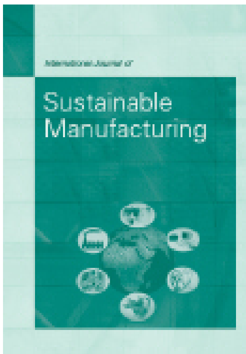

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Data fusion for improved circularity through higher quality of prediction and increased reliability of inspection

Robert Schimanek, Pinar Bilge, Franz Dietrich

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Data fusion for improved circularity through higher quality of prediction and increased reliability of inspection

Robert Schimanek*, Pinar Bilge and Franz Dietrich

Chair of Handling and Assembly Technology Research,
Institute of Machine Tools and Factory Management,
TU Berlin, Pascalstraße 8-9, Berlin 10587, Germany
Email: r.schimanek@tu-berlin.de
Email: p.bilge@tu-berlin.de
Email: f.dietrich@tu-berlin.de
*Corresponding author

Abstract: In order to meet customer requirements and regulations, such as low carbon footprint, companies are implementing AI-enhanced applications in production. However, AI is often used in stand-alone applications and lacks integration into the overall life cycle of products. To address this gap, this article proposes a framework for improving circularity through data fusion methods in product inspection. Data fusion combines multiple sources of data, such as sensor and business data, to improve machine-based predictions. The framework analyses AI applications, prediction during inspection, and data fusion methods, and addresses challenges in integrating business data into predictions. It demonstrates how data fusion improves prediction quality and stability in inspection. The framework is applied and evaluated in a case study from the automotive sector, showing an increase in good-quality predictions based on sensor data, leading to improved resource efficiency and circularity. This framework can be applied to any sector seeking sustainable manufacturing (SM).

Keywords: data fusion; inspection; artificial intelligence; AI; remanufacturing; circular economy.

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Biographical notes: Robert Schimanek studied Physics at Freie Universität Berlin and Aerospace Engineering at Technische Universität Berlin (TU Berlin) in Germany, where he obtained his Master's degree in 2021. Currently, he holds the position of Research Engineer at the Chair of Handling and Assembly Technology Research at the Institute of Machine Tools and Factory Management (IWF) of TU Berlin. He is part of the research group focused on digitalisation and human factors in a system's context. This group's research focuses on the process-oriented integration of digital assistance systems to improve assembly, disassembly, and reassembly processes for sustainable value creation.

Pinar Bilge is affiliated with the TU Berlin, specifically the IWF, where she holds a position as a Business Developer at the Chair for Handling and Assembly Technology Research. She has been a research group leader for digitisation of assembly and human involvement on a system level since 2019. Concurrently, she is a Research Affiliate of the International Academy of Production Engineering (CIRP).

Franz Dietrich is affiliated with the TU Berlin, specifically the IWF, where he holds a position as a Full Professor and Chair for handling and assembly technology. He is an associate member of CIRP and a member of the German Scientific Association for Assembly, Handling, and Industrial Robotics. He has co-chaired multiple conferences in the field of production engineering.

1 Introduction

As societies and politics in many developed countries, among others in the European Union, strive for a zero-carbon future, industrial companies plan to move from cradle-to-grave supply chains to circular economies. This move requires holistic consideration of all value creation activities. The holistic review and rethink include any activities from the design of products that support safe, fair, and easy manufacturing, use, repair, end-of-life (EOL) activities, such as return, collection, identification, inspection, reuse, and remanufacturing to the development of ecosystems to deliver all required through-life services (Jayal et al., 2010).

Life cycle assessment methods measure a set of indicators and calculate the impacts of alternative value creation chains quantitatively to determine the solution with a lower carbon footprint (Bilge et al., 2016). One of the key solutions with a lower carbon footprint is to consider today's products as resources for the future and to increase the value created by those resources through multiple life cycles. Circularity refers to the closed-loop nature of a circular economy, where resources are used responsibly and efficiently, with minimal waste and negative environmental impact. By implementing strategies that keep products in circulation for multiple life cycles, creating a more sustainable and efficient economic model is possible. One key strategy for reducing carbon footprint is adopting a circular economy model, as proposed by authors such as Kate Raworth in 'Doughnut Economics' (Raworth, February 2017) and Walter R. Stahel in 'The product life factor' (Stahel, 1982) and Gunter Pauli in 'The Blue Economy' (Pauli, 2015). Circularity refers to the closed-loop nature of a circular economy, where resources are used responsibly and efficiently, with minimal waste and negative environmental impact. Strategies for achieving a circular economy include: designing products for disassembly and material recovery (Akanbi et al., 2019), implementing extended producer responsibility and product take-back schemes (Maitre-Ekern, 2021), fostering collaboration and partnerships in the supply chain (Islam and Huda, 2018), incorporating circular business models (Vermunt et al., 2019), and promoting circular consumption patterns through education and awareness campaigns. These strategies can be implemented by companies, governments, and individuals to create a more sustainable and efficient economic model, and also a lower carbon footprint.

To keep products in circulation for multiple life cycles, the quality and efficiency of EOL activities that prepare them for reuse are crucial. These activities include inspecting products to ensure that they meet the specifications for the EOL market or repairing and cleaning the product to bring it up to a satisfactory standard for reuse. Ensuring the quality of EOL activities enables multiple life cycles. In addition, it lowers the carbon footprint as part of a circular economy strategy.

In the context of curative return management, inspection is a crucial step in: identifying the problem that has caused the product to be returned and determining the appropriate course of action to take.

Curative return management is a process that involves taking steps to correct or remediate issues that arise in the supply chain, such as defective products or incorrect orders, and returning them to their point of origin or an appropriate destination. The goal of curative return management is to minimise the impact of these issues on the supply chain, reduce costs associated with returns, and improve customer satisfaction.

Decisions about whether to accept product returns for reprocessing or reject out-of-specification products also impact the quality of EOL activities. This article is about improving decision-making for life cycle enhancement of product returns. The better the quality of decision-making, the higher the value of EOL and return activities and the better the contribution to circularity.

The recent boom in artificial intelligence (AI) has accompanied a rise in AI-enhanced applications in production and EOL. The scientific production engineering community has positively contributed to this development with white papers, including use cases (UC) for AI in manufacturing, assembly, and logistics. These contributions highlight AI's benefits for closed-loop manufacturing by improving efficiency, quality, and flexibility to preserve value. AI is implemented in many prototypes, where it contributes to value preservation by automating and improving various processes within an organisation.

AI can optimise the supply chain and circular infrastructure. By analysing data and identifying inefficiencies, bottlenecks, or potential disruptions, organisations can make data-driven decisions that improve their supply chain performance. Additionally, AI can help build and improve the reverse logistics infrastructure required to 'close the loop' on products and materials by improving the processes to sort, disassemble, and recycle materials (Ellen MacArthur Foundation, 2019).

Additionally, AI can be used to inspect product returns to help organisations preserve value. At the end of the product lifetime, AI systems can assist processes such as inspection, sorting, separation and disassemble in order to circulate materials and return products in the economy using the AI function of classification and pattern recognition to identify objects or materials (Gailhofer et al., 2021). This can also help to improve the overall customer experience by reducing the risk of customers receiving defective products. AI can identify defective or fraudulent products and reduce financial losses. AI can assist in identifying and classifying returned products, which can aid in determining the most appropriate course of action for each returned item, whether it will be repair, refurbishment, or recycling.

However, AI in manufacturing is still a relatively new research field and there are still many challenges that need to be overcome for AI to be fully integrated into the manufacturing process, and more research is needed to fully understand its capabilities and limitations. Today, machines with advanced visual and analytical capabilities can inspect some specifications of product returns. Depending on the application, it is possible to automate the inspection to reduce costs and increase stability. This article focuses on AI-enhanced inspections for product returns. The principles and results of this article are valuable for inspection processes for more sustainable manufacturing (SM).

However, recent research has mainly addressed single applications and has limitations regarding the integration of AI into value creation (Sjödin et al., 2021). One of the limitations refers to the integration of data fusion into businesses, which can be categorised in cost and resources, data quality and governance, technical limitations, process, and cultural issues.

Integrating multiple algorithms on the shop-floor can present significant challenges and limitations, including difficulty in ensuring compatibility and coordination among the different algorithms, each of which may have its own unique inputs, outputs, and parameters, and may be optimised for specific tasks. Additionally, integrating multiple algorithms can add a significant layer of complexity to the manufacturing process, making it more difficult to understand, troubleshoot, and optimise. The integration also may bring challenges in data management and real-time decision making, which are the challenges that persist on the integration of multiple algorithm-based manufacturing for circularity (Wan et al., 2021).

Limitations of multiclass classification in the inspection of similar products include the increasing complexity of the problem as the number of classes or of the feature space increases, making it hard to generalise to new unseen similar products (Liu et al., 2021; Jain et al., 2014). The class imbalance problem, where one class has more samples than others, also causes bias in the model (Qin et al., 2022; Han et al., 2019). Additionally, many algorithms require large amount of labelled data (Abu et al., 2021; Krüger et al., 2019), and the assumption that classes are mutually exclusive may not always be the case in real-world problems. Furthermore, complex decision boundaries can make it difficult to interpret and explain to domain experts (Kim and Kim, 2020).

Limited validation studies are currently available for the integration of AI in inspection systems. These studies tend to be limited in scope and focus on specific UC, showing promising results but not providing a comprehensive view of the challenges and limitations encountered when integration and scaling up AI in inspection systems (Lickert et al., 2021). Many studies are conducted in controlled laboratory environments with curated data, making it hard to generalise to real-world scenarios. Furthermore, many studies use simulation or synthetic data for evaluation, which may not reflect real-world scenarios (Schlüter et al., 2018; Krüger et al., 2019). Despite these limitations, the studies suggest that AI holds great potential for improving efficiency and accuracy in inspection systems for a circular economy, but more research is needed to fully understand the challenges and limitations of applying AI in inspection systems and to validate its performance in real-world scenarios (Sjödin et al., 2021).

