned reuse, ultimately expediting design tasks. This concept encompasses a broad spectrum of activities, from individual component design to entire product creation. There are two primary facets of design automation: information handling, which involves data storage and retrieval, and knowledge processing, which leverages expertise for problem-solving [18].

In the context of DA, a new discipline has emerged in the 1980s called Knowledge-Based Engineering. KBE systems are dedicated software tools that capture and systematically reuse engineering knowledge related to both products and processes. The primary objective of KBE is to reduce the time and costs associated with product development by automating repetitive and non-creative design tasks and supporting multidisciplinary design optimization across various phases of the design process [19].

KBE represents an evolution in Computer-Aided Engineering (CAE), merging principles from object-oriented programming, AI techniques, and CAD technologies. By harnessing these elements, KBE empowers engineers to create customized or variant DA solutions to enhance efficiency, and reduce manual efforts, ultimately leading to more cost-effective and optimized product development [20].

A notable utilization of KBE is exemplified by the introduction of High-Level CAD Templates (HLCts) [21], in which product knowledge finds its
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repository. These templates enable topological modifications, thereby broadening the scope of design possibilities beyond the confines of parametric CAD systems. When these templates are integrated with various other disciplines, such as simulation tools for evaluating performance, such as finite elements, and considering factors like manufacturing feasibility and cost constraints, it creates an ideal blend for the application of genetic algorithms in pursuit of the optimal design. This holistic approach is referred to as multidisciplinary design optimization (MDO), where a comprehensive exploration of design options is conducted to arrive at the most advantageous outcome [21].

However, as Kügler has pointed out [22], despite a decade of scattered literature in the field, the challenges identified by Verhagen [23] remain unresolved. These challenges can be summarized into three: the absence of a well-defined conceptual framework for KBE research with quantitative assessment of costs and benefits [23], insufficient connections between knowledge sources and automation, and a tendency to overlook the diversity of application areas in KBE [22].

While the methodology underpinning this thesis is rooted in action research within industrial contexts, the appended publications relate to the second and third challenges mentioned by Kügler. Paper II and IV main contribution line up with the second problem stated, by finding alternative ways to extract knowledge from engineering products.

Conversely, Paper I and III are oriented towards a different yet equally significant aspect. They target a common application object prevalent across multiple engineering domains, namely engineering drawings. This approach seeks to generalize the application of KBE to diverse fields, recognizing the widespread utility of engineering drawings as a shared foundation.

2.2 Design Automation in the Manufacturing System

The manufacturing system can be viewed as a subset of PDP with a strong emphasis on the manufacturing process itself and all the elements that contribute to bringing a component to physical materialization. Recognized as a critical factor that impacts design by imposing manufacturability constraints, it has been a focal point of DA in the literature.

At a higher level, one aim of KBE is to seamlessly integrate insights derived from prior product iterations or phases within the PDP into the design stage. This integration is undertaken with the primary objective of enhancing both the quality of the end product and the efficiency of lead times. Figure 2.1 introduces the manufacturing system cycle, illustrating the direct factors impacting the design phase, including financial considerations such as project budget, research and development activities encompassing design analysis.
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Figure 2.1: Manufacturing system cycle and the direct influences on the design stage. A design-oriented simplification from Black [13] manufacturing system.

and improvements, as well as the stages of production planning, manufacturing, quality control, and valuable input from consumer feedback.

The optimal scenario envisions a seamless process where knowledge is extracted from all stages influencing the design, continually updating a comprehensive knowledge base, and facilitating automated parametric and topological adjustments [18], all without the need for manual intervention in subsequent stages.

In the pursuit of enhancing the design, Research and Development serves as the driving force, and MDO emerges as the vehicle to automate this crucial stage. While MDO frameworks commonly incorporate influences from neighboring stages such as finance [24, 25] and production planning [21, 25], it is noteworthy that traditional MDO frameworks often overlook the invaluable insights from previous iterations, including manufacturing, quality control, and customer feedback. In addressing this gap, ML emerges as a fitting approach to extract and seamlessly embed this wealth of knowledge into the design process [26].

The initial point of disruption arises during the preparation of essential production documents. Engineering drawings, or their contemporary counterpart, Model-Based Definition (MBD), serve as the primary means for conveying crucial manufacturing information. Surprisingly, there has been limited research dedicated to automating this pivotal step. In an effort to address this gap, Paper I endeavors to delve into the automation of this phase using ML techniques.
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While it demands a considerable investment, the automation of the production planning stage becomes feasible if an ample amount of knowledge is effectively extracted from this phase [27]. Nevertheless, the true complexity lies in the comprehensive extraction of pertinent knowledge from intricate production setups. This challenge can be effectively addressed through the collection of data from previous iterations, enabling data-driven methodologies, as exemplified in the findings presented in Paper II.

In the domains of manufacturing and quality control, the application of neural networks, particularly in the field of computer vision, assumes paramount importance due to the role of visual input in both of these stages. Computer vision finds application in a diverse range of tasks including surveillance, robot control, material sorting, object tracking, non-destructive testing, dimensional measurements, and processes such as welding, assembly, and surface inspection [28]. An identified bottleneck in the quality control phase involves the interpretation of measurements for subsequent equipment programming [29]. To address this challenge, Paper III introduces a cutting-edge computer vision package designed to extract and utilize drawing information, offering a state-of-the-art solution to this critical aspect of quality control.

