Commercialization Potential for Deep Machine Learning Technology Using Line Scan Camera

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ABSTRACT

In the paper, it is proposed to transfer a food industry`s machine learning knowledge to wood or construction industry. The universal machine vision system has great potential for the scalability. In modern industrial processes, fast and efficient detection of defects plays a crucial role in quality control. In most industrial processes, the defect detection process still relies on the visual inspection of trained workers with low detection efficiency and precision. Wood or metal defect detection increases the automation of the industry, making it less labour intensive, less costly and with improved efficiency. During the project, we proved that quality control inspection system with Machine Learning technology developed for the industry can be scaled up and using the same technology stack moved to the wood and construction industry. The main difference is the size, form and speed of conveyors. During the project, the inspection system achieved the necessary functionality and precision. A further scalability opportunity of the system using Machine Learning is obvious, requiring less time and labour than conventional quality control methods.

Keywords: Quality control, Machine Vision, Machine Learning, knowledge transfer, scalability, commercialisation

1. INTRODUCTION

The machine vision system detects any artefacts on the wood or metal surface (stain, shallow pit, shallow tumours, scratches, edge defects, pattern defects). It provides necessary quality control regarding the processing of the size, diameter, eccentricity, height, thickness and other parts of the non-contact numerical parameters of detection. Ability to identify machining processes that produce specific machined surfaces is crucial in modern manufacturing production. Image processing and computer vision technologies have become indispensable tools for automated identification with benefits such as a reduction in inspection time and avoidance of human errors due to inconsistency and fatigue [1]. The development of a machine learning detection systems will contribute to technological innovation, industry, national development and other applications.

Often, workers manually carry surface quality control. Companies train workers to identify complex surface defects due to their wide variety and sophistication in requirements. Such control is; however, very time consuming, inefficient, and can contribute to a severe limitation of the production capacity [2]. Nevertheless, dynamic environment paradigm and the Industry 4.0 trend is moving towards the generalisation of the production line, where rapid adaptation to a new product is required [3]. Classical machine-vision methods are unable to ensure such flexibility. Typically, in a traditional machine-vision approach, features must be predefined to suit the particular template or pattern. Hand-engineering of features still plays a vital role in classical methods. Usually, it is challenging to transfer hand-engineered features based systems to another domain, and it leads to the long process to adapt systems to different products or even domains. Data-driven, machine-learning approaches provide a solution that allows for improved flexibility where the developed methods can be quickly adapted to new types of products and surface defects using only the appropriate number of training images [4]–[7].

Compared to classical machine vision methods, the deep learning can directly learn features from low-level data and has a higher capacity to represent complex structures, thus completely replacing hand engineering of features with the automated learning process. With a rapid adaptation to new products, this method becomes very suitable for the flexible production lines required in Industry 4.0 [2]. CNN (Convolutional neural networks) has the capability of learning more powerful representations of the defects and better balance the identification of one defect against misclassification of another, achieving an overall accuracy of 93.4% [8]. Technologies are moving fast from electrified to automated, to digitalised manufacturing, such as big data, autonomous robots, IoT, cybersecurity and augmented reality are transforming the modern manufacturing landscape towards Machine Learning capabilities, increasing its popularity.

Previous studies have shown that vision systems can be used to analyse to estimate any quality of surfaces, detect defects and damage, and estimate physical properties of product and packages in many industries [9]–[14] [15]. Over the past few years, deep learning has demonstrated outstanding performance in classification [16], detection [17], and recognition [13], [18]–[20].

Machine vision can interpret and adapt to any data as needed, verify and process then transmit the results to the systems of the value chain in every phase of production leveraging its scalability opportunities [21], [22].

2. SCALABILITY AND APPROACH

Nevertheless, the question about scalability still remains: what is the volume of annotated data required, what kind of data and how precise do the annotations need to be to achieve a performance suitable for practical applications? This is a particularly important question when dealing with deep-learning approaches as soon as deep models with millions of learnable parameters often require thousands of images (dataset) and sophisticated requirements, which in practice is often difficult to obtain and define. According to VDMA Organization, In German and Europe, the machine vision in industry sales records more than doubled in the years 2005 – 2015. In the last ten years, the turnover of the German machine vision industry has doubled. Between 2013 and 2017, the industry grew by an average of 13 percent per year. According to current surveys, the VDMA expects the record level of 2.6 billion euros to be maintained in 2018. Applying Machine Vision leads to improved quality, greater reliability, increased safety and cost-effectiveness [23].