The article presents a detailed discussion on the methods used for applying fusion in inspection systems. The authors have developed a framework for fusing predictions from business data and AI-enhanced computer vision to achieve stable and high-quality inspection of product returns. The framework is specifically designed to overcome data quality and technical limitations that may be encountered in real-world scenarios. The article provides a comprehensive analysis of the different fusion methods available, with a focus on algebraic methods, and compares them based on qualitative literature research. The authors also present a use case in the context of the circular economy and SM, where they validate the effectiveness of the proposed framework and methods through a detailed case study. Overall, the article provides a comprehensive and scientific overview of the methods used in the integration of AI in inspection systems, with a focus on applications in the circular economy.

This article investigates this potential, divided into five sections: the introduction provides an overview of the current field of study. Section 2 summarises the state-of-the-art of prediction in production, existing fusion methods, and challenges in application, especially in circular economy. Section 3 addresses the shortcomings of data fusion when integrating business data into machine-based prediction. Section 4 illustrates the framework for applying data fusion in inspection, and applies it in a use case. Section 5 presents the authors' conclusions on how their findings enhance SM.

2 State-of-the-art on data fusion for inspection

Companies have widely used predictions for procurement since the second industrial revolution to increase economic benefits. Since the beginning of the third industrial revolution, companies have collected business data (e.g., product, process, and customer data), deriving product and process development strategies. Business data are usually any data recorded in the enterprise resource planning (ERP). Companies apply statistical methods to describe, predict, and improve business performance. With the fourth industrial revolution, AI and, as its integral part, machine learning (ML) make its way into manufacturing, value creation and reverse logistics, contributing to predict process and product characteristics. The use of AI and ML in manufacturing can further enhance SM by enabling more efficient, precise, and data-driven decision-making. Multiple studies explore the intersection of AI, decision-making and SM (Enyoghasi and Badurdeen, 2021; ElMaraghy et al., 2021; Jamwal et al., 2022a). Their findings highlight potentials of improvements based on correlation of these domains. For example, AI and ML can be used to optimise production processes, identify and reduce waste in manufacturing as well as in the aftermarket, improve energy efficiency, and monitor environmental performance. Additionally, by predictive analytics, manufacturers can better anticipate and respond to changing demand, supply, and regulatory environments, and make more informed decisions that support keeping resources in multiple life cycles instead of disposal, which improves circularity. In this way, AI and ML support manufacturers to reduce their environmental footprint, enhance their competitiveness, and contribute to SM and enable circular economy. Further discussion of specific contributions is discussed in Section 2.4.

For example, ML-applications predict tool change intervals, reduce auxiliary materials, or predict optimal process flows to reduce energy or resource consumption, thus lowering carbon footprint. Production engineers furthermore apply AI in other fields, such as assembly, inspection, maintenance, disassembly, and logistics (Takeda-Berger et al., 2020; Wang et al., 2018; Weichert et al., 2019; Petzoldt et al., 2020a; 2020b; Chen et al., 2020; Çınar et al., 2020; Huang et al., 2019). In short, prediction methods based on algorithms are increasingly part of successful applications in production. Hence, the larger the number of algorithm-based applications, the more important it becomes to define and optimise their integration, which this article contributes to.

Inspection is a relevant enabler of circularity between product use and EOL stages. It already offers many promising solutions in AI-enhanced computer vision (Schlüter et al., 2018; Krüger et al., 2019; Schlüter et al., 2021; Bogue, 2019). However, in classifying lots of different classes, i.e., multiclass classification with a high number of classes n_C, of similar products, these applications are not yet reliable enough, which this article addresses. In addition, the inspection is often an interface to other stakeholders, such as customers, suppliers, authorities, and processes. Although some authors highlight ideas and concepts for exchanging and sharing data between stakeholders for better inspections and follow-up processes (Blömeke et al., 2020; Kintscher et al., 2020), existing concepts lack detail and validation that this article provides.

Likewise, inspection is a prerequisite for value-determining and sorting in the circular economy. Retailers incur high costs because of product returns and the associated loss of value (Asdecker et al., 2021; Asdecker and Karl, 2018). So far, the set of measures used in curative returns management is not suitable for the volume of returns. Inspection requires high quality in determining product states and prediction process reliability. This article contributes to value preservation with stable and high-quality inspection of product returns by fusing predictions from business data and AI-enhanced computer vision.

Section 2.1 summarises the state-of-the-art of prediction in inspection based on business data and AI. Section 2.2 analyses existing fusion methods and their potential for inspection. Section 2.3 addresses the challenges of application challenges. Section 2.4 analyses the previous work about the intersection of AI, decision-making and SM, and describes the challenges of circular economy. Finally, the research gap regarding the integration of business data into AI-enhanced predictions is summarised.

2.1 Prediction in inspection

Predictions based solely on business data during inspection have limitations because of the variety of product states. Therefore, business data provides mostly strategic values with limited information about the certain state of products (Lickert et al., 2021). Even though it is possible to predict the probability of product returns from transaction data (Asdecker and Karl, 2018), it is so far not possible to predict the state and the residual value of a product return. The better an inspector knows the product state, the more viable the inspection is. Therefore, it is important to use enough sensors to measure the state of the products and predict a target value, e.g., by computer vision.

AI is a powerful tool to determine the state of a product. AI includes: the ability to learn, adapt, and make decisions based on data, the ability to process and analyse large amounts of data and information and the ability to perform tasks that would typically require human intelligence. AI systems often use algorithms and data to process and analyse information, and then use that information to make decisions or take actions. This enables them to perform a wide range of tasks that are hardly possible for humans to do on their own. AI is a rapidly growing field, with many applications in a wide range of fields, including healthcare, finance, transportation, and education.

In inspection, computer vision digitally captures and evaluates products and contexts with neural networks trained in object detection (class) or recognition (class and location) in real-time to streamline the processes. With visual and non-visual sensory, AI detects and evaluates and thus helps to inspect a product's characteristics (Schlüter et al., 2021). Today, AI widely uses optically detectable product characteristics for this purpose. These are surface properties and geometric dimensions or missing subcomponents.

Several sorting systems already make automated decisions based on the type of material (Bogue, 2019). However, these systems limit their application to a relatively small number of different classes. As a result, different classes of the same material and similar dimensions experience poor sorting quality with these solutions.

Other AI solutions evaluate products according to visually measured dimensions (Abdelrahman and Keikhosrokiani, 2020). These solutions predict the accuracy of manufactured products. However, in product returns, the dimensions of some classes are the same. For example, product lines receive new class names even though little has changed externally and much internally.

For example, AI performs well in detecting missing subcomponents of an assembly (Burresi et al., 2021; Weichert et al., 2019). This is helpful for damage detection. However, procedures for detecting missing subcomponents represent only a part of the inspection for many product classes, since there are many other potential damages.

Acoustic sensors provide another source of data that allows AI to assess the sound of an object and thus its completeness. Even on a noisy production floor, these AI applications quickly predict a product's integrity (Zhang et al., 2021). However, acoustic sensor-based AI applications are limited to specific products and classes.

AI-enhanced applications in inspection refers generally to the use of AI in the process of inspection, which involves examining products to ensure that they meet certain standards or specifications. This can be done by AI-enhanced computer vision, which is a technology that allows machines to analyse and understand visual data, such as images or videos. In this context, AI-enhanced computer vision can be used to automatically inspect products and identify any defects or issues. AI-enhanced applications in inspection, on the other hand, refer more generally to the use of AI to enhance the accuracy, speed, and reliability of inspection processes with available data.

AI-enhanced applications in inspection predict high-quality product states and stable processes. Nevertheless, they are limited in predicting a class out of many similar classes connected to a product group (multiclass classification). The classification as categorisation is an enormous challenge for products with a high number of similar classes. The various AI-enhanced applications are good at a particular task, usually with a few output classes. However, there is the problem that different classes are sometimes not differentiable by one sensor type.

Data fusion provides an optional way in order to overcome the limitation of AI-enhanced applications in predicting a class out of many similar classes. Data fusion is the process of combining data from multiple sources to improve the accuracy and reliability of the information being analysed. This can be done through a variety of fusion methods, such as decision-level fusion, where data from different sources is combined to make a final decision, or feature-level fusion, where data from different sources is combined at the level of individual features, such as colour or texture. Data fusion is commonly used in a wide range of fields, including computer science, information technology, and engineering.

This subsection concludes that it is helpful to combine different sensors to make classes differentiable, e.g., by including the core mass in predicting an AI-enhanced computer vision (Schlüter et al., 2018). However, the combination of different sensors to inspect a high number of different classes is still insufficient. The realisation of this potential through business data integration is vital. Data fusion contributes to this integration with some limitations. This article extends the approach to further available information about the product and supplier.

2.2 Fusion methods in inspection

Fusion methods are already being used to improve inspections. These include methods that use sensor data fusion to enhance predictions. Multi-sensor imaging systems have increased flexibility in production and inspection (Gil et al., 2007; Petzoldt et al., 2020b). Fused sensor sources are, for example, near-infrared spectroscopy sensors, three-dimensional laser sensor systems, high-resolution red-green-blue (RGB) cameras, imaging metal detectors, or visible light sensors. Areas of application include picking and sorting items from moving conveyor belts (Gil et al., 2007; Bogue, 2019). In brief, fusing data from multiple sensors to measure products in inspection is common in industrial applications. However, this fusion usually senses similar characteristics, e.g., dimensions of a product, for enhancing inspection. Following paragraphs describe an exploratory study for fusion methods, in which the authors investigate the suitability for a fusion of different characteristics.

Various fusion methods are already successful in fusing predictions from two or more information sources, thus improving prediction quality by determining the most appropriate source to achieve maximum utility or combining multiple sources to reduce uncertainty. The topology of fusion methods differs according to application and objective: fusion methods are centralised, decentralised, or hierarchical (Xiong and Svensson, 2002). However, fusion methods rely on algebraic, statistical, and AI-enhanced methods. Here are the advantages of acknowledged fusion methods.