2.3 Neural Networks

Neural Networks represent a vast and intricate domain in the realm of AI, often perceived as black-box functions capable of establishing non-linear connections between input and output. With a multitude of types and variants available, classifying them comprehensively can be a daunting task, compounded by the rapidly evolving nature of the field. [30]

Due to this complexity, many authors opt to categorize models not based on architectural distinctions but rather on their training characteristics. Depending on whether these algorithms require labeled data for training, they can be broadly classified into supervised learning, where they acquire knowledge from labeled examples, or unsupervised learning, where they unveil underlying data patterns without the need for explicit labels. However, there are neural network frameworks that utilize both types of training, known as semi-supervised networks. [30]

In navigating this chapter, the author has chosen to focus on neural networks relevant to the attached publications and those pertinent to future research endeavors. The chapter is subdivided into three sections: supervised learning, unsupervised learning, and generative networks. Within the supervised learning section, particular emphasis is placed on CNNs, as they have played a central role in the studies presented in the appended publications.
2.3.1 Supervised Learning

One of the most widely adopted supervised learning algorithms is probably the feedforward neural network (FNN). FNNs are composed of fully connected neurons employing nonlinear activation functions. These networks typically comprise a minimum of three layers and are particularly recognized for their capability to discern non-linearly separable data. In a FNN, information follows a unidirectional path, moving from the input layer through one or more hidden layers before reaching the output layer. In contemporary FNN training, the backpropagation technique is commonly utilized.

In contrast to FNN, Recurrent Neural Networks (RNN) are designed to handle sequential data, such as time series or natural language. RNNs have connections that loop back on themselves, allowing them to maintain a form of memory of previous inputs. This recurrent structure enables RNNs to capture temporal dependencies in data [30]. One of the most powerful RNNs is the Long-Short Term Memory (LSTM) [31].

While FNN and RNN are the two most prominent neural network architectures used in supervised learning, note that there are other variants, like Graph Neural Networks (GNN), which are specifically tailored for handling graph or network data [32]. Furthermore, supervised learning encompasses a broader spectrum of ML algorithms beyond neural networks. This includes algorithms such as Support Vector Machines, Decision Trees, and k-Nearest Neighbors.

A special type of FNN is the CNN, they are a specialized type of neural network designed for tasks involving grid-like data. CNNs are characterized by the presence of convolutional layers. These layers employ a set of learnable filters (kernels) that slide over the input data, detecting features and patterns. The power of CNNs lies in their ability to automatically learn hierarchical representations of features. [30]

Convolutional Neural Network

CNNs have played a central role in computer vision tasks, commonly categorized into three main types: classification, object detection, and semantic segmentation.

Classification involves assigning a single label, often one-hot encoded, to each sample, representing its class. While it is the simplest of the three problems, it forms the basis for the other two. Notable models for classification include AlexNet [33] and ResNet [34], with CIFAR-10 being a well-known classification dataset.

Object detection demands more detailed annotations, defining both the position (and perhaps orientation) of objects with bounding boxes and their classification. Approaches include two-step methods like the R-CNN family
and single-step methods like the YOLO family. Datasets like COCO, DOTA (oriented bounding boxes), and ImageNet are commonly used.

Semantic segmentation entails applying a filter or mask to an image to segment objects of interest. It essentially transforms the task into pixel-level classification. Notable architectures for this task include Mask R-CNN from the R-CNN family and U-Net. The Cityscapes dataset is popular for segmentation training.

While computer vision predominantly deals with 2D images, it is important to recognize that human perception extends into the 3D realm, and so do the architectural solutions designed for 3D environments. PointNet represents one of the pioneering architectures tailored for processing point cloud data, specializing in tasks such as part or scene classification and segmentation. While point cloud-based networks have showcased impressive benchmark results in classification and segmentation, there exist alternative approaches for handling 3D input.

These include Volumetric CNNs, which apply 3D CNNs to voxelized shapes, and Multiview CNNs, which project the point cloud into 2D images for classification using CNNs. Feature-based DNNs transform 3D data into a feature vector, enabling feature extraction, while Spherical CNNs employ projections of 3D data onto a sphere and process it using spherical filters.

### Synthetic Data Generation

Supervised learning indeed demands substantial data, but deep learning offers a remedy through transfer learning. Transfer learning encompasses various methods to overcome data scarcity, with one common approach being the retraining of a preexisting model to learn new features with limited new data.

Another strategy involves altering the model’s context, exemplified by self-supervised learning. For instance, in computer vision, this entails actions like image rotation, with annotations indicating the degree of rotation. The network then creates a latent space that can serve as a pretrained model for further training with a small set of correctly labeled samples. This approach, known as transformation prediction, aligns with other techniques in computer vision, including masked prediction, instance discrimination, and clustering.

While there are numerous datasets available for common tasks such as object detection, classification, or segmentation, they often fall short of being suitable for engineering applications. In the realm of engineering, data is frequently held privately and may not be readily deployable for training models. To make it viable for model training, this data must undergo a series of preparatory steps, including preprocessing, skew detection, and annota-
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In cases where data sample annotations are entirely absent or not readily accessible, engineers have the option to generate their own data, a process known as synthetic data generation. This approach involves constructing an automated framework capable of producing both data samples and corresponding annotations, enabling the training of supervised learning models. One of the key advantages of synthetic data generation is the complete control it affords engineers over the annotation process, minimizing the risk of labeling errors. Another advantage is the ability to tailor specific label types for unusual or specialized applications. However, there are drawbacks to this approach, notably an increase in complexity when aiming for a diverse dataset. This can result in intricate data generation processes or datasets that do not fully encompass the range of possible use cases.

