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Integrating deep learning and rule-based systems into a smart devices decision support system for visual inspection in production

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Abstract

Due to the increasing implementation of cyber physical systems and the internet of things in industry, there is a trend towards flexible, multi-variant production with a very high degree of automation to strengthen the resilience of the company. Each variant is subject to high quality requirements that must be checked to ensure quality. A common means for this is quality assurance through visual inspections, which are carried out manually. Visual inspections are time-consuming yet prone to wrong decisions, since they are subjective, inconsistent, and susceptible to uncertainties. The quality of the inspection relies heavily on the experience of the personnel. This work addresses this issue through the concept and design of a system for objective decision making in visual inspection by integrating Deep Learning (DL) models with a Belief Rule Based Expert System (BRBES) inside a smart devices application. Smart devices like tablets and smartphones serve to generate information by recording and evaluating image material of the components being inspected. Based on this data, DL models are trained and used to classify defects on new image material to automate part of the inspection process. Furthermore, smart devices serve to provide context-dependent decision recommendations in the visual inspection process, which were calculated by the BRBES with the inclusion of uncertainties. The knowledge base of the BRBES is fed by the expert knowledge of experienced visual inspectors using knowledge elicitation techniques. In this way, the system can enable optimized and objectified visual inspection based on the data-driven and knowledge-driven approaches used. This paper outlines the concept of integrating DL and BRBES into a smart devices decision support system.

Keywords: deep learning; belief rule-based expert system; rule-based system; visual inspection; decision support; smart devices; production; quality assurance

1. Introduction

Production is characterized by increasing flexibility and adaptability across all industries. Due to the variability of products, the requirements towards quality characteristics can change frequently and quality assessments are thus not easily reproducible. Due to increasing individualization [1], the already high number of manual visual inspections is further increased [2]. Furthermore, quality assessments conducted by employees are subjective [3]. The reliability of the quality assessment depends on the experience of the employee. Trained employees or experts recognize defects more reliably [4]. Therefore, objectivity and reliability of visual inspections are dependent on expertise along with training and are not always given. This creates a need for skilled employees and use of their knowledge as efficiently as possible and - if possible - to empower unskilled employees.

On the one hand, current approaches to automating visual inspections often replace manual visual inspections completely instead of building on existing expertise and knowledge of skilled employees [5]. Several potential systems for automated visual inspection exist, using industrial cameras for example. These systems often involve a high investment and are not economically viable, especially for small and medium-sized

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enterprises (SMEs). In this regard, belief rule-based expert systems (BRBRES) make use of expert knowledge for decision support of unskilled employees.

On the other hand, due to the digitalization and implementation of cyber physical systems (CPS) and internet of things (IoT) in production, expert knowledge and data are increasingly available to be leveraged effectively [6]. Specifically in visual inspection, there is a need to implement the objectivization of subjective quality criteria. On this basis, deep learning (DL) for an objective assessment of the condition of a component offers great potential.

This paper presents a concept for objectivizing manual visual inspection on smart devices, like tablets and smartphones, by integrating a DL model and a BRBES into a joined system. The goal is to make use of available data and knowledge to improve and objectify employees' decision making in visual inspection. Smart devices serve to provide access to and make use of the system where visual inspections are to be carried out.

2. Related works

Supporting visual inspectors in production to objectivize their quality assessment requires relevant methods and procedures to be considered. These include visual inspection itself, DL methods on smart devices, rule-based expert systems such as BRBES and concepts in which DL and BRBES have been integrated. This chapter presents related works.

2.1. Visual inspection

The main task of visual inspection in production is to assess a component and its characteristics against quality criteria to meet the customers' requirements. A general outline of the procedure is defined in the European norms DIN EN 13018, EN 13927 and EN 1330-10. The inspection involves an inspector, a test component with defined surfaces, and an inspection protocol, which lays out the product-specific extent of the inspection [7]. Possible inspection criteria include optical properties, surface condition and completeness of product assembly [8]. Inspection instructions inside the protocol, in which the inspection criteria are specified, are used to guide the visual inspection and to fulfil the requirements of customers and standards. Inspection criteria can be individually specified and used as benchmarks for evaluation with the help of references or examples. [9]

In general, the qualification level of visual inspectors is not defined in detail by norms and standards. Accordingly, both untrained and trained inspectors perform visual inspections. However, DIN EN 13018 sets certain requirements on inspectors, who must be aware of the product specifications and experienced in all steps of the production process. [7] In practice, these are not always fulfilled. Experienced inspectors reliably recognize characteristics and should - if possible - carry out the visual inspections. Due to the low technical effort and flexibility, visual inspections are widely used in industry [9].