2.2.1 Algebraic methods

Algebraic methods like averaging, intersection, and multiplication rules fuse different sources based on the rank or score information (Kittler et al., 1998; Kittler and Alkoot, 2003). For example, Friedman's procedure identifies and evaluates the differences between respective sources to assess the quality of their evidence. Algebraic methods are easy to interpret and compute, but they are vulnerable with few predictors and large variations in ranks (Tubbs and Alltop, 1991). They are simple and cost few resources, have no learning overhead, consider each predictor equally, and are therefore examined in an application.

2.2.2 Weighting methods

Weighting methods combine long-term offline data with short-term online data to fuse historical and current data (Liu and Aberer, 2014). Both sources relate to user behaviour and link basic behaviour with dynamic adaptation. This is advantageous for processes that change. However, they involve high complexity and definition effort. In inspection, this is of particular interest when changing objects of investigation arise or predictions about the time that include changing parameters. It is possible to determine the weights using statistical methods. These include the *Bayesian and Dempster-Shafer* approaches, which are based on assigning weights to the postulated states of the system to be measured (Challa and Koks, 2004). Whereas the former is more suitable for dynamically predicting a changing state, the latter can be used for one-off observations, such as product inspection. The implementation in this article involves one-off observations, which is why Bayesian methods are not pursued further.

Multi-sensor fusion based on the *Dempster-Shafer theory of evidence* (DST) presents a helpful method to fuse data from multiple sensors to gather information (Shafer, 1990). Engineering initially used it for condition monitoring of rotating equipment. It is also used in maintenance to improve the information base within operating equipment. Multi-sensor fusion combines, e.g., temperatures, vibrations, and measured currents to predict machine failure and product quality. This statistical method applies, for example, in additive and subtractive manufacturing processes (Rao et al., 2015). The widely applied Dempster-Shafer rule fuses the states of the different sensors (Rogova, 2008). Assigning reliability to a particular prediction is helpful because it includes the historical differences in sources for the prediction. The disadvantage is that counter-indexed or anti-symmetric predictions of sources lead to counter-intuitive predictions of DST (Myler, 2000). However, as we aim for a high probability of predictions from all sources, the advantages outweigh the disadvantages from our point of view, so the theory is applied and investigated in the following.

2.2.3 Ensemble methods

Ensemble methods combine multiple algorithms to achieve better predictive performance than would be possible with any of the individual algorithms alone. Ensemble learning methods aim to optimise the overall result by generating multiple predicting sources from one dataset rather than fusing different independent sources of information (Valcarce et al., 2017). They divide into three groups: The first group learns on one dataset with different algorithms. The second group focuses on testing different training parameters of an algorithm. The third group uses different learning algorithms for different datasets. The third group is of interest to the fusion of different sensor types. In the following, *stacked generalisation* is introduced as an example for groups one and three, and a *bucket of models* as an example for group one.

For example, *stacked generalisation* is an ensemble method that uses a high-level model to combine lower-level models to achieve higher predictive power. First, different models train with one type of dataset. These are subsequently tested. Later, e.g., a regression model trains on the test results (Wolpert, 1992). Stacked generalisation is suitable for the application case because it does not require knowledge about the parameterisation of the individual predictors.

The so-called *bucket of models* is another ensemble method. The models are trained, and the best method is assigned to each bucket of input data. Inputs can be divided into ranges or bins, and different models or combinations can be selected for each input range. The resulting predictions are similar to those of the best sources involved (Qu and Wu, 2009). In the case of product returns, this is of interest because the input variables vary a lot. Furthermore, there is the possibility that inputs are missing, which other models with fewer input variables could then compensate.

2.2.4 Learning to rank

Learning to rank enables a fusion of probabilities for search queries, e.g., using logistic functions focusing on user-centric relevance. These methods, such as *RankNet*, *LambdaRank*, and *LambdaMART*, apply to information retrieval systems alongside various similar methods (Liu and Aberer, 2014; Burges, 2010; Burges et al., 2005). Applying these methods to inspection tasks that work with varied equipment or face changing requirements at different operating sites is conceivable. However, unambiguous decisions about the state of the products or processes must be made independently of the agents during the inspection. Therefore, in the following elaborations, special attention is paid by the authors to the implementation of how decision-makers train learning to rank without letting their personal preferences enter it.

2.2.5 Machine learning algorithms for neural networks

ML algorithms that allow for the training of neural networks that fuse different sources or choose an optimal path include, e.g., unsupervised competitive learning or supervised backpropagation. Others serialise or parallelise proven architectures, e.g., a convolutional neural network and a multilayer perceptron for predicting tool wear on a milling machine (Huang et al., 2019), whereby the topology and parameterisation of the layers quickly become confusing.

In *competitive learning*, competitive layers determine which subnet or node achieves the best possible result for an input (Rumelhart and Zipser, 1985). Therefore, each source should represent information whose errors are independent of the others to fuse information productively. Nevertheless, competitive learning can lead to the complete exclusion of neurons. Apart from this, it is of interest for industrial application because of its unsupervised nature.

Backpropagation adjusts neurons to generate the desired fused output for an input (Rumelhart et al., 1986). A disadvantage of backpropagation is the parameterisation effort. Of course, it is possible to train a centralised or serialised fusion model that incorporates all raw data sources from sensors and business data and uses them to predict the state of products and processes. The challenge here is how to make changes later in production operations. The model must be completely retrained or redesigned if changes are made to the sensors or topology. Due to the high efforts needed, this method is not investigated further.

2.2.6 Implementation of fusion methods in inspection

A variety of fusion methods are intended by the authors to be used for improving the accuracy of AI-enhanced applications in inspection, including algebraic fusion, ensemble methods, and ML algorithms. Algebraic fusion is simple to implement, making it a good choice for applications where data fusion needs to be performed quickly and efficiently. Ensemble methods, on the other hand, can provide improved performance by combining the predictions of multiple models and are also simple to implement. Meanwhile, ML algorithms are hard to implement but promise to be trained on data from multiple sources to improve their accuracy and reliability.

2.3 Challenges of applying fusion methods in inspection

From an inspector's perspective, there are some challenges regarding the applicability of existing fusion methods. One of the major challenges is *missing standard formats*. Available sources in an inspection system must be transferred in a uniform format to perform applicability and sufficient flexibility for later changes.

Fusion methods with low learning and parameterisation effort cannot afford this transfer. Instead, they use prediction lists of a number n_S of different sources to achieve a fusion of the prediction (Tubbs and Alltop, 1991). These fusion methods are limited to the fusion of classification or ranking results. Here, the number of classes n_C of predictors is the same. Each class C_i of $i = 1 \ldots n_C$ is assigned a score (often termed confidence) s and a rank r by the predictor. And yet, the number of classes n_C that can be captured by each source may be different because, for example, classes do not have these characteristics. We address this challenge, for example, with intersectional and ML methods.

A further relevant challenge of applicability is the *objective of the algorithms*. For instance, fusion methods for information retrieval systems do not look for the best result. However, they want to present a set of predictions optimally for the user. This user orientation is a disadvantage in tasks that aim at unambiguous identification or evaluation, such as inspection. The decision-maker, for example, the inspector on the shop floor, should receive a unique prediction that stands out from the others to indicate the right decision. The preferences of the inspector should not influence the decision. We develop short and differentiable predictions that improve through collective decisions by all inspectors.

2.4 Challenges of circular economy

This subsection introduces the essential terms and challenges in order to provide a clear understanding of the authors' perspective on inspection impacting circularity. This perspective is based on the state-of-the-art analysis about the intersection of AI, decision-making and SM.

SM aims to create products that meet the needs of the present without compromising the ability of future generations to meet their own needs (Seliger et al., 2011).

Jamwal et al. (2022b) found that ML technologies play an important role in SM by improving the overall efficiency of the manufacturing industries. They have developed a ML-based SM application framework for the manufacturing industry that includes four phases of SM: pre-production or planning, processing, production, and product recovery. ML techniques are suitable for handling large, complex data generated in these phases and are found to improve the performance of the SM system. AI-based decision making is emphasised as an important aspect of the study, which finds that ML and AI-based technologies are important for developing Industry 4.0 practices with regards to sustainability. The study highlights that ML approaches have the potential to bring new improvements in resource utilisation, tool life prediction, and quality management in manufacturing industries. Furthermore, it was found that ML techniques in SM offer a wide range of opportunities for sustainable development, such as supply chain management, condition monitoring, and predictive maintenance.

SM is the practice of designing, producing, and using products in a way that minimises negative impacts on society, the economy, and the environment (Seliger et al., 2011).

In the social dimension, SM aims to create products that are safe and healthy for people to use and that support the well-being of workers and communities. This can include ensuring that products are made with non-toxic materials and that workers are provided with safe and healthy working conditions.

In the economic dimension, SM seeks to create products that are affordable and accessible and that support the long-term viability of businesses and industries. This can include using sustainable production processes that are cost-effective and efficient. Such processes create high-quality products that are in demand by consumers.

In the environmental dimension, SM aims to minimise waste and pollution and to use natural resources responsibly and efficiently. This can include designing products that are easy to recycle or repurpose and that use renewable materials and energy sources.

Sousa Jabbour et al. (2018) discuss the importance of environmentally-SM decision-making, which includes the green design of products and processes, and environmental management of supply chain operations. It also lists and classifies practices addressing environmentally-SM decision-making, such as design for environment, cleaner production, and green supply chain management. The use of technology is highlighted as a key component for environmentally-SM decisions, as it can lower resource use and minimise environmental damage. The article also suggests that Industry 4.0 technologies can enable efficient resource allocation and more SM decisions. It highlights the potential benefits of connecting machines, tools, and devices through the internet, sensors, and RFID to improve data collection, tracking, and decision-making.

The circular economy is a broad economic system in which resources are kept in use for as long as possible, and waste and pollution are minimised. This can be achieved by designing products and processes that are efficient and sustainable and by reusing, repairing, and recycling materials and resources. The goal of the circular economy is to create economic growth and development without causing harm to the environment or depleting natural resources. In a circular economy, waste and unused products are designed to be recycled back into the production process, reducing the need for new raw materials and helping to conserve natural (Hauschild et al., 2020).