Both Paper I and Paper III employ synthetic data generation techniques to create samples for training their respective models. In the case of Paper I, object programming within CAD software is used to generate images of drawings, while Paper III generates text strings within blank images to train the character recognizer.

Data augmentation, while distinct from genuine data generation, serves as a powerful tool in deep learning. It involves artificially expanding the size of a training dataset by applying various transformations to existing data. Notably, Paper II extensively utilizes data augmentation to increase the dataset size, transforming just seven data points into a dataset of 2000 samples.

2.3.2 Unsupervised Learning

Self-supervised learning encompasses techniques that create artificial labels, whereas unsupervised learning operates without the need for annotations. In unsupervised learning, the model discerns inherent patterns within the data to facilitate clustering. Popular methods for data grouping in this context include K-Means clustering or hierarchical clustering. The fundamental concept involves iteratively relocating data points based on their distance from the center of an initial suboptimal group, recalculating the center, and repeating this process until a convergence criterion is met. Consequently, the choice of initialization becomes crucial, prompting the development of various techniques. Hierarchical clustering follows a similar principle, constructing a family tree of clusters.

An unsupervised learning approach employing neural networks is the autoencoder. This architecture comprises a contracting path, known as encoder, and a corresponding expanding segment, referred to as decoder. During training, the model is optimized to ensure that the decoder can repro-
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reduce the input image from compressed and up-sampled information. Similar to self-supervised learning, the overarching objective is to construct a latent space conducive to knowledge extraction [49].

2.3.3 Generative Algorithms

While traditional generative models include RNNs or LSTMs, today, generative algorithms are often associated to complex and large neural network models that utilize a blend of unsupervised and supervised training techniques to generate new data. Advanced architectures, such as the Transformer, have greatly surpassed LSTM capabilities in the realm of text generation [50]. Generative algorithms are experiencing rapid growth and have found applications in various domains, including text [51], image [52], audio generation [53], as well as image-to-3D conversion [54].

These algorithms also play a crucial role in the generation of synthetic data. A standard autoencoder, when trained perfectly, may not be suitable for this task since it tends to create a strictly segmented latent space that aligns closely with individual clusters. To illustrate this, consider training an autoencoder to reconstruct circles and triangles. When overfitted, it does not foster the development of a shared space, leading to the generation of nonsensical outputs when presented with random inputs between these geometric shapes.

Variational Autoencoders (VAEs) [55], on the other hand, introduce a novel approach by constructing a continuous latent space. VAEs encode not just a single point but a distribution of potential inputs, thus imposing regularization on the latent space. Building upon the earlier example, when a random point is mapped to the latent space in a VAE, it will be decoded as a triangle with rounded corners, the proximity to a circle determining the radius of these corners. This results in the creation of new samples, even when the model has been trained solely on circles and triangles.

As an alternative to VAEs, Generative Adversarial Network (GAN) [56] was introduced as a simple yet powerful idea. This idea consists of two networks opposing each other, namely discriminator and generator. The generator aims to create realistic data, such as images, while the discriminator’s role is to differentiate between real data and the data generated by the generator. This dynamic interplay between the two networks results in the generator continually improving its ability to produce increasingly convincing fake data.

An open-source state-of-art model for image generation is stable diffusion [52]. The method uses diffusion models, which are a type of generative model that create images by gradually adding noise and then removing it with denoising autoencoders. However, instead of applying diffusion models directly on pixels, the method uses them on the latent space of pretrained autoencoders. This way, the method can reduce the computational cost and
improve the visual quality of the generated images. The paper also introduces cross-attention layers, which are a way of connecting different parts of the model to enable more flexible and expressive generation. The technology, publicly available through Stability AI, demonstrates that the method achieves state-of-the-art results on several image synthesis tasks, such as inpainting, super-resolution, and text-to-image synthesis.

In the field of natural language processing, the Transformer architecture, introduced in 2017 [50], serves as the foundational framework for today’s large language models (LLM). Prominent examples built upon the Transformer architecture include BERT [57] and GPT [51]. BERT, developed by Google AI, is a pre-trained LLM renowned for its comprehensive bidirectional comprehension of word context. In contrast, GPT, created by OpenAI, adopts an autoregressive approach to text generation. Both BERT and GPT harness the Transformer’s self-attention mechanism, with BERT excelling in providing contextual word representations, while GPT exhibits remarkable capabilities in natural language generation and understanding. These models have ushered in a revolution in various NLP tasks and continue to drive advancements in AI language processing.

2.4 Thesis Frame

In summary, this thesis is situated within the framework of three distinct disciplines: KBE, neural networks, and manufacturing systems. These disciplines exhibit interconnectedness, as illustrated in the Venn diagram presented in Figure 2.2. The overlapping regions are denoted as Zones A, B, C, and TF.

A This zone represents the fusion between KBE and manufacturing. It encompasses methodologies within these two disciplines that do not incorporate neural networks. Any traditional MDO framework incorporating manufacturing constraints falls within this zone.

B Many neural network applications in design do not necessitate the use of a knowledge base. Examples include quality inspection, object tracking, or surveillance.

C This area includes applications where the utilization of KBE and neural networks extends beyond the realm of manufacturing processes. For instance, these technologies can find application in logistics.