Quality scales can be used in inspection instructions to objectivize manual, visual inspections. The scales are used to express, among other things, subjective inspection characteristics and their properties with a quantitative value. The Likert scale or the multi-level ATZ scale can be used in the evaluation process, e.g., to quantitatively assess the haptic properties of an inspection characteristic. [10]

Efforts to replace subjective, manual visual inspections with automated visual inspection is a very active area of research due to the high economic potential for the manufacturing industry. Automated solutions lack human shortcomings like fatigue and subjectivity and instead yield impartial and reproducible results of constant quality [8]. However, in practice they need to be tailored to a specific inspection task and implemented into the production line. They reach their limits when complex geometries or highly reflective surfaces need to be inspected.

Two major categories emerged as general trends: traditional image processing-based approaches and methods based on deep learning (chapter 2.2). Traditional automated defect detection from digital images consists of two steps: feature extraction and defect identification [8]. The extraction of features is specific to the defect detection task and requires a substantial amount of domain knowledge. The extracted features are then classified subsequently by an additional algorithm. Algorithms for classification can be based on probabilities (Bayesian Classifier, Gaussian Mixture Models) or regression of a separating hyperplane (Multilayer Perceptron, Support Vector Machines) [8]. Overall, applying traditional approaches to automated defect detection assume in-depth knowledge of different feature extraction techniques and are not compatible with changing production environments.

2.2. Deep learning on mobile devices

In recent years DL methods have been established as the state of the art in machine vision applications [11]. These methods have the advantage of learning feature representation directly from the data instead of manually crafting hand-engineered features [12]. DL models are artificial neural networks that have a large number of hidden layers [13]. Depending on the properties of the data set, such as the number of data points and requirements on the DL model (such as the computation time), suitable DL models are selected. Recent approaches apply DL models for classification, detection, and segmentation of defects. All three approaches have been reported to perform well on recognizing surface defects in various kinds of industries from manufacturing of steel [14,15] or textiles [16] to construction [17,18].

Although applications in literature are specific to the use case, certain general conclusions can be drawn from these implementations:

- DL models consistently outperform traditional defect detection systems in all tasks investigated
- Data augmentation enables the data basis to be increased by turning, rotating, and mirroring the images
- Data augmentation is also effective in ameliorating class imbalances in the dataset

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.

- Light-weight DL models can run on resource-constraint hardware with low latency
- Transfer learning from pre-trained models to defect datasets leads to considerable results
- In problem cases, where defects only cover small areas of the image, multi-stage approaches or processing the image in patches are necessary

Suitable DL models include the Multilayer Perceptron (MLP) or the Convolutional Neural Network (CNN). To achieve better results in image recognition, DL models are constantly being developed or refined. CNN models such as ResNet152, GoogleNet and AlexNet achieve good results. [19,20] Although these heavy-weight neural networks score better results on image classification benchmarks, their deployment to smart devices is impaired by their computational requirements and memory footprint. The inference time of ResNet152 is up to 10 times larger than of state-of-the-art mobile models when running on modern hardware of smart devices [21]. Long latency times make heavy networks impractical for mobile applications. Fortunately, a lot of effort has been made to develop mobile networks which can operate in real-time under the performance constraints of smart devices. Notable mobile networks are the MobileNetseries [22], NASNet [23] and the EfficientNets [24]. The inference time of a network cannot be estimated solely on the number of parameters and differs depending on the framework and the device [25]. Additional methods can be used to further decrease the inference time and memory footprint of a model. Deng et al. [26] provide an extensive overview of techniques for model compression and hardware acceleration.