Circularity is a systemic approach to economic growth that seeks to eliminate waste and promote the continuous use of resources. The term circularity focuses on closed-loop resource use and waste management systems (Jawahir et al., 2006).

The circular economy and SM are both focused on reducing waste and increasing efficiency in the use of resources. One way to do this is using AI-enhanced inspection systems, which can help identify and sort materials for reuse. AI-enhanced inspection systems classify and identify products materials and can be used to detect defects and improve the accuracy of inspections. This can help to ensure that only high-quality materials are reused, improve sorting, reducing waste and improving the overall efficiency of the manufacturing process.

Carbon footprint indicators, such as the saved CO_2 per reused product, are also closely connected to the circular economy and SM. By measuring and tracking the carbon footprint of products throughout their life cycle, organisations can identify areas where they can reduce their environmental impact and improve their sustainability. By reusing materials, organisations can significantly reduce their carbon footprint, as it requires less energy to process and manufacture products from existing materials than from raw materials.

An AI enhanced inspection system can contribute to the reduction of CO_2 emissions by improving the efficiency and accuracy of product inspections. This can lead to a reduction in the number of defective products that are shipped to customers, which in turn reduces the need for re-inspections and remanufacturing. Additionally, the AI system can help identify products that are suitable for reuse, which can reduce the need for new products to be manufactured, thereby lowering the overall carbon footprint.

Liu et al. (2020) suggest that smart technologies should facilitate the sharing of data and knowledge among various sources of product life cycle management, leading to more efficient decision-making. Future research should focus on using data and knowledge in areas such as product design, production, operation, and maintenance, as well as supply chain management. Additionally, they recommend research into sustainable product life cycle management, AI-based decision-making, and innovative strategies for design, manufacturing, service, and maintenance, leading to digitalisation in cleaner production.

The EOL of a product refers to the stage at which it is no longer used by consumers and is no longer useful for its intended purpose. At this stage, the manufacturer may discontinue technical support, software updates, and replacement parts for the product, making it difficult for users to continue using it. This may require users to upgrade to a newer model, which can be costly and impractical.

EOL can also impact the environment, as discarded products may need to be disposed of safely and sustainably. In some cases, manufacturers offer EOL services, such as recycling programs or trade-in offers to help users return a product. Afterwards, the returned products can be remanufactured and sold as new products. Therefore, business-to-consumers (B2C) need to be aware of a product's EOL status to make informed purchasing decisions.

In the field of business-to-business (B2B), companies which are stakeholders in the aftermarket collect, transport, store, inspect, and repair these products. Each returned product is unique since its use and conditions during its lifetime are case-specific. Additionally, little data and information about its manufacturing and use stages and status are available.

Little data and information are one of the biggest challenges of the aftermarket, including all B2B stakeholders and processes such as inspection. Consumers prefer paying less for remanufactured products than new ones (Wewer et al., 2020). Making any business case profitable and resource-efficient in the aftermarket contributes to keeping more resources in closed life cycles. This article investigates the contribution of AI and data fusion to inspection for this purpose. Combining these methods with business data is a potential field discussed in the next subsection.

2.5 Research gap in integrating business data into AI-enhanced predictions

Inspection is a prerequisite for value-determining by product returns and, hence, sorting processes to increase the value preservation in multiple lifecycles. AI is a powerful tool to enhance predictions for inspecting various product returns after the use stage. Nevertheless, data fusion for AI-enhanced applications results in three major shortcomings. They are related to integrating business data into prediction:

AI-related efforts have focused on equipping specialised classifiers in inspection. For instance, AI streamlines only optical inspections by rapidly classifying products. However, integrating AI into further process-relevant information is insufficient. For example, inspection systems rarely fuse predictions from business data with AI. In addition, there are only a few ML algorithms that automatically supplement business data with AI-enhanced knowledge from domains other than inspection. As a result, remanufacturers lose valuable domain or expert knowledge. This loss of knowledge must be reduced to improve inspection' performance.

So far, sensor failures and errors in pre-processing of data lead to misinterpretations of the AI, creating a need for process stabilisation. Even the most minor disturbances or failures can severely affect the following value creation process. Foremost, non-machine-learned products or correlations lead to incorrect predictions. In addition, specific patterns challenge the identification and evaluation of products, even with AI-enhanced computer vision. Therefore, the computer vision of such products must be improved.

Business data evaluation (BDE) and AI-enhanced computer vision suffer from concept drift, like any prediction method. Learned models degrade and produce worse predictions because of product (returns) with different characteristics that were not learned by the learning algorithms. The fused predictions vary according to concept drift of participating sources. The impact of this variation needs to be addressed.

From the above-described shortcomings in AI-enhanced inspection, research questions arise. The remainder of the article addresses the following research questions.

Q1 What are the requirements for fusing predictions from business data and neural networks, e.g., AI-enhanced image recognition, to enable higher quality and more stable predictions? The objective of this research question is to identify the requirements for fusing predictions from business data and neural networks to enable higher quality and more stable predictions. The outcome of this research could be a set of recommendations for data fusion techniques that are suitable for AI-enhanced image recognition.

Q2 Which fusion methods can improve the quality of predictions for the decision-maker? The objective of this research question is to evaluate different fusion methods in terms of their ability to improve the quality of predictions for the decision-maker. The outcome of this research could be a comparison of different fusion methods, highlighting the strengths and weaknesses of each approach.

Q3 Which fusion process design is appropriate for providing higher process stability in case of failures by any contributing predictor? The objective of this research question is to determine the best fusion process design for providing higher process stability in case of failures by any contributing predictor. The outcome of this research could be a recommended fusion process design that is appropriate for ensuring stability in the presence of failures.

3 Framework for data fusion in inspection

This article addresses the research questions by investigating fusion methods that combine AI with business data. This section describes the proposed framework for applying fusion methods in inspection. It highlights key aspects to make the application successful.

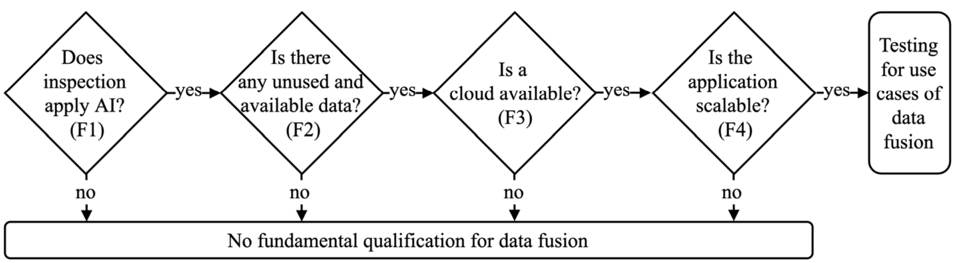
The proposed framework comprises five steps, which follow each other sequentially. The first step examines the fundamental qualification for data fusion (see Section 3.1). The second step examines obtainable business data and characteristics of the predictions of AI (see Section 3.2). The third step comprises an explorative data analysis along the value creation chain (see Section 3.3). The fourth step helps to select a suitable fusion method (see Section 3.4). In the last step, the fusion methods are tested and evaluated (see Section 4).

3.1 Preconditions for data fusion

The first step of the framework addresses the fundamental qualification for applying data fusion in inspection. In this step, the tester justifies the technical and economic feasibility. Technical feasibility means assessing the practicability of implementing data fusion in an inspection system. Economic feasibility means assessing the value and cost of data fusion. Figure 1 presents the examination of the fundamental qualification for data fusion with four framework questions (F1–F4).

Testing of UC for data fusion by combining AI and business data evaluation begins when the answer to four fundamental questions is 'yes', including the existence of the use of AI (see F1 in Figure 1) and business data (F2). F3 addresses the need for the greatest possible connection between process steps and data via a cloud/data availability between processes and the participating stations of the inspection system. Quick access to business data is important. Otherwise, predictors wait or miss data that is essential for prediction. F4 addresses the scalability of the inspection application. There is no fundamental qualification if the answer to any question is 'no'.

Figure 1 Preconditions for testing for UC of data fusion



3.2 Characteristics and data in inspection

In the second step of the framework, the analyses of the collectable data and the data basis already used and still available must be examined to identify a use case for data fusion.

First, the user must answer which characteristics the AI-enhanced application predicts and which data it uses for the prediction. The goal of AI in inspection is to predict one or more characteristics. In doing so, AI-enhanced applications rely mostly on a combination of historical and present measurable data (Schlüter et al., 2021). This data must be explicitly analysed.

Characteristics of products, equipment, and processes can be divided into observables, assignments, and performance indicators:

- Observables are physical properties that can be measured indirectly or directly. For example, sensors that measure physical properties collect cardinal or interval scaled observable data.
- Assignments denote given titles and names representing a particular set of observables, often nominally scaled. In terms of processes, assignments are, e.g., name of a model or a method.

- Performance indicators are qualitative data characterising performance, price/value/cost, or quality. For example, a product may have damage from several nominal damage categories, an ordinal quality class, and cardinal raw material values.

In many processes, it is impossible to measure values of the state variables that describe the system state in-line, which are essential for process control. Instead, one measures quantities that depend on the state variables (Weichert et al., 2019). Therefore, mainly indirect rather than direct data can be collected, even though the latter allows more precise differentiation.

Next, the user needs to search the value creation chain for available data for the inspection process. The user must answer whether data already exists for these characteristics. If no data is available, the user must obtain the data about the characteristics through suitable measurements or observations or acquisition (Kintscher et al., 2020). When analysing the obtained data, it makes sense to prioritise the data first for the most promising business data for the inspection purpose.

Data from sensors, documented product movements, or observations of employees are measured data (Weichert et al., 2019). In contrast, simulated data represent only model processes or products that play a major role in inspection, but as a prediction itself rather than as the data basis for modelling the prediction.

Production environments generate data on the shop floor (Dittmann et al., 2021) or receive data from suppliers and pass on data to customers (Blömeke et al., 2020). Occurring characteristics during measurement can therefore be set in relation to the stakeholders. Stakeholders have incorporated their features into objects. These features are differences that can be used for inspection.