Lastly, the combination of these three fields is depicted in brown and labeled as the Thesis Framework (TF).
2. Frame of Reference

Figure 2.2: Venn Diagram Representing the Thesis Framework
This chapter provides an overview of the research conducted in this thesis. The research has resulted in four appended papers that offer detailed descriptions of application cases, tools and methods developed, and research findings. As mentioned briefly in Chapter 1, the work in this thesis was carried out as part of two separate research projects, each contributing one application case. These cases involve automating and interpreting engineering drawings, and planning fixtures for body-in-white components.

3.1 Paper I - Automation of Production Drawings

Annotating a 3D model in engineering design can be an incredibly time-consuming and non-creative task, often causing bottlenecks in manufacturing. This bottleneck occurs whether the data is being transferred to traditional mechanical drawings, which have been the standard vehicle for conveying information, or if a MBD approach is being pursued. In Paper I, the authors present a pioneering automation framework, which, to the best of their knowledge, is the first of its kind in the literature that incorporates neural network technology. The initial challenge faced, a common one in ML applications within design engineering, was the automatic generation of synthetic data, as no training data with the desired label system was readily available.

The case study in this research draws inspiration from sheet metal production, where parts are typically represented in a single unfolded view, as illustrated in Figure 3.1. This simplified problem involves the utilization of up to five basic shapes and encompasses as many as 14 distinct measurements.

The inference framework is comprised of two interconnected neural networks and interfaces with the commercial CAD software, CATIA v5. Ini-
3. Application Cases

![Figure 3.1: Above, toy problem inspiration and below, data generated sample.](image)

Initially, the first neural network, leveraging the widely-used computer vision algorithm YOLO v5 [58] for object detection, identifies and localizes the bounding boxes that enclose the various shapes within the 3D model. Building upon this boundary box information, the second algorithm predicts the specific bounding box where the measurement annotations should be positioned.

Subsequently, a rule-based system is employed to translate these annotations into the mechanical drawing to outline the measurement dimensions. This system employs a parameter error approach to identify the vertices and circle centers within the predicted bounding boxes. It is worth noting that the magnitude of the error directly correlates with the likelihood of generating inaccurate dimensions. For example, in Sample 4 as depicted in Figure 3.2\(^1\), any shape smaller than 6 mm would either be omitted or a measurement incorrectly placed due to this error. This error measure can also serve as the performance metric for the entire system, where a smaller error equates to a higher level of accuracy.

The presented framework exhibits clear limitations when it comes to its broader applicability beyond the specific case it addresses. Firstly, it demands extensive training on a substantial non-synthetic dataset that encompasses a diverse array of sheet metal unfolded designs before it can be effectively applied in an industrial context. Secondly, the current classification scheme, which includes only circles and rectangles, falls short of encompassing the full range of shapes commonly encountered in such drawings. Therefore, expanding the number of classes to encompass shapes with round corners or irregular configurations is imperative.

Paper I encapsulates the four key challenges initially outlined in the introduction. The first challenge arises from the unavailability of pertinent

\(^1\)Extracted from Paper I - Reformatted.
3.2 Paper II - Sheet metal fixture planning

Figure 3.2: Last step in the framework: Translating predictions into CAD.

data, leading to the production of synthetic data as a necessary workaround. The second challenge relates to the system’s susceptibility to high error rates, given that even minor deviations can result in undesirable measurements. The third challenge pertains to data processing, specifically how shapes and measurements are represented as bounding boxes for the neural networks. Lastly, the authors’ limited familiarity with ML techniques at the time of developing the framework led to inefficiencies and required extensive background study.

Concurrently, the paper introduces an innovative approach with the aim of capturing the attention of the research community concerning the annotation problem within the realm of mechanical parts. It presents a complex KBE framework with multiple layers and integrated software components, designed to automate a well-known but under-researched design problem. For more details, please refer to Paper I.

3.2 Paper II - Sheet metal fixture planning

If we consider Paper I as an illustration of the challenges encountered in applying ML to design engineering, the second paper takes a more in-depth approach by following all the steps within the traditional ML framework, using an action research methodology scenario (as depicted in Figure 1.2). In this particular case, the study focuses on fixture planning within sheet metal designs, specifically the task of identifying locations that adhere to the 3-2-1 fixture principle (which requires a minimum number of fixing points to ensure no rotation and no translation in any axis) based on prior design examples.

The dataset utilized in this research comprises CAD parts for automobile b-pillars, which were collaboratively collected with an industrial partner as part of the AutoFix Project.

In contrast to Paper I, Paper II does not introduce a simplified problem, but rather tackles the challenge of working with highly complex CAD parts,
3. Application Cases

as depicted in Figure 3.3\(^2\). The central concept underpinning this developed framework involves the transformation of CAD data into an image format that can be processed by a CNN. To achieve this, the researchers capitalized on a fundamental property of sheet metal components: they can be regarded as shell designs, rendering them 2.5D in nature rather than strictly 3D. This enables the selection of the most representative face, which can then be projected onto a two-dimensional plane. Subsequently, the height of the points relative to this plane is translated into a grayscale image, resulting in a low-resolution representation of the geometry.

Despite efforts to collect and process data to reduce its dimensionality, the available dataset remains severely limited, since there is just one b-pillar per car model. As a result, substantial data augmentation becomes necessary to augment the dataset size from a mere 7 samples to over 2000.