Approach and value proposition

The question of applicability and scalability is very topical nowadays since learning factories provide an encouraging environment to apply and integrate technologies associated with digitised production environments and cyber-physical systems [24]. Learning Factories can be structured so that learners apply theory and calculation analysis to predefined problems or so that the learner employs heuristic methods to iteratively provide suggestions for problems which are not previously defined [25], [26]. The development of machine vision applications demands the combination of multidisciplinary knowledge and the identification of potential application areas. Learning Factories provide a promising environment for developing the competencies required from a future workforce to apply and integrate such technologies associated with Industry 4.0 [27], [28].

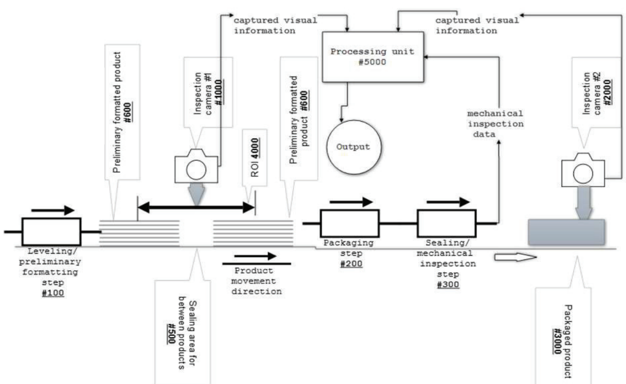

Figure 1. Schematic of Machine Vision system for detection of contamination of sealing and label inspection.

The key goal of this paper is to use Learning Factory in order to effectively develop Machine vision competency for other industries. Machine vision is an encompassing term which includes the integration of both hardware and software for practical application. We have identified the following groups for our framework – the hardware and software. Our R&D process uses two camera hardware setup from the current project as an example, as shown in Figure 1.

The system hardware consisted of a transport trailer, machine vision cameras, a host computer for image acquisition control (#5000 Processing unit) and data processing. Hardware control modules, controlling high-speed machine vision light controller and controlling lights allowing multiple pictures in one scan with different light and camera settings. Integrated annotation and quality evaluation system, capturing current results of the inspection together with the original pictures collected. Annotation system is set on the cloud for external annotators to be able to:

- Annotate new original pictures
- Estimate the quality of quality and precision of the existing system
- Annotate new artefacts on the pictures
- Export ground truth data for training new weights for neural networks

System management module (software), allowing them to separate different modules and their dependencies, meanwhile connecting them in one system. Containerisation approach allows using different frameworks, languages and dependencies on the same computer, isolating every execution environment. As for the software, the proposed approach is demonstrated to be already suitable for a variety of application (Figure 2).

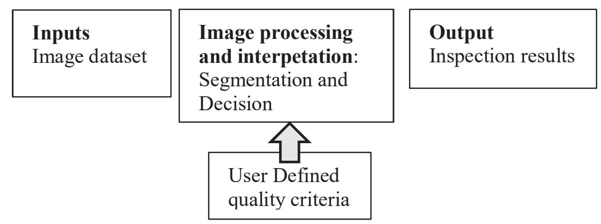

Figure 2. Quality inspection system overview

Scanning application (inputs) includes the following operations:

- Capturing image of the product passing the scanner from different angles and light conditions
- Delivering the image to the modules which analyse and reports findings
- Controlling external physical equipment like ejectors and sorters
- Collecting captured images and delivering them the annotation system to generate ground truth data for training machine learning systems
- Connection the production management system for automated control, reporting and analysis
- Despite the difference in different industries, the same set of operations shall be executed on any line and any product.

An example of User-Defined quality criteria implemented during the project, is shown on Table 1.