There is time-variable data and data tied to the entities, product, process, or operating equipment from production and the value creation chain. Time-variable data differentiates between continuous data and data that contains data points sequentially or periodically (Weichert et al., 2019). These are particularly valuable as they allow conclusions to be drawn about the development of a residual value of assets. Today, they are more likely to be found in processes and operating equipment than in products. It is desirable to obtain the data tied with the characteristics from a digital twin connected to the entities (Blömeke et al., 2020; Dittmann et al., 2021). If no digital twins of a product are available during inspection, a prediction can be made based on products of the same class, production period, or other features (Lickert et al., 2021). Similar products can also be used as a reference for inspection.

If the user has prioritised the data along the value creation chain, the user must aggregate and investigate chunks of data. The data are examined whether they are suitable for the determination of characteristics.

3.3 Explorative data analysis along the value creation chain

In the third step of the framework, the available data candidates shall undergo an exploratory data analysis to determine their significance for prediction in the inspection process. Inspections often serve as an interface to other stakeholders and processes. Therefore, some processes are likely to generate certain data types concerning the product characteristics. The following example steps represent typical data fusion UC.

UC1 Supplier data, product quantities, and packaging patterns occur upon incoming product returns. Determining the time of arrival assigns an age to the product returns in the workshop (Lickert et al., 2021). Patterns of characteristics appearing in the later inspection refer to a supplier or delivery of products. If two different suppliers return the same product class at different times, later measurements of product characteristics reference the time and the supplier. For later retrieval, creating a unique inspection ID becomes necessary, e.g., via a label on the product.

UC2 The inspection identifies, measures, checks, and documents characteristics. The inspection covers observable product characteristics, e.g., visual condition, sound, mass, and completeness. In addition, the collection of process-related data, such as the reject rate or product quality, allows a parameterisation of the process variables of the same and subsequent process steps. If the data forms characteristics, the AI-enhanced manufacturing steps can improve product quality prediction, for example, to better adapt the process variables to the material.

UC3 Warehouses store and buffer incoming and outgoing materials and (intermediate) products. Stocks are recorded and can be traced back to class and the product ID, if an ID is available. The derivable data describe the material state, the material flows over time and allow conclusions about the productivity of processes. For example, if warehouses record the environmental conditions, subsequent AI-enhanced inspection can use these with the material properties and the dimension of the materials to optimise predictions regarding, e.g., product quality.

UC4 Manufacturing and assembly change material and products in their dimensions and visual appearance and thus influence the product properties. If deviating process properties or, for example, supplier-specific properties of the input products are known to the AI during the inspection of the incoming material, the prediction of product quality can be optimised by merging the data.

3.4 Selecting a data fusion method for a specific use case

Given the use case, some data fusion methods are more appropriate than others. Table 1 lists available methods for data fusion of business data and AI-enhanced inspection.

Algebraic fusion methods (Type A) come into consideration when prediction from the retrievable business data infer the same format, characteristics, and quality as the AI prediction. Then they are suitable for reducing the uncertainty of already good predictions by the sources.

UC, which involve sources that produce eligible predictions for inspection can apply weighing fusion methods (Type W) such as *DST* approaches. Each participant receives a weight on his past predictions. UC involving time-series data or multiple product inspections are more suitable for *Bayesian* approaches.

UC, which involve many locations and different equipment for inspection of the same goods, can utilise their characteristics for prediction in the local production environment (Type ML). They integrate their local requirements into the prediction by fusion with, e.g., *learning to rank* methods.

Table 1 Methods for data fusion of business data and AI-enhanced inspection

Method	*Type*	*Uncertainty reduction*	*Sensitivity to divergence*	*Training*	*Fusion speed*	*Stability*	*Interpretable*	*Operating site adaption*	*Topology*
Averaging	A	yes	high	-	high	high	yes	no	all
Multiplication	A	yes	high	-	high	high	yes	no	all
Intersection	A	no	high	-	high	high	yes	no	all
Dempster-Shafer (DST)	W	yes	high	low	high	high	yes	yes	all
Bayesian	W	yes	med.	low	high	high	yes	yes	all
Stacked generalisation	E	yes	low	med.	med.	med.	no	no	all
Bucket of models	E	no	low	med.	high	med.	yes	yes	d/h
Learning to rank	ML	yes	low	med.	med.	med.	no	yes	d/h
Competitive	ML	no	low	med.	low	med.	no	no	c
Backpropagation	ML	yes	low	high	low	med.	no	yes	c

Notes: A-algebraic, W-weighting, E-ensemble learning, ML-machine learning, c-centralised, d-decentralised, h-hierarchical, med.-medium.

UC, which involve prediction sources relying on different input data, which also result in differing predictions, may apply ensemble methods (Type E) like *stacked generalisation or backpropagation* ML techniques. UC that either has sources on the same input data or produce differing predictions can apply a *bucket of models* for fusion to identify the best quality predictions for a given input.

UC with high freedom or the concatenation of characteristics lend themselves to this ML fusion methods like backpropagation. The more diverse the task and the higher the interconnection between the actual task and the measurable characteristics, the more likely ML algorithms might find use in fusing the data.

UC with a proprietary AI-enhanced inspection source or a topology from an AI-service provider that does not disclose its predictive algorithms for sorting or evaluation. Here, algebraic, weighing, and ensemble methods offer a possibility of leaving existing solutions in the value creation chain and extending them with further process-relevant information.

When going through the framework for the application of fusion methods, it is important to keep in mind the technical feasibility and the economic feasibility. Certainly, integrating expensive sensors and the continuous expansion of cloud networking in companies can improve the inspection processes, but this must always be weighed against the effort and the resulting success.

In the final step of the framework, the chosen method must be implemented and tested on the use case. The implementation and test strategy depend on the respective UC and the given data. Regardless of the fusion method and the test strategy, a sufficiently large database must be available that corresponds to productive operation. Experts from the respective domain are crucial for assessing the representativeness of the dataset.

Circularity, on the other hand, refers to the degree to which a product, system, or process is designed to be part of the circular economy. A circular product, for example, might be designed to be easily repaired, upgraded, or recycled to keep it in use for as long as possible. A circular system, such as a recycling program, might be designed to capture and reuse materials that would otherwise be wasted. Finally, a circular process, such as closed-loop manufacturing, might involve using waste products as inputs for new products to minimise waste and pollution. In all of these cases, the goal is to move toward a more circular economy where resources are used efficiently and sustainably.

In this section, a framework is proposed that enables the integration of business data with AI-enhanced inspection. The proposal of the framework highlights the necessity for integration of both, an informational linkage of the business data and the observed characteristics of the products or processes. Furthermore, it becomes clear that a deeper analysis of the business data and the AI-enhanced application is necessary to identify the possible positive effects of a fusion. Additionally, the proposal explicitly illustrates that the fusion for the respective identified UC must be implemented and tested to measure its impact on inspection. Section 4 demonstrates hereafter the implementation and testing of the methods for a specific application.

4 Implementation of data fusion for inspection of product returns

This section explains how returns can be inspected using prediction from AI-enhanced computer vision on the one hand and business data on the other. The explanation includes shortcomings of the current prediction methods. It, therefore, develops suitable fusion methods to reduce the effects of the limitations on the inspection. A prototypical implementation provides a basis for investigating the quality and stability gains, which result from data fusion. An inspection process between reverse logistics and remanufacturing in the automotive aftermarket serves as an example for UC1 and UC2.

In the automotive industry and aftermarket, returned EOL motor vehicle parts are called cores. The core inspection process seeks to identify the product class (original spare parts number or original equipment number (OEN)) and assess damage types of product returns (cores) from motor vehicles. Each core belongs to a product group, e.g., a starter motor or an alternator. Each product group shows several typical damage types, e.g., corrosion or carbonisation. The inspection of the cores takes place in customer-related batches. Therefore, each core is already uniquely locatable to a supplier (Su) with the inspection ID. The inspector (and decision-maker) independently determines the product class and group in the conventional process. In addition, each inspector ensures that the product characteristics (inspection ID, Su, EAN, m, OEN, damage class) enter a database accessible to all inspection stations of the company.

AI-enhanced computer vision and analysis of collectable business data improve the inspection process. Both sources fuse their predictions to achieve the best possible predictions of product characteristics. Each source has requirements for selecting the best method for data fusion in terms of quality and stability.

The following subsections detail the enhancement. First, a brief introduction to AI-assisted inspection, its shortcomings and potential for improvement are given. Secondly, the implementation of statistical sensory predictions is explained. Third, the statistical sensory predictions are tested. Fourth, results are discussed regarding the research questions. Fifth, the impact of the results on circularity is discussed. Sixth, a topological design for implementing the fusion method is presented, and seventh, the fusion methods are chosen for testing. Finally, the impact of data fusion on circularity is explored.

4.1 AI-enhanced inspection

Optical sensors collect visual data to enhance identification and damage evaluation. Afterwards, the visual data from the cores enter a learning process. Therefore, a well-known architecture for convolutional neural networks (CNN) comes into action. The architecture has already shown the positive effects and enormous possibilities of computer vision for inspections in the circular economy. The architecture of the network currently in use, a ResNet50, is 50 layers deep and uses residual blocks to detect cores with a balance between effort and accuracy (Schlüter et al., 2021). In a study with 1,440 sample cores, the architecture had a recognition accuracy of 96%. This study presents the increased stability in prediction and thus decision-making for a few selected product returns of cores. However, with an estimated number of 135,000 different product classes, further measures need to be implemented to improve identification.

Visual sensors record the cores, and software forwards this data to the trained neural network. Then, the neural network generates predictions about the product class from the visual data. The predictions comprise a list containing the product class and reliability (score). In application, AI provides predictions that carry an inherent probability (score), which an instance (decision-maker) uses as a basis or an indication for a decision regarding a core. This list is as long as the number of product classes learned by the neural network. Based on the verification of the user and the recognised product class, another neural network will predict possible damage types from the visual data.