![Data Processing of an inner b-pillar into depth map. Fixture locations predicted are translated to the CAD part.](image)

The initial training of a model serves as a baseline to facilitate hyperparameter tuning and to identify the optimal model architecture for solving this specific problem. The loss per epoch during training is illustrated in Figure 3.4\(^3\), and it is used to compare performance between the baseline model and two subsequent architecture optimizations.

\(^2\)Extracted from Paper II.
\(^3\)Extracted from Paper II.
While the network successfully converges and accurately replicates previous designs, it is crucial to note that its applicability is limited solely to the b-pillar. In both Paper I and Paper II the primary emphasis lay on the development and integration of algorithms rather than their practical industrial implementation. To broaden the scope of Paper II model and make it viable for production, it would be necessary to train more extensive models on various sheet metal parts.

This paper offers two significant contributions. First, it introduces a pioneering framework that facilitates the prediction of fixture locations within complex shapes, thereby advancing the automation of the production planning phase. Second, it presents a method for adapting any sheet metal design, enabling it to be processed by a CNN for tasks such as classification, object detection, or segmentation. For further details, see Paper II.

3.3 Paper III - Information extraction from Production Drawings

A production-ready ML algorithm necessitates a substantial amount of well-balanced and high-quality data. In both Paper I and Paper II, the primary focus has been on presenting the framework, with the anticipation that future work will facilitate its deployment in production settings. The i-PROD project has provided an opportunity to develop a production-ready framework, albeit using synthetic data. The problem identified by the authors in collaboration with their industrial partner pertains to a bottleneck in quality control, where engineers spend considerable time manually extracting information from engineering drawings and recording it in spreadsheets.
3. Application Cases

While optical character recognition (OCR) has been a subject of extensive research since the 1950s, the OCR systems implemented in the literature for engineering drawings up to now have often lacked the features required for practical production use. An effective OCR system must possess the intelligence to recognize the type of item it is reading and how to process that information.

Challenges specific to OCR for mechanical drawings, distinct from traditional OCR, encompass the following:

- Reading tolerances. Mechanical drawings often include tolerances, which can be presented as superscript or subscript characters, depending on the ISO or company standard. Traditional OCR systems struggle with recognizing and interpreting these specialized characters accurately.

- Location and Orientation. Unlike most documents with a left-to-right horizontal layout, text in mechanical drawings can be arranged in various orientations and angles. This variability complicates the task of OCR, as the text may not follow a conventional reading path.

- New Symbols. Traditional OCR systems lack the ability to identify and interpret geometric dimensioning and tolerancing (GD&T) symbols, which are prevalent in mechanical drawings and critical for understanding the design intent.

- Grouping and Segmentation. Mechanical drawings often contain tables and various types of information, such as measurements or GD&T details. Effective OCR must be capable of distinguishing between these different content types, as they serve distinct purposes.

In contrast to traditional OCR, which primarily involves detecting and classifying individual letters to obtain a digital representation of the text, the challenges outlined above elevate the complexity of the problem. Addressing these challenges often necessitates the use of multiple processing pipelines, segmentation techniques, post-processing for text, and the recognition of a broader array of characters and symbols.

The tool developed in Paper III, known as eDOCr, stands out as the most sophisticated open-source OCR system designed for processing mechanical drawings to date. It involves a multi-stage process, encompassing the following five steps:

1. Segmentation and Isolation. In the initial stage, eDOCr isolates boxes and tables relevant to the information block and GD&T from the drawing. Following segmentation, the drawing is divided into three distinct layers: the information block and tables, GD&T boxes, and dimensions. These layers are subsequently processed individually through separate pipelines.
3.3. Paper III - Information extraction from Production Drawings

Figure 3.5: Dimension Pipeline results on a piece of mechanical drawing.

2. Information Block Pipeline. This stage involves separating the text within different boxes and then reading the characters. Each box corresponds to a distinct line in the resulting spreadsheet.

3. GD&T Pipeline. Within this pipeline, each GD&T box undergoes analysis, splitting, and recording.

4. Dimension Pipeline. In this step, the remaining portions of the drawing are segmented into overlapping areas to identify all dimensions, which are recorded individually. Additionally, the tolerance of each dimension is analyzed. A partial result of this pipeline is illustrated in Figure 3.54.

5. Output Generation. Finally, the segmented image is provided along with three spreadsheets generated by the three distinct pipelines, offering a comprehensive representation of the processed mechanical drawing.

In terms of results, eDOCr has achieved commendable performance metrics, including a precision and recall rate of 90% in detection, an F1-score of 94% in recognition, and a character error rate of 8% (see explanation of the metrics in Paper III). It is important to note that these numbers could see substantial improvement with the inclusion of real data samples encompassing

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4Extracted from Paper III - Reformatted.
3. **APPLICATION CASES**

different fonts. Up to this point, all training has relied on synthetic generated data, which brings us to the framework’s initial limitation.

The primary limitation is that the overall character error rate and F1-score, while promising, fall short when compared to contemporary OCR systems like Google Vision. However, it is crucial to recognize that these mainstream OCR systems may not support as many specialized symbols as eDOCr does, and they have been trained on extensive volumes of labeled data. Importantly, eDOCr’s versatility means that if a dataset of mechanical drawings becomes accessible in the future, it can retrain each pipeline model, potentially closing the performance gap and enhancing its capabilities further.

### 3.4 *Paper IV* - Large Language Model Supported Research

In contrast to the earlier technical publications discussed in this chapter, *Paper IV* delves into the potential benefits of utilizing LLMs, particularly since the release of the popular chatbot ChatGPT in November 2022. This paper presents an application study that represents the future work outlined in *Paper II*, wherein we aim to expand the application scope from individual parts to entire assemblies within a novel framework.