2.3. Expert systems

Expert systems (ES) are computer-aided knowledge-based systems that can provide recommendations in decision-making processes by means of a knowledge database created by experts. Through ES, an increased objectivity in decision-making processes can be achieved. In this respect, ES are suitable for visual inspection, as the visual inspector is supported in decision-making irrespective of the level of qualification. Furthermore, quality characteristics can be evaluated more objectively. [27]

An ES usually consists of a knowledge base as well as an inference, an explanation, a knowledge acquisition, and a dialogue component. The knowledge base stores the context-specific knowledge of all knowledge carriers (experts) and forms the basis of all other components. The knowledge base is filled with the help of the knowledge acquisition component, in which various knowledge elicitation techniques are applied. An inference mechanism uses this knowledge and derives solutions for an instance in the context of a problem, usually by applying algorithmic procedures. [27] An ES provides the user with conclusions or decisions that are substantially better or more often correct than the user could be [28]. In addition, there is an explanatory component that presents the inference or decision-making in a comprehensible way. [27]

A promising ES modelling tool is belief rule-based expert systems (BRBES) [29]. BRBES use knowledge representation and an inference mechanism. In BRBES, there are many if-then rules that constitute the knowledge representation. The knowledge representation, in the form of belief rules, include belief degrees, a rule weight and an antecedent attribute weight. The belief degrees are used to express different types of uncertain information. [30]

BRBES have already been used in a variety of successful applications. The advantages relate to the ability to handle and interact with both quantitative and qualitative data from heterogeneous sources. [29]

The deployment of ES in socio-technical systems such as production imposes requirements on the design of the dialogue component. Information must be available as needed and in a short time. This is also the case for use in visual inspection. In this context, dialogue components for assistance systems based on smart devices have already been used in numerous manual processes in production [31]. Exemplary applications range from maintenance and repair, assembly, and logistics to employee qualification [32].

2.4. Integration of DL and BRBES

The integration of DL and BRBES combines the advantages of both methods for use in a context-specific problem. DL automates the classification, detection, and segmentation of objects in image data with potentially high accuracy. BRBES delivers decisions objectively and substantially better or more often correct than the user could be. The integration of DL and BRBES was realized by Kabir et al. [33] and Ahmed et al. [34].

Kabir et al. [33] used the output of a DL model as input in the form of the antecedent attribute for a BRBES. The DL model uses outdoor images to predict the concentration of particles in the air. In addition, sensor data are added as input to the BRBES, which then calculates the belief degrees of six categories to determine the air quality index.

The system proposed by Ahmed et al. [34] classifies the mental state from facial expressions of video sequences. A DL model generates probabilities for each class for one frame of the video, which in turn are used as referential values of the antecedent attributes of a BRBES.

3. Application cases from production

The proposed system needs to adhere to the requirements from visual inspections and the employees using it. A total of eight companies from the production sector that use visual inspections were consulted. All of which provided specific use cases containing a range of products with varying defects. From each use case, images of the products and defects were taken. Expert knowledge was provided from experienced employees as well as inspection protocols and customer requirement sheets. Common defects include deviations in form, appearance as well as surface defects of the products. These defects either render the products unusable for certain applications or undesirable to specific customers because of aesthetic reasons. The defects vary in size and shape. Defective areas on some products show no repeating pattern or appear to occur in random locations. To prevent the shipment of defective products, visual inspection routines are integrated into the production cycle. Based on these use cases the following requirements (Rx) were derived:

R1 - integrable into production: The system must be integrable into physical environments in which the products are inspected. Both the use of hardware and the integration into existing processes and procedures must be considered. For example, taking into account inspection cycles, the evaluation of a product in the visual inspection is limited to a certain period of time. In extreme cases, the inspection must be finished in a few seconds.

R2 - objectivity: For the inspection to be less dependent on the subjective evaluations of the visual inspectors, an objectivity of the quality evaluation must be ensured. For this purpose, uncertainties must be considered. The evaluation basis or rules for the evaluation should be transparent and visible for untrained or inexperienced employees. Regardless of the levels of expertise in inspection, employees should be able to work with the system.

R3 - evaluation quality: The quality of the evaluation and thus the validity of the system's results must at least reach the level of quality that employees would achieve without assistance. Inexperienced employees learn the rules set for the evaluation by using the system. Consequently, the system must be robust to guarantee operation under changing production conditions. After all, visual inspection cannot always take place under controlled conditions.

R4 - scalability and adaptability: The system must be scalable to several workplaces and employees. Visual inspections take place at multiple stages in the production process. Due to the individualization of products and the diverse requirements of customers, the demands on quality also vary greatly. In addition, different products exhibit different defects. Adaptability of the systems to these aspects must be realized. Ultimately, future, or new variants of products will need to be added.