To further improve computer vision for inspection, methods are currently being tested at the Fraunhofer Institute for production systems and design technology that enable the fusion of colour and depth information from different sensor types (Schlüter et al., 2021). In this data acquisition, different sensors capture the cores from multiple perspectives. They enable the simultaneous acquisition of unique positions and orientations and optimise training. Thus, they reduce the minimum number of inspections required for predictions. In addition, uniform illumination improves depth information already during acquisition.

4.2 Sensor and business data evaluation

The business data evaluation (BDE) statistically crawls historical data. It gains core characteristics from sensors to predict the cores class, its product group, and its condition. The statistical component relies on characteristics relevant for distinguishing vehicle cores as product returns. Altogether, the dependencies of the core class on the supplier *Su*, packaging *EAN* and mass m result from explorative data analysis. For example, suppliers ship different parts. The European Article Number (*EAN*) on the packages can break down a core's belonging to an Original Equipment Manufacturer or aftermarket programme. The mass of each core varies depending on the dimension and thus on the product group and class.

In the first step, the evaluation of historic data calculates the relative frequency $f_n(Su)$ with equation (1) for each core class C to determine how often each supplier *Su* sent this core class.

$$f_n(Su) = \frac{n_i(Su)}{n} \tag{1}$$

$$f_n(EAN) = \frac{n_i(EAN)}{n} \tag{2}$$

In addition, the evaluation determines according to equation (2), the relative frequency $f_n(EAN)$, of how often each type of package *EAN* occurred for each core class C. Further, the conditional probabilities are determined for all classes on condition of the customer number and *EAN* $f_n(Su \wedge EAN)$. Each core class receives a mass distribution $M(x)$ by the statistical evaluation of the historical data.

However, the statistical evaluation alone cannot ensure a qualified prediction about the core class. Two measurements allow considering the dynamics of the process and distinguishing the number of different cores. The sensory components comprise a barcode scanner measuring the *EAN* and a scale measuring the mass m. After measuring the characteristics, the evaluation can predict the product classes occurring in the historical data.

$$P(m_{min} < m < m_{max}) = \int_{m_{min}}^{m_{max}} M(x)\, dx \tag{3}$$

The evaluation uses measured characteristics to include pre-computed predictions and excludes inconsistent predictions from historical data. It determines the mass probabilities $P(m)$ from measured mass m for all core classes that occurred in the past, according to equation (3), with the confidence of the scale (m_{min}, m_{max}).

From the determined probabilities of occurrence, the authors apply different algebraic methods to fuse the statistical evaluations, as shown in Table 2. In an algebraic approach, we multiply the calculated relative frequencies to receive the probability of encountering a core class based on measurement (PSE). A second approach (SSE) weights by a linear combination with parameter a. The mass probability $P(m)$ multiplies PSE, SSE, and the conditional probability $f_n(Su \wedge EAN)$, and gives the respective fused predictions: product of mass probability and the relative frequency of packaging (EAN) and the supplier (Su) – CPM, product of mass probability and sum of the relative frequency of the packaging (EAN) and the supplier (Su) – CSM, and product of mass probability and conditional probability under the condition of the supplier (Su) and package (EAN) – CSEM. Finally, each prediction list contains probable core classes with an associated score. The score assigns a rank to each entry in the list.

Table 2 Statistical sensory methods

Title	*Description*	*Formula*
CPM	Product of mass probability and the relative frequency of packaging (*EAN*) and the supplier (*Su*)	$P(m) \cdot f_n(Su) \cdot f_n(EAN) = P(m) \cdot PSE$
CSM	Product of mass probability and sum of the relative frequency of the packaging (*EAN*) and the supplier (*Su*)	$P(m) \cdot (af_n(Su) + (1-a) f_n(EAN)) = P(m) \cdot SSE$ with $a \in [0, 1]$
CSEM	Product of mass probability and conditional probability under the condition of the supplier (*Su*) and package (*EAN*)	$P(m) \cdot f_n(Su \wedge EAN)$

4.3 Backtesting of sensor data and business data evaluation

A comparative analysis of predictive accuracy, through cross-validation, evaluates the quality of BDE methods. An algorithm randomly splits a dataset of 213,879 core inspections with 7,122 different core classes 20 times into 80% training and 20% test data. The training data prepare the predictions and represent a historical dataset. The test data serve as samples for the generation of prediction lists. After generating the predictions, an algorithm checks each test sample's rank and prediction score appearing in the prediction list. 20 test runs are started, in which the performances are calculated as the average of the performances of the 20 individual runs.

In the context of multiclass classification, the rank of a predicted class reflects the model's confidence in its prediction. The rank is determined by the position of the predicted class in a list of predicted classes, ordered by the model's confidence in the prediction. This information can help evaluate the model's performance, allowing the user to see how confident it is in its predictions for each class. It can also help to identify cases where the model is unsure about its predictions, which may indicate areas where the model could be improved. The average rank of a model's predictions can also impact the overall quality and speed of inspection. A low average rank generally indicates that the model is confident in its predictions, leading to a higher likelihood of correct classification and faster inspection. On the other hand, a high average rank suggests less confidence in the predictions and a higher likelihood of incorrect classification, requiring more thorough inspection.

In this article, score (usually termed confidence) refers to the level of certainty that a model has in its prediction or classification. It is usually represented as a probability, with higher probabilities indicating higher confidence and lower probabilities indicating lower confidence. The score is important because it can show the reliability of a model's predictions. High-score predictions are more likely to be accurate, while low-score predictions are more likely to be incorrect. The score can also impact the quality and speed of inspection. If a model makes high-score predictions, the inspection process will likely be more efficient and accurate. If a model makes low-score predictions, the inspection process will likely be less efficient and inaccurate.

By calculating the average rank and score for all test samples and folds, it is possible to compare the success of the different statistical sensory prediction methods. As Table 3 shows, identification solely by suppliers performs the worst with an average rank of 172.9. The test samples are, on average, at position 34.4 of the prediction list by mass. The best prediction in terms of average rank delivers a prediction from the CSM of 24.1. The worst combination delivers an average ranking of 76.8.

Table 3 Core class prediction performance

Method	*Average prediction performance*							
	Rank	*Rel. rank*	*Score*	*Rel. score*	*Top 1*	*Top 2*	*Top 3*	*Top 5*
$f_n\ (Su)$	172.9	0.44	0.01	0.0001	0.06	0.08	0.10	0.14
$f_n(EAN)$	28.4	0.06	0.46	0.0023	0.59	0.75	0.82	0.89
$f_n\ (Su \wedge EAN)$	77.2	0.21	0.40	0.0017	0.46	0.56	0.60	0.63
$P(m)$	34.4	0.08	0.07	0.0007	0.07	0.16	0.24	0.37
SSE	24.5	0.06	0.26	0,0014	0.60	0.75	0.81	0.87
PSE	70.8	0.20	0.43	0.0018	0.47	0.58	0.62	0.65
CSM	**24.1**	**0.05**	**0.51**	**0.0026**	**0.66**	**0.80**	**0.85**	**0.90**
CSEM	76.8	0.21	0.46	0.0019	0.51	0.59	0.62	0.64
CPM	70.4	0.19	0.50	0.0021	0.53	0.62	0.64	0.66

Table 3 shows the average scores for the methods for all test samples. The simple, algebraically fused methods SSE, PSE, CSM, CSEM, and CPM, achieve an average score of 0.26 to 0.51. While the sole prediction from the EAN still achieves a score of 0.46, the fused methods can improve their confidence by combining data. Including the mass probability improves the prediction for the algebraically fused methods: CSM, CSEM, and CPM.

The accuracy of the predictions presents a similar pattern. In ML, 'TOP X accuracy' refers to the percentage of times that a model or system correctly predicts the correct outcome or label out of all possible outcomes or labels, where X is the number of ranks included, starting with 1. Higher TOP X accuracy is generally desirable because it indicates that the model can make more accurate predictions. Furthermore, in the context of an inspection, higher TOP X accuracy can lead to more efficient and accurate inspection processes because fewer resources will be needed to verify the accuracy of the predictions. On the other hand, lower TOP X accuracy may require more resources to verify the accuracy of the predictions. It may result in less efficient and accurate inspection processes.

During the inspection at review of the predictions, it is important to display predictions clearly and briefly. Thus, the user can seize the current core from the display list. An algorithm counts the occurrence of the predictions in TOP 1, 2, 3, 5 of the prediction lists to measure the success rate. The CSM method performs best. CSM can display the sample cores in the TOP 1 in 66%, TOP 2 in 80%, TOP 3 in 85%, and TOP 5 in 90% of all test samples.

4.4 Discussion of results

The sensor and BDE predicts the ID of cores. Each of the implemented methods can create and present predictions to a decision-maker for identification and verification during inspection.

These results show that the use of multiple features leads to an improvement in fused prediction. The improvements vary in magnitude depending on the method used.

Furthermore, it turns out that the information about its mass for product returns can contribute significantly to detection. This is of particular interest because mass measurements of products cost little and can be carried out reliably.

It also reveals that simple statistical analysis can make qualitative predictions, especially for frequently occurring products. However, the prediction for rare products is too weak. Outliers occur that worsen the predictions to a magnitude that is unacceptable. The right proposals must end up at the top of the first page of the inspector's proposal list during an inspection. Although the simple algorithms partly manage this, it is not enough for an industrial application.

We expect 99% of the inspected cores among the TOP 3 predictions for an application in the production environment. This is because the inspection process involves verifying the model's predictions, which can be time-consuming. If 99% of predictions fall within the TOP 3 making the inspection process more efficient and easier to understand. In addition, it would be desirable if the minimum score of each prediction is 51% on the respective prediction list, which corresponds to a 100% occurrence of each inspected core on TOP 1. This is because it shows that the ML model is confident in its predictions and can accurately classify items with a high level of certainty. This can also improve the human-machine interface, as the inspector will only need to review one prediction for each core, rather than a list of multiple predictions, making the inspection process easier to understand and more straightforward. Fusion methods are used to achieve the targeted metrics of predictions.