The framework introduced in *Paper II* was constrained by the 3-2-1 location principle for individual parts. In this research, we aspire to delve deeper into the selection of assembly locations, a context characterized by varying numbers of components and fixture points. An illustrative example of such an assembly is depicted in Figure 3.6.\(^5\)

In this context, with the objective of exploring innovative solutions, this paper introduces a series of interviews with ChatGPT, which subsequently lead to concise literature reviews on model architectures and recommended frameworks. Consequently, *Paper IV* places significant emphasis on addressing the fourth challenge highlighted in the Introduction: the gap between the engineering and data science domains. It suggests ChatGPT as a promising alternative for investigating potential remedies to this disconnection.

Within the realm of ML model architecture exploration, three critical factors need to be established: the input requirements of the architecture, the anticipated output, and, crucially, an architecture capable of processing the input data and generating the desired output. After engaging with ChatGPT in pursuit of a potential solution, users can request keywords from ChatGPT to guide them towards relevant literature reviews. An iterative process en-

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\(^5\)Derived from *Paper IV*. 
The literature reviews generated from the keywords obtained in four interviews encompass the following topics:

1. Image segmentation. ChatGPT recommended to convert the 3D model into a 2D projection and perform image segmentation. One of the architecture suggestions for this purpose is U-Net [38].

2. 3D CNN. Another approach is to utilize 3D space segmentation by inputting the neural network with the assembly’s point cloud. Architectures capable of handling this task include PointNet [39] and subsequent contributions to this architecture.

3. Seq2Seq. Given the variability of input and output, ChatGPT recommends adapting a Seq2Seq network approach to identify the fixation points. Architectures such as Point2Seq [59] align with this approach.

4. Graph Neural Network. Transforming 3D CAD models into network-compatible input can be effectively achieved through the use of graphs. Various approaches exist to enhance this transformation, including point-based [60], boundary representations [61], or STEP-focused methods [62], which are trending in ML for design.

After carefully considering various avenues, the decision has been made to focus on Image Segmentation for three compelling reasons. Firstly, from a technical standpoint, this choice aligns with the framework developed in
3. APPLICATION CASES

**Paper II**, making it a logical progression for future research. Secondly, opting for Image Segmentation offers the advantage of data augmentation capabilities through the reduction of dimensionality from 3D to 2D. Lastly, it is worth noting that all preceding publications in this thesis have centered around neural networks applications, forming a cohesive theme that lends itself well to the current research and any potential future PhD endeavors.

![The Johari Window in the context of knowledge and knowledge awareness.](image)

Figure 3.7: The Johari Window in the context of knowledge and knowledge awareness. In black arrows, the research process to become expert in a field.

The Johari Window is a psychological and interpersonal communication model developed by Joseph Luft and Harry Ingham in 1955. It is designed to help individuals and groups better understand their relationships and improve communication and self-awareness. The inspiration to frame the intentions of this paper is drawn from the Johari Window. Here, the horizontal axis represents the extent of knowledge about a specific technology, while the vertical axis denotes the awareness of this technology, as depicted in Figure 3.7. The four distinct areas within this conceptual window are as follows:

1. **Known Knowns (Usage Phase):** In this phase, the researcher is fully aware of and proficient in implementing the technology. They possess both knowledge and skills related to the technology.

2. **Known Unknowns (Curiosity Phase):** Positioned to the right, we encounter the realm of known unknowns. Here, the researcher is aware of the technology’s existence but has yet to acquire expertise in its ap-
3.4. Paper IV - Large Language Model Supported Research

This phase signifies a curiosity-driven endeavor, where the individual must invest effort in learning the technology.

3. Unknown Unknowns (Exploration Phase): This area, which is the focal point of the paper, pertains to scenarios where the researcher is entirely unaware of the technology. In such cases, there is no opportunity for the researcher to learn about or apply the technology to a research problem.

4. Unknowns Known (Investigation Phase): On the bottom left, we encounter the domain of unknowns known. In this phase, the researcher possesses an exceptional level of expertise in the field and can identify gaps or areas of interest to explore further. This phase is characterized by a proactive approach to investigating uncharted territories.

In Figure 3.7, the black arrows delineate the anticipated path of the researcher as they navigate through these phases. Notably, one of the valuable contributions of ChatGPT and other large language models to the realm of science is their ability to engage users in discussions about alternative approaches, a phase akin to exploration.
This chapter delves into the primary contributions and limitations of the work conducted, offering both a general and case-specific analysis. Future research directions are also considered for the projects to which this work has contributed. This chapter sets the stage for addressing the research questions outlined in the introduction.

### 4.1 Analysis of Results and Limitations

This section provides an overview of the challenges, analysis of results, and limitations associated with the technical contributions presented in the papers appended to this thesis. It is divided into two main segments: the first block focuses on experimental ML frameworks, encompassing the findings and contributions of Paper I and Paper II, while the second block delves into traditional ML applications, discussing the insights and contributions of Paper III.

#### 4.1.1 Experimental Machine Learning Frameworks

The first challenge encountered in novel ML frameworks revolves around data acquisition. Given their reliance on specific annotation systems, there are often no pre-existing labeled datasets available. Consequently, these applications resort to either synthetic data generation (as highlighted in Paper I) or employ extensive data augmentation processes (as discussed in Paper II). It is worth noting that the generation and sharing of synthetic datasets have emerged as a prominent trend in the field of ML for engineering design over the past few years.