Table 1. User-defined quality criteria examples

fault_type	#code	Description
END_HOLE	174	Contaminated or damaged sealing
IMAGE_ERROR	125	System could not capture and extract the package image. Usually it's happen during setup or dirty camera
LABEL_PRINT	6	When label is not printed or printed not in quality
SEAM	5	Final seal damage

During the project following technology stack is developed concerning software-hardware system predefinition:

- Hardware control modules, controlling line scan cameras
- Hardware control modules, controlling high-speed machine vision light controller, controlling lights allowing multiple pictures in one scan with different light and camera settings
- Data collection module on the factory floor for ground picture collection to improve system
- Integrated annotation and quality evaluation system, capturing current results of the inspection together with the original pictures collected. Annotation system is set on the cloud for external annotators to be able to:
- Annotate new original pictures
- Estimate the quality of quality and precision of the existing system
- Annotate new artefacts on the pictures
- Export ground truth data for training new weights for neural networks
- System management module, allowing to separate different modules and their dependencies, meanwhile connecting them in one system. Containerisation approach allows using different frameworks, languages and dependencies on the same computer, isolating every execution environment

This project is using the deep-learning approach to surfaced defect detection with a segmentation network from the point of view of specific industrial application. A two-stage approach is presented. The problem of surface-anomaly detection is addressed as a binary-image-classification problem. This is suitable for surface-quality control, where an accurate per-image classification of the anomaly's presence is often more important than a precise localisation of the defect. The first stage included a segmentation network trained on pixel-wise pictures of the defect. The second stage included an additional decision network build on top of the segmentation network to predict the presence of the anomaly for the whole image.

Segmentation network will consist of several layers (based on goals) with different zoom ratio, to increase the rate of precision during the learning. The network is designed with two important requirements: the requirement for a large receptive field size in a high-resolution image and the requirement to capture small feature details [2], [29], this increases the capacity of features with large receptive field sizes (e.g. Figure 3).

As for the decision network, the network performs global maximum and average pooling, resulting in output neurons. With a micro-defect image as the input, in the convolutional layer, the convolution kernel convolutes the feature map of the upper layer to generate the feature maps.

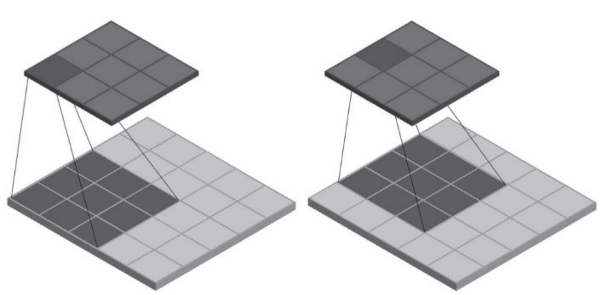

Figure 3. Convolutions dynamics within CNN. Convolution between a feature map of dimension 5 × 5 (yellow) with a kernel of dimension 3 × 3 (brown), stride 1 and padding image 0. The result is another feature map of dimension 3 × 3 (green). [8]

The design of the decision network follows two important principles. First, the appropriate capacity for large complex shapes is ensured by using several layers of convolution and down-sampling. This enables the network to capture not only the local shapes, but also the global ones that span a large area of the image. Second, the decision network uses not only output feature volume of the last convolutional operation from the segmentation network before channel reduction with 1 × 1 kernel, but also the final segmentation output map obtained after the channel reduction with 1 × 1 kernel. This introduces a shortcut that the network can utilise to avoid using a large number of feature maps, if they are not needed. It also reduces the overfitting to a large number of parameters. The shortcuts are implemented at two levels: one at the beginning of the decision network where the segmentation output map is fed into several convolutional layers of the decision network, and another one at the end of the decision network where the global average and maximum values of the segmentation output map are appended to the input of the final fully-connected layer. In contrast to other approaches, they use only a single layer and no down-sampling in the decision layers, and do not use a segmentation output map directly in the convolution but only indirectly through global max and average pooling. This limits the complexity of the decision network and prevents it from capturing large global shapes [2].

In the *decision network* learning takes place separately from the segmentation network. First, only the segmentation network is independently trained, then the weights for the segmentation network are frozen and only the decision network layers are trained. By fine-tuning only the decision layers the network avoids the issue of overfitting from the large number of weights in the segmentation network. This is more important during the stage of learning the decision layers than during the stage of learning the segmentation layers. Since the losses are applied for different scopes, i.e., one at the per-pixel level and one at the per-image level, the accurate normalisation of both layers played a crucial role. The two-stage learning mechanism, therefore, proved to be a better choice and will be subsequently employed in all future experiments.