It is important to note that different applications may require different levels of TOP X accuracy depending on the specific needs of the task at hand. For example, a model with a high TOP 1 accuracy may be sufficient for a task where it is important to have a single, highly accurate prediction. On the other hand, a model with a high TOP 5 accuracy may be more suitable for a task where it is important to have a list of several highly accurate predictions to choose from. In general, it is important to consider the trade-off between the level of accuracy desired and the resources available for inspection when determining the appropriate level of TOP X accuracy for a given task.

The test of the business data analysis also contributes to answer the specified research questions (see Section 2.4).

Q1 Regarding the requirements for a stable and high-quality fusion of AI and business data, the implementation demonstrates the necessity of measurements during inspection in order to make qualified predictions from business data. Historical data alone are not sufficient.

Q2 In terms of quality improvements from the fusion of business data, algebraic and weighted fusions show slight improvements over non-fused predictions.

Q3 The stability of the simple algebraic and weighted method is so far insufficient for operational use. Albeit the quality increase and the numerical stability, 10% of the cores receive inadequate predictions with poor average ranks and scores, which leads to instability in the inspection and subsequent processes.

4.5 Impact of results circularity

In summary, the quality of the fused predictions of the BDE is already good enough to reduce the possibility space for the inspector from 135,000 to about 95 classes in 90% of the inspections, assuming linear scaling of the tests performed. In view of this, in Germany, between 5-7% of about one million cores per year are mistakenly sorted out because their class cannot be identified (Schlüter et al., 2021). This leads to the destruction of value through material recycling, which is not sustainable. Further shortening the range of possible classes helps the inspector to dispose fewer cores wrongly.

The results indicate that the better the quality of prediction, the more contribution to resource efficiency keeping products in multiple life cycles. This contributes to value preservation by implementing data analytics as SM. This finding improves circularity of products in the automotive sector and can be applied to any sector seeking SM.

Further, AI and data fusion are closely related because data fusion involves the combination of multiple data sources to generate a more comprehensive and accurate understanding of a situation or phenomenon. This can be useful in many applications, including manufacturing, where data fusion can help improve decision-making and optimisation of processes. This potential is explained within the next subsections.

The next subsections examine the implementation of fusion methods for the use case. First the design of stable processes is highlighted in order to use fast fusion methods for the use case.

4.6 Importance of the topological design of data fusion

The topological design of data fusion refers to the way in which data from multiple sources is integrated and processed. There are several approaches to topological design in data fusion, including centralised, decentralised, and hierarchical approaches.

In *centralised data fusion*, all the data is collected and processed at a central location, where it is integrated and analysed. This approach is often used in systems with limited data sources or when the data sources are highly correlated.

In *decentralised data fusion*, the data is collected and processed at multiple locations, and the results are then combined and analysed. This approach is often used in systems with large, disparate data sources or when the data sources are not highly correlated

In *hierarchical data fusion*, the data is collected and processed at multiple levels, with each level performing a specific task. This approach is often used in complex systems where the data needs to be analysed and processed at multiple levels of abstraction.

One of the main advantages of data fusion is that it allows businesses and organisations to extract more information and insights from their data, which can improve decision-making and operational efficiency. The topology of data fusion plays a crucial role in this process, as it determines how the data is collected, processed, and analysed. The choice of topology has a significant impact on the performance and effectiveness of the data fusion system, as well as its efficiency and scalability.

For example, a centralised data fusion system may be more efficient in its use of resources, but it may be less adaptable and less able to scale than a decentralised or hierarchical system. On the other hand, a decentralised or hierarchical data fusion topology may be more adaptable and scalable, but it may be more complex to design and implement and may be less efficient in its use of resources.

The topology of data fusion is also important in terms of reliability and accuracy. A well-designed data fusion system should be able to handle a wide range of data sources and data fusion tasks. It additionally should be able to provide reliable and accurate results even if there is some uncertainty or noise in the data.

In summary, the topology of data fusion is an important consideration when designing and implementing a data fusion system, as it can have a significant impact on the performance, efficiency, scalability, and reliability of the system. The choice of topological design for a data fusion system will depend on the specific needs and constraints of the application, including the volume and complexity of the data, the resources available for processing and analysis, and the desired level of accuracy and reliability.

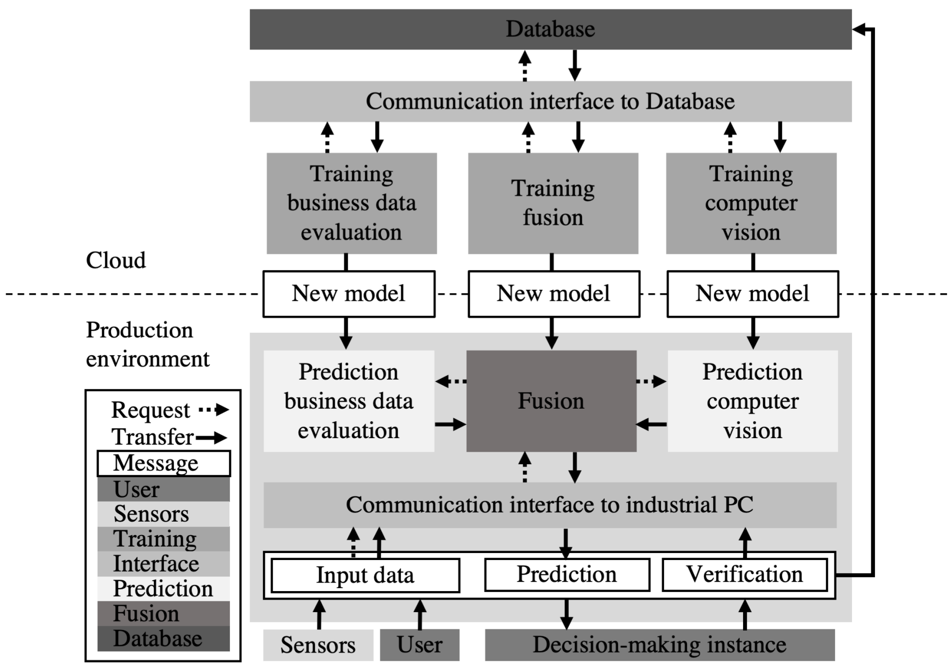
4.7 Topological design of data fusion for the use case

Various topological design measures increase the stability of the predictions (see Figure 2). The first measure is to calculate the training of the models for prediction to the cloud. That relieves the industrial PC in the production environment from computational tasks and allows it to focus on executing the predictions. Thus, the training and predictors are independent of each other. As a result, the predictions can continue to operate based on the latest functioning version in the event of a failure, e.g., during training. In addition, the topological design ensures that the training units within the cloud act independently of each other to increase stability.

In the cloud, the training modules for BDE, fusion, and computer vision are separated from each other and the database. Each training module retrieves the training data from the company-wide database. This ensures that the training does not affect the company's existing database.

The training modules use historical inputs, predictions, and verifications to train the predictors and improve the models' predictions. Only those models that need an update because of inadequate predictions are trained selectively. It is important to learn models selectively because it can improve the energy efficiency of the models by reducing the number of calculations required to make accurate predictions. It can also contribute to resource efficiency by reducing the data and computational resources needed to train and run the model. Selective learning can also reduce the human labour required to maintain and update the whole ensemble of models and improve the overall performance by making more accurate predictions. These factors contribute to sustainability by reducing waste and improving resource utilisation in various applications. For this purpose, the training modules examine the decision-makers' verifications and compare them with the predictions for each inspection. If the concept drift is too large, the modules train only these samples and add them to the models in batches or incrementally. This will contribute to low energy consumption of the learning modules. This first option is the design case and is favoured.

Figure 2 Topological design for stable predictions



In addition, it is possible to apply a fixed long-term cycle for updating the models. Here, the training modules update the models after several inspections or a period. This cycle should cover a sufficiently large interval to reduce energy consumption. Of course, it depends on the application, the frequency, the variance of the products, and the resulting concept drift of each participating source. However, it is also possible for the user to instruct the individual training modules to train new models with specific parameters. The latter option allows the user to trigger the training if the predictions are insufficient. After one of the options, when a new model is learned, the communication between the cloud and the production environment occurs.

The predictors are separated on the industrial PC to assess the process or event independently. Then, during an inspection, on request, the sources generate predictions about the class and state of the core from the respective input variables (see Sections 4.1 and 4.2).

The fusion method affects the learning effort and preparation of the predictions. Algebraic fusion methods do not require a learning unit in the cloud. However, more complex statistical methods and AI approaches to data fusion require a learning unit in the cloud. This fusion unit fuses the predictions based on the selected method. After fusion, the unit can pass its prediction to a communication module to display it on the industrial PC on demand from the production environment. If a source does not provide a prediction, the fusion unit still considers the prediction of the functioning source. Should none of the source units predict the inspection, the decision-maker can still inspect the product autonomously.

As for the BDE and the fusion methods, each verification of the decision-maker will trigger an incremental rescaling and learning of the model. This compensates for the local concept drift of the inspection station.

4.8 Fast fusion methods for the use case

A high operational speed characterises the inspection of the cores in the use case. On average, an inspection of a core takes just one minute. This includes scanning, unpacking, measuring, and commissioning the cores. The time between recording the core characteristics and identification is even shorter. Therefore, a fusion method should be as lean as possible to identify and evaluate the cores quickly.

The mathematical fusion methods, like averaging, products, and intersection, without further training effort and the explicit mathematical notation for these cases are shown in Table 3. Fusion methods that only consider rank do not allow subsequent calculation of the fused score. In contrast, a derivation via a fused rank can be made from the fusion of scores. The SS and SR methods can, of course, be weighted with any parameters, but this requires a very high parameterisation effort.