Another common challenge during the development of these frameworks pertains to the selection of models tailored to specific applications. In many instances, such models must be crafted from the ground up to align with
4. DISCUSSION

the framework’s input and output requirements. In these scenarios, establishing baseline performance results becomes an intricate task since there are no existing benchmarks to compare against. Furthermore, given that these frameworks often comprise multiple models, conventional ML performance metrics may not be applicable to the entire system. In Paper I, both models demonstrate high performance individually, but when combined, a novel performance metric is introduced—specifically, the error parameter in the final step for translating measurements into the CAD system. In Paper II, an initial model is employed as a baseline to showcase improvements in loss compared to optimized models, while the assessment of testing performance remains primarily qualitative in nature.

However, it is important to note that the primary objective of these frameworks is not to yield exceptional results, but rather to introduce novel methodologies for working with ML models in scenarios where traditional rule-based methods fall short in capturing knowledge. Consequently, both of the presented frameworks serve as proof-of-concept for potential applications in industry, rather than being considered production-ready models.

In the case of Paper I, one notable limitation is the challenge of generalizing from the toy problem it addresses to other cases, which may necessitate restructuring the framework depending on the type of engineering drawing involved. On the other hand, the most significant limitation of Paper II is the limited availability of data, preventing the comprehensive testing of the framework on various sheet metal components. This limitation raises concerns about the fallacy of composition, where the assumption that the framework is universally applicable to all sheet metal designs is drawn from its success with just two components (inner and outer b-pillar). Additionally, inherent to ML in general, there is the critical assumption of ground truth. In Paper II, the previous designs are deemed to be suitable applications of the 3-2-1 principle without the support of physics analysis or simulations to validate this assumption.

As a concluding remark regarding this approach, it is essential to highlight the contribution of Paper IV. The use of LLMs has the potential to simplify the exploration of models and potential solutions for the development of novel frameworks. The use of ChatGPT has shed light on a promising avenue for future research within the AutoFix project.

4.1.2 Traditional Machine Learning Applications

One of the primary advantages of applying traditional ML frameworks to new engineering contexts lies in the accessibility of pre-trained models and datasets. In the context of Paper III, the framework leverages the keras-OCR Application Programming Interface (API) for various OCR pipelines integrated within it. To adapt this API to the task at hand, modifications were made to the keras-OCR synthetic data generator, ensuring compatibil-
ity with engineering drawing fonts and characters. Additionally, transfer learning was employed to fine-tune the OCR classification networks, while the vanilla text detector required no further tuning.

Given the well-established nature of OCR challenges in various applications, specific metrics, such as the character error rate, are readily available for evaluation. Furthermore, to demonstrate the efficacy of the entire framework, it was benchmarked against the most recent and outstanding open-source contribution in the field, as exemplified by the work of Scheibel et al. [29]. Consequently, the proposed framework has the potential to establish itself as the premier open-source OCR system for mechanical drawings. The framework’s elevated complexity, in comparison to previous attempts, is a key factor contributing to its potential recognition as such a distinguished system.

In contrast to the experimental nature of Paper I and Paper II, the framework discussed here is production-ready and has been packaged for easy installation through the pypi platform, making it accessible for widespread use and further contributions to its development.

However, certain limitations remain with respect to the framework, primarily associated with the data used to train the OCR classifiers. The limited number of drawings available was primarily reserved for testing purposes, and the training process relied solely on data-generated samples, featuring a limited diversity of fonts that support GD&T symbols. To attain state-of-the-art performance, particularly in detection and recognition, it is crucial to leverage a more diverse dataset of drawings, akin to those publicly accessible for traditional OCR, such as the COCO-text dataset. The creation and release of such a dataset could potentially serve as a promising avenue for future research and development.

4.2 Future Directions

Reflecting on the methodology employed in the research conducted thus far, it becomes evident that the future trajectory is influenced by coming projects, collaborative opportunities, and unaddressed automation gaps within the industry. Consequently, the course of future work appears somewhat uncertain. Nevertheless, this thesis hints at potential avenues for future endeavors stemming from the two projects.

In the case of the research project AutoFix, there exist at least two plausible directions. First, as outlined in Paper IV, the use of the proposed architecture in component assembly presents a logical continuation of the work undertaken in Paper II. The methodological approach aligns closely with the preceding research.

Another conceivable path within this project involves addressing one of the limitations identified in Paper II. This entails the implementation of
physics-aware models to facilitate the optimal selection of fixturing points. While substantial research exists in the realm of MDO for fixturing devices, this envisioned framework seeks to employ neural networks for real-time analysis and simulation of deflection and stress on the part based on chosen fixturing points. Engineers would then have the capacity to adjust positions and receive immediate feedback on the resultant changes.

Within the research project i-PROD, previously mentioned in the preceding section, one future direction entails the publication of a fully annotated mechanical drawing dataset for OCR applications. This dataset is poised to capture the interest and engagement of computer scientists, providing them with a valuable resource for benchmarking and conducting research on novel OCR models tailored to the unique demands of this particular application domain. While traditional OCR may have reached a saturation point in terms of research, this specialized dataset offers a fresh and compelling avenue for advancing OCR technology, addressing the distinctive challenges posed by mechanical drawings and their associated text. Within the research project i-PROD, previously mentioned in the preceding section, one future direction entails the publication of a fully annotated mechanical drawing dataset for OCR applications. This dataset is poised to capture the interest and engagement of computer scientists, providing them with a valuable resource for benchmarking and conducting research on novel OCR models tailored to the unique demands of this particular application domain. While traditional OCR may have reached a saturation point in terms of research, this specialized dataset offers a fresh and compelling avenue for advancing OCR technology, addressing the distinctive challenges posed by mechanical drawings and their associated text.