4. Integrated approach of DL and BRBES for visual inspection

We propose a novel approach through the design of a system for objective decision making in visual inspection. By integrating a DL model with a BRBES and the use of a smart devices application, the system provides the visual inspector with decisions on the quality of components and the resulting consequences. This is done using data as well as the knowledge from experienced employees. The system is depicted in Figure 1. In the following, the main components are described

4.1. Smart devices application

The smart devices application shown in the upper part of the figure serves to generate information by recording and evaluating image material of the components being inspected.

Visual inspectors record image data with the smart devices of the products under inspection. In a pairwise comparison, the visual inspectors assess the quality characteristics and properties of the product. The assessment serves as antecedent attribute to the BRBES. Recorded images are labeled according to which defect and property is present on the product. The labeled data is used to train DL models that classify defects on new image material to automate part of the inspection process.

Furthermore, the smart devices serve to provide context-dependent decision recommendations to the visual inspectors, which were calculated by the BRBES with the inclusion of uncertainties. In this regard, the smart devices application serves as the dialogue component of the BRBES and frontend of the system.

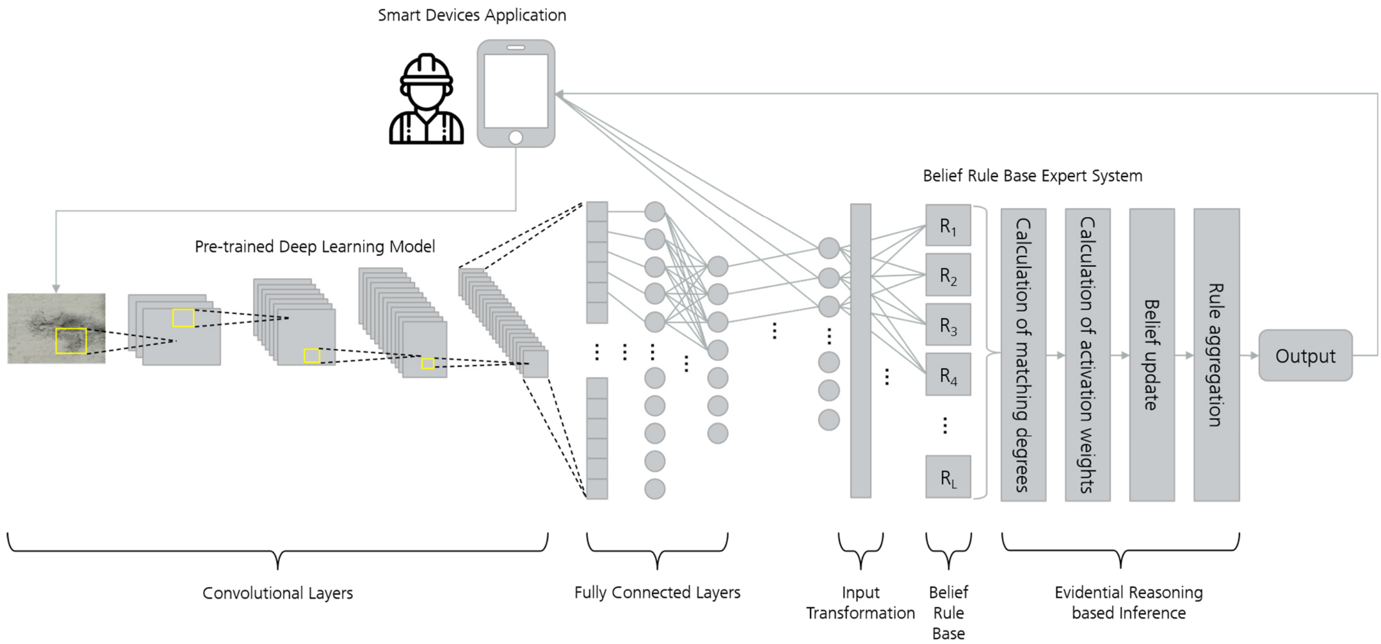

Figure 1: Design of system integrating DL-model and BRBES along with smart devices for visual inspection.