Table 3 Algebraic and weighted methods for data fusion

Method	*Description*	*Formula*
SS	Average score from j sources	$\frac{1}{n_s}\sum_j sj$
SR	Average rank from j sources	$\frac{1}{n_r}\sum_j r_j$
PS	Product of score from j sources	$\prod_j sj$
Intersection	In the fused prediction list are only those classes (C) that occur in all sources j	$\max\left(s_j\left(\bigcap_j Cj\right)\right)$
Dempster-Shafer rule score	Weighted fusion of scores based on the historical accuracy of the sources $\overline{A_h}$	$\frac{1}{n_s}\sum_j A_{h,C,j}s_j$
Dempster-Shafer rule rank	Weighted fusion of ranks based on the historical accuracy of the sources $\overline{A_h}$	$\frac{1}{n_s}\sum_j A_{h,C,j}r_j$

The effort required for parameterisation is estimated to be comparatively high, as the quantities of classes and their properties vary with the model years and the use of the parts. Therefore, a weighting based on the Dempster-Shafer combination rule is applied. Two approaches are applicable. It can be based on individual proposals or based on entire lists.

For example, if a source performs poorly on a specific task, Fusion's training module in the cloud can compare the predicted and actual events. The average accuracy of the

$\overline{A_{h,S}}$, with which the individual sources predict events, can then fuse the lists. Another method is to determine the average accuracy with respect to the classes $\overline{A_{h,S}}$, These class-specific weights can then be integrated into the fused predictions.

A third method combines the results of the individual predictors using a stacked generalisation ML method. The prediction source algorithms are trained for this in the cloud. The predictors are then tested. Finally, the predictions are input for higher-order learning procedures, e.g., logistic regression.

The bucket of models method combines the advantages of the different BDE models. For this purpose, the input parameters are segmented into clusters. The best predictors of each then act on a subset of the inputs.

4.9 Impact of data fusion on circularity

Data fusion help companies to make better use of available data, which supports efforts to implement circular and sustainable practices in manufacturing.

This article focuses on the aspect that data fusion enables the determination of inefficiencies and waste in manufacturing and EOL processes. The proposed framework enables the integration of business data with AI-enhanced inspection to identify the possible positive effects of a fusion. The case study demonstrates the effects based on statistical sensory predictions and tests with a selected fusion method. The results lead to a higher quality and more reliable results in prediction, i.e., more cores are identified correctly during inspection, less core are wrongly selected for disposal. These determinations reduce waste as well as environmental impact and improve resource efficiency.

There are further ways how data fusion support companies to track and monitor the sustainability of their manufacturing processes over time, allowing them to make ongoing improvements and adjustments to support their sustainability goals. For example, data fusion can combine data from different sources, such as production logs, energy usage records, and supply chain data to gain a more comprehensive understanding of their environmental impact and the resources they use. By doing this, companies can identify inefficiencies and areas where resources are being wasted. This information can then change the manufacturing process to reduce waste and improve resource efficiency, supporting circularity.

Furthermore, data fusion can also support SM by providing organisations with the data they need to make informed decisions about their production processes. For example, data fusion can combine data on market demand, resource availability, and environmental impact to help organisations identify the most sustainable production options and make decisions that support their sustainability goals. Data fusion is crucial in supporting SM by providing organisations with the data they need to make informed, sustainable decisions.

In conclusion, data fusion is a powerful technique that enables the integration of AI into business operations, resulting in the optimisation of processes and the minimisation of waste. By combining multiple data sources and information from various sources, data fusion creates a more comprehensive and accurate representation of a particular topic or issue, allowing businesses to make more informed decisions and improve their performance. Utilising AI techniques such as ML and natural language processing in conjunction with data fusion allows for the real-time analysis and interpretation of large volumes of data, providing insights and recommendations to decision-makers. Through the integration of data fusion and AI, businesses can leverage the power of these technologies to optimise their processes and minimise waste in the pursuit of SM. This includes the identification of patterns and trends in production and supply chain data, the analysis of customer and market research data to identify opportunities for product reuse and remanufacturing, the use of predictive maintenance to extend equipment lifespan and reduce downtime and waste, the optimisation of the supply chain and logistics to reduce emissions, and the optimisation of energy use to minimise the environmental impacts of operations. Data fusion is therefore a crucial enabler for the integration of AI into business operations, ultimately supporting the transition to a circular economy and a more sustainable future.

5 Conclusions

One of the key aspects of the circular economy is investigating product returns as resources to increase the value created by those resources through multiple life cycles. Improvement of the decision-making about product returns can increase the number of products in second and further lives with high value and reduce cost in curative return management. This article provides a framework for precise decision-making. The framework focuses on data fusion of business data and AI in order to enhance the integration of AI into inspection processes.

Recent AI-enhanced applications for inspection in reverse logistics and return management were reviewed and presented. AI-enhanced applications with multiclass classification are still limited in their performance. ML methods, such as machine vision, can be improved to cope with the large number of classes that will be identified. Some of them are dedicated to the classification of products and their condition. Excursive research shows that there are already many different methods suitable for UC in the inspection of product returns.

Statistical analyses were carried out to bring customer and shipping data into a fusible format. Sensor measurements supplement the statistical analyses with the mass of the products in order to improve the predictions about the product classes. It has been shown that even the statistical sensory predictions can help the decision-makers to generate proposals that appear in the TOP 5 by 90%. This already offers a precise reinforcement that allows the decision-makers a more reliable classification of products, given the possibility of more than 7,000 classes. This reliable identification of the products promotes more consistent information for further life cycles of these products or their components. In this way, the statistical sensorial prediction already contributes to processing resources in multiple life cycles, i.e., preservation of product value in closed loops and advancement of SM. Nevertheless, these predictions are not yet sufficient for stable operation. They must be improved in quality.

Different fusion methods are evaluated as suitable for the use case of product returns. The topology of the fusion methods must also be considered during the evaluation of these methods. On the one hand, it must allow all workstations to benefit from the know-how of inspections at other stations. On the other hand, it must maintain stable operation if the network or a single workstation stop working or communicating. The proposed decentralised topology of the framework provides a stable basis for each participating source so that reliable predictions are possible even if any other or all other participating prediction sources fail.

It is also important to include all the inspectors at all operating sites for verifying and training the prediction models and fusion. Using a four-eye principle, human inspectors and machine-based predictors work continuously together. The topology facilitates this cooperation, which offers different possibilities of testing and training, if requested, based on time, batch, or concept drift way.

The proposed concept for the integration of AI into core inspection includes a topology that enables the identification and evaluation of products based on sensors across products and business processes. This concept is already implemented and validated in the automotive aftermarket. The case study results demonstrate positive effects based on statistical sensory prediction and testing with a selected fusion method. These results confirm the indicated increase of quality and reliability in prediction. As a consequence, waste of core is reduced, more core is correctly inspected for the next life cycle and so resource efficiency for cores is increased. This consequence also improves the circularity of cores for automotive aftermarket.

The concept can be transferred to further components and sectors, since it applies to many value creation processes with a suitable adaptation of the participating predictors and data. Future research and applications will realise the high potential of this concept in other areas of curative return management and circular economy.

The contributions of this article to academia include the development of a framework for integrating data fusion and AI into inspection processes in order to improve decision-making about product returns in the circular economy. This framework represents a novel contribution to the field of data fusion and could be used as a basis for further research in this area. The article also reviews AI-enhanced applications for inspection in reverse logistics and return management, including their limitations and potential improvements. This review represents a summary of current developments in this field and serves as a reference for future research. In addition, the article evaluates different fusion methods as suitable for the use case of product returns, including considering the topology of these methods. This evaluation represents a systematic approach to selecting fusion methods and could be helpful for researchers and practitioners. Finally, the article presents a case study demonstrating the successful implementation and validation of the proposed concept in the automotive aftermarket. This case study represents a real-world application of the proposed framework and could be used as a model for future implementations in other industries.

In terms of contributions to practice, the proposed framework can improve the integration of data fusion and AI in the circular economy, potentially leading to increased resource efficiency and circularity. The review of AI-enhanced applications for inspection in reverse logistics and return management identifies potential improvements and limitations, which can inform the development of these applications in practice. The evaluation of different fusion methods as suitable for the use case of product returns, including the consideration of topology, guides the selection of suitable fusion methods for practitioners. Finally, the case study demonstrating the successful implementation and validation of the proposed concept in the automotive aftermarket serves as an example of how the proposed framework can be successfully implemented in real-world settings, potentially leading to improved resource efficiency and circularity in the automotive aftermarket and other industries. The proposed concept can be transferred to other components and sectors since it applies to many value creation processes with a product return focus. The proposed concept can improve resource efficiency and circularity in other industries by improving the identification and evaluation of products based on sensors across products and business processes.

One of the critical limitations of the work presented in this article is the focus on the use of data fusion and AI in inspection processes for product returns in the circular economy rather than on the entire system or other aspects of reverse logistics and return management. Future work could address this limitation by expanding the scope of the analysis to include other aspects of the circular economy and considering the entire product life cycle. Another limitation is that the framework is applied only in a case study in the automotive aftermarket, which may not represent other sectors or industries. Future work could address this limitation by conducting additional case studies in different sectors to confirm the findings' generalisability and identify any sector-specific challenges or opportunities for adopting and implementing data fusion and AI in the circular economy. A further limitation is the lack of analysis of the potential impacts of data fusion and AI on employment and skills development in the circular economy. Future research could address this limitation by examining the potential impacts of data fusion and AI on employment and skills development in the circular economy and identifying ways to enhance the benefits and mitigate any negative impacts. The authors also note that AI-enhanced applications for inspection in reverse logistics and return management are limited in their performance and can be improved, particularly in multiclass classification. Future work could address this limitation by exploring different ML methods and techniques that can improve the performance of AI in inspection processes. Another limitation is the lack of consideration of potential barriers and challenges to adopting and implementing data fusion and AI in inspection processes. Future research could address this limitation by exploring these potential barriers and challenges in more detail and identifying strategies to overcome them. Finally, the authors discuss the use of statistical analyses and sensor measurements to improve the prediction of product classes but note that these predictions are not yet sufficient for stable operation and need to be improved in quality. Future work could address this limitation by exploring different approaches to improving the accuracy and reliability of predictions.

In future, fusion methods and topology must undergo testing with the predictions of AI-enhanced computer vision. This testing would evaluate the contribution of the data fusion to enhanced decision-making and value preservation of product returns for more SM.

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