A second avenue involves the development of an automated robot programming framework for quality control. This framework would empower robots to discern which tools to employ and where to make measurements based on specified measurement and tolerance parameters. This framework will be composed on several concatenations of ML models.

Another intriguing prospect within the i-Prod project is the creation of an AI assistant tasked with periodically assessing the manufacturability of designs. This could manifest as a classifier that determines whether a part can be manufactured using traditional methods or additive manufacturing, or as a classifier that identifies the appropriate manufacturing technique based on the object’s geometry.

In a broader context, the overarching goal is to bridge the domains of AI, design engineering, and manufacturing with the objective of enhancing DA. To realize this aspiration, it is imperative to identify repetitive tasks that stand to benefit from ML, take proactive measures, and construct enabling frameworks that facilitate the integration of this technology into specific application scenarios.
This chapter presents answers to the research questions posed in the thesis introduction, drawing upon the examination of the engineering applications discussed, along with their associated challenges, contributions, and limitations. Additionally, the author’s perspective on the future of AI for design engineering is presented.

5.1 Answering the Research Questions

Two questions were raised in the introduction regarding the implementation of ML in DA frameworks within the realms of design and manufacturing.

RQ1. How can data-driven methods, particularly neural networks, improve design automation and integrate seamlessly into manufacturing systems?

Regarding the publications included in this thesis, addressing this research question offers two distinct perspectives. As exemplified in Paper I and Paper II, neural networks can be seamlessly integrated into DA frameworks that involve various software components. In these scenarios, the development of innovative and experimental frameworks becomes necessary, where ML models act as key components. This approach becomes crucial when rule-based systems are either inefficient or impossible to establish due to limitations in domain expertise or the inherent complexities of the problem being tackled.

It is worth noting that implementing such novel frameworks in an industrial context is often not effective and typically requires additional refinement, extensive training with sparse datasets, or a combination of both. Nevertheless, their primary contribution lies in the proof-of-concept demonstration, which lays the foundation for companies to incorporate specific models
into their workflow (as seen in Paper II) or explore new research directions (as evident in Paper I).

The second perspective, exemplified in Paper III, involves the implementation of established and mature ML technologies within engineering applications. In this context, the contribution primarily lies in the application itself rather than the novelty of the technology. These solutions can attain industry-standard performance and are readily deployable, even though ongoing performance enhancements through new data training could be pursued.

The consideration of these two perspectives raises an important question: Is it more practical for engineers to focus on leveraging well-established solutions and identifying relevant applications within their field? In this scenario, the research problems addressed in design automation as outlined in Paper I and Paper II may remain unattended. Repetitive and non-creative tasks might persist without automation, leading engineers to allocate resources to these tasks indefinitely instead of more innovative endeavors.

RQ2. What are the current limitations of machine learning in design engineering and manufacturing?

Commencing with the examination of present limitations, it becomes evident that data management stands out as a pivotal challenge when addressing design engineering and manufacturing issues. The scope of data management encompasses a spectrum that includes data collection, preprocessing, and postprocessing. Even though considerable endeavors have been dedicated to constructing synthetic datasets, the intricate and sporadic nature of the problems at hand necessitates an array of diverse data input types and architectures.

It is worth noting that this limitation is not unique to manufacturing systems; it resonates with other domains as well. Take, for instance, the field of medicine, where the diagnosis of heart-related issues demands distinct input data and expertise compared to the examination of brain-related conditions.

Once a model advances to the production stage, its ongoing maintenance becomes imperative due to the potential impact of data drift, which can render the model obsolete. Typically, maintenance involves retraining the model with fresh data, reintroducing the initial limitation concerning data collection and processing.

Another significant drawback arises from the "black box" nature of ML models, as it disrupts the maintainability common to rule-based systems. This presents a notable disadvantage in this context, as it complicates the ability to understand and update the model, thereby increasing the challenges associated with its long-term sustainability.
5.2 Embracing AI in Design Engineering: Future Aspirations

The application of large AI models today is predominantly confined to serving as suggestion frameworks rather than assuming roles as critical decision-makers. Examples of non-critical AI development include social network recommendation systems, artistic image generation, video game playing, or chatbots, often accompanied by explicit warnings about potential content inaccuracies.

In the realm of design engineering, a similar philosophy should be embraced. AI systems should ideally function as recommenders and assistants to engineers rather than substituting primary decision-makers. This approach aligns with the understanding that critical decision-making in design engineering carries significant ethical and accountability considerations that AI systems cannot bear responsibility for. Hence, the focus should be on augmenting human expertise and decision-making rather than supplanting it.

It appears unlikely that this paradigm will undergo substantial changes in the near future. Many design engineers envision an AI future reminiscent of the science fiction character "J.A.R.V.I.S. (Just A Rather Very Intelligent System)" from the Marvel Cinematic Universe. Such a system would possess the capability to unify all engineering concepts and provide design recommendations, akin to the way GPT processes text. However, the path to building such a system presents significant challenges, primarily stemming from the diversity of data and problems encountered in engineering.
Bibliography


BIBLIOGRAPHY


Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

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