3. BUSINESS MODEL

The future business models rely on the differences with the conventional commercial software. The experiments show that the predefined commercial software performs significantly worse than the proposed method when using lower resolution images. Usually, the commercial software struggles to capture finer details of the defect and requires a higher resolution for good performance.

Learning on new domains is possible without any modification. The architecture can be applied to images that contain multiple complex surfaces, or it can be applied to detect another different defect [2]

Commercialisation opportunities are highlighting three important aspects of the current situation:

- the required manual inspection has dynamic detection rate with problems regarding human error (by additional manual verification of detections, double-check problem),
- the required human work is leading to the high human labour costs and time consumption

- the designed network is shown to outperform the related state-of-the-art methods (predefined templates), including the latest conventional ML commercial products.

An effective vision system which is developed to identify defect fragments of packaging (sealing and labels) and surface to assess the level of product quality is a considerable value preposition (discussed previously). Therefore, the objectives of this research were to develop a scalable Machine Vision system that is able to fit into the requirements of different industry quality standards.

With the popularity of Machine Vision, an inspection of surface and packaging has become very popular among manufacturers who strive to improve product quality and production efficiency towards digitalisation [30]–[32].

Early defect detection reduces the risk of lost production. Manufacturing companies are trying to fit their digitalisation strategies according to the environmental feedback created by these strategies (or will find themselves at a relative disadvantage in exploiting their environments/resources in digitalisation strategies). In the current, more competitive and dynamic digital environment, the sustainability of competitive advantage exists when the system of competitive advantages is the high and overall value-added generated from all the components in the business model proposition is strong.

It is necessary to recognise a mismatch of quality and price for new customer value. Considering the requirement of maintaining faster measurement speeds, tactile (contact) measuring instruments (e.g. conventional optical instruments) are often not suitable for in-line measurement because, while accurate, they are slow and can only measure a limited number of points on the surface of a part. [33]–[35].

Subsequently, in many cases, standard optical instruments may be suitable for in-line measurement due to their advantages over tactile instruments, including the ability to obtain high-density data within relatively short measurement times, to gain access with complex geometries, and to measure surfaces without the risk of damage. However, there are many challenges that hinder the development of standard in-line optical instruments, including measurement methodology, speed, system integration and control, traceability and system intelligence [36]. Abovementioned challenges are not only relevant for standard optical instruments, but also for tactile measuring instruments, such as the ability to undertake multi-scale measurements (a measurement of form at hundreds of millimetre scales and surface texture at sub-micrometre scales) and to measure in noisy environments (for nanometric accuracy). Visual defect detection requires inspecting units from various view angles, given the non-constant relationship between illumination angle and the unit's surface for this task. Machine Vision with the help of Machine Learning could successfully overcome optical and tactile instrument limitations in measurement working principles [37].

Companies are trying to perceive actual customer behaviour for any products and services through feedback in order to develop consumer-oriented offers [38]. Nowadays company willingness to develop the latest digitalisation advantages is a key element for Machine Vision development opportunities, should take into consideration also availability of current digital Machine Vision environment.

Also, customer values could be affected due to limited knowledge or industry peculiarities. Digitisation transforms business process models and processes (labour intensive) in many enterprises. However, many of them need guidance, how digitisation is impacting the design of their manufacturing process systems. It is not always possible to choose the new Machine Vision proposal that will determine and match with quality requirements values to succeed in the market. Often new Machine Vision business models could lead to misunderstanding among newly implemented quality standards and overall Machine Vision proposal capabilities.

4. CONCLUSIONS

Therefore, we proved that quality control inspection system developed for the food industry can be scaled up in size and basically using the same technologies and the same technology transferred to wood or construction industry where the main difference is the size, form and speed of conveyors.

This paper explored a scalable deep-learning approach for surface defect detection with a segmentation network from the point of view of specific industrial application. A two-stage approach was presented. The first stage included a segmentation network trained on pixel-wise labels of the defect, while the second stage included an additional decision network build on top of the segmentation network to predict the presence of the anomaly for the whole image.

Based on the framework created from the project it is possible to reduce labour costs within the visual inspection and increase efficiency compared to manual, semi-automated, and automated conventional optical systems.

Machine Vision could eliminate optical and tactile instrument challenges concerning methods; speed; system integration and control; traceability; and intelligence limitations. Using Learning factory (in collaboration with the university) could develop interdisciplinary cooperation with respected entrepreneurial ecosystems partners.

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