The decision to implement the frontend of the application on smart devices is based on the requirements R1 and R4. Individual devices can be used regardless of location. Interaction with the application can take place during or directly after the inspection, so that the process is not disturbed. In addition, webcams can be controlled by the application to record footage wherever the deployment of personnel is too dangerous or impractical. The frontend is realized as a web application with the React framework and thus enables easy scaling to other locations where visual inspection is to be carried out. The backend, with components such as the BRBES and the DL models, is implemented with Flask and Docker.

4.2. Pre-trained deep learning model

The images acquired from the smart devices application and additional cameras need to be processed before using them in the training process of the DL models. During image acquisition, the products are photographed under varying conditions that occur in production (e.g., change of light conditions). In image processing, the acquired images are divided into patches, labeled, and subsequently processed into different datasets for training, validation, and testing.

Enabling visual inspectors with the tools to improve and objectivize their visual inspection procedures, certain considerations for the DL models must be made. A selected model should be promising in terms of the accuracy of the detected defects classes. Moreover, the model should be able to run under the hardware constraints of smart devices and the effort for the implementation should be kept minimal. Under these considerations, a single-stage approach of a CNN-classifier with a sliding-window implementation is selected. A lightweight pre-trained CNN is considered as a classifier to be fine-tuned to the respective defect dataset. Possible candidates include EfficientNetB0, MobileNetV3Large, MobileNetV3Small, and NASNetMobile due to their performance and computational efficiency.

Each model is used as a pre-trained version without the original classification head so that just the convolutional base of the model is used. On top of the convolutional base a global average pooling layer is added to reduce the number of features. After pooling, the values are classified by a new classification head, which predicts the probability of membership to a specific class within the respective defect dataset. For the baseline model, the classification head consists only of a fully connected layer from the global pooling layer to the output. In the classification head of the model candidates, an additional hidden layer is integrated.

The application of DL models is comprised of three steps. First, the baseline model is trained on the optimization dataset to receive benchmark values. In the second step, the four candidate models are trained within a hyperparameter optimization framework on one fold of the optimization dataset. The most promising configurations of models and hyperparameters are then trained in cross-validation to gain an overview of model performance. The best-performing model and its respective hyperparameters are selected among the candidate models. In the third step, the best model is trained and evaluated on the evaluation datasets.

The output of the DL model is comprised of a classification of the image segments according to the defects that are present on the component. Implementing DL models into the system fulfils R2 and R3, as the models provide objective results based on the recorded data. The evaluation of the models ensures the quality of the results fulfil the requirments made (R3).

4.3. Belief rule base expert system

The BRBES uses two different antecedent attributes for the calculation of quality levels of the product and consequences in the form of decisions to be made (e.g., scrap product or rework). The output of the DL model and a quality assessment via the smart device application. Both are processed separately by the BRBES. This means that the visual inspector can carry out evaluations by himself and receive decision recommendations. Alternatively, decision recommendations from the results of the DL models can be received. Thus, the uncertainties required from R2 are included for an evaluation that is as objective as possible.

To develop the knowledge base of the BRBES, inspection characteristics are first identified from expert knowledge, customer requirements and existing inspection instructions and protocols. Experts then determine the properties of the characteristics using the ATZ scale. The characteristics are also prioritized, which represent the antecedent attribute weights. Finally, the rules consisting of the antecedent attribute and a consequence are established. The rules are also given weights to express differences in the importance of the rules. Individual rule bases can be created for each individual product, ensuring scalability (R4) to other products or customer requirements.

Once the BRBES is set up, the following steps are performed:

- Input transformation of the antecedent attributes, value and belief degrees of smart devices application and DL model
- Calculation of the matching degree of the input to the rules
- Calculation of activation weights indicating the importance of a rule in the knowledge base given an input
- Generation of a result by rule aggregation with evidential reasoning (RIMER)

Each input and the output calculated from are stored for the purpose of documenting inspection operations. Providing means of integration into existing enterprise information systems.

5. Conclusion and future work

In this paper a novel concept to support visual inspection is proposed. A system is designed for objective decision making in visual inspection. It is comprised of a DL model that is integrated with a BRBES. A smart devices application serves as interactive interface between the visual inspector and the system. The DL model automates the classification of defects on products based on recorded image data with potentially high accuracy. Both the evaluation by the visual inspector and the classified defect of the DL model serve as input to a BRBES. The BRBES delivers decisions in the form of quality levels and subsequent consequences or actions to be performed.

A pending deployment and validation of the system will reveal its potential performance in the field of visual inspection.

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