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Machine learning for metrology in manufacturing

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A B S T R A C T

Machine learning is transforming manufacturing metrology by enabling data-driven modeling, automation, and real-time decision-making across the measurement process. This keynote reviews recent advances and future directions for integrating machine learning (ML) throughout the measurement workflow—from system setup to decision-making—by structuring the analysis of the state of the art using a data flow framework. Key applications include ML-assisted setup and calibration, enhanced measurement, virtual measurements, and classification-based inspection. The remaining key challenge is the integration of metrological traceability, standardized uncertainty quantification, explainability, and reproducibility. Bridging the underlying conceptual gap in understanding and evaluating uncertainty is essential to establish scientifically rigorous and industrially reliable ML-driven metrology for future manufacturing systems.

1. Introduction

Metrology is a critical enabler for reliable decisions in manufacturing. Measurements offer quantitative information about processes and products for purposes such as evaluating product conformity, operating high-precision manufacturing equipment, and controlling automated manufacturing systems and autonomous robots. A measurement result does not only contain the value quantity itself, but also a statement on its associated uncertainty. Proper estimation of the uncertainty is essential for regulatory compliance and risk management, particularly in manufacturing when assessing conformity with specified tolerances [69].

In many manufacturing processes, the quantitative value of a measurand can only be determined via an indirect measurement [88]. In such cases, a measurement model must be derived that expresses the measurand in terms of the input sensor data and relevant influencing factors. The conditions under which the measurement is taken must be analyzed and well understood, and the derivation of the model and its validity must be carried out with appropriate rigor.

Yet, as manufacturing processes and products become more dynamic, diverse, and complex, creating a suitable measurement model poses a significant challenge. Often, cause-and-effect relationships are only partially understood, and traditional modeling techniques may fail to provide a closed-form mathematical representation—particularly when dealing with high-dimensional or multi-modal input data. To meet the demands of modern and future manufacturing processes, metrology therefore requires suitable modeling strategies.

Artificial intelligence (AI), more specifically the subfield of machine learning (ML) has introduced a continuously growing set of new, advanced modeling techniques. By learning complex patterns directly from data, ML models can represent a wide range of functional relationships, tackling the challenges in manufacturing mentioned before. Most recently, Large Language Models (LLMs) raised public and cross-industry attention to the progress in AI. In a short time, it has become a commodity-like tool with applications in nearly all economic sectors as well as end-user software such as ChatGPT [124]. Manufacturing is no exception – A comprehensive overview of AI applications is given by Gao et al. in their 2024 CIRP keynote paper [59].

X-ray computed tomography (xCT) is illustrative for the pace of adoption of machine learning in metrology. The keynote of Dewulf et al. in 2022 observed machine learning as a recently developing technique relevant to xCT research [41], yet in 2026 machine-learning-based tools for xCT are already commercially available. Examples are given by Hexagon AB [201] and ZEISS Group [232]. In a use case, the AI Toolbox of Hexagon was able to reduce the mean deviation in measurement of pores from 188 µm to 36 µm in turbine blade manufacturing [165].

In addition, the potential of ML for metrology in manufacturing falls in line with the paradigm of integrated metrology, which has

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gained particular attention in highly automated manufacturing lines, where continuous inspection and immediate feedback loops are essential for zero-defect production. Archenti et al. [6] point out that future integrated metrology solutions may benefit from ML tools for improved decision-making, data fusion, and real-time analysis of complex metrology data.

The purpose of this keynote paper is to review and outline the potential of combining ML techniques with metrology in manufacturing. Rapid advancements in data-driven technologies present a unique opportunity to enhance measurement processes, yet integrating ML into established metrological workflows raises new challenges—especially when adherence to metrological concepts such as traceability, accuracy, and measurement uncertainty is mandatory.

The remainder of this work is structured as follows: Chapter 2 briefly revisits the fundamental concepts and terminology of both metrology and ML. Chapter 3 introduces the data flow framework, which explains the distinction of different ML approaches and the resulting allocation of literature to chapters 4–9.

Chapters 4–9 are organized along the typical workflow of a measurement process in manufacturing, from initial setup to final decision-making. The foundation of these chapters is a literature review, combining large-scale database queries with manual refinement steps to ensure a comprehensive and focused selection of relevant publications.

In detail, chapter 4 covers ML-based setup and parametrization, including sensor selection, calibration, and configuration. Chapter 5 addresses ML-enhanced measurement for data preprocessing, feature extraction, and model development. Chapter 6 introduces virtual measurements (VM), where ML predicts quality characteristics without physical sensors. Chapter 7 focuses on Classification and Inspection for defect detection and functional verification. Chapter 8 discusses how ML supports insight generation and feedback to operators and systems. Chapter 9 examines uncertainty and risk evaluation of ML-based results, and chapter 10 concludes with key findings and future research directions.

2. Foundations

This chapter introduces the core principles of metrology (2.1) based on the International Vocabulary of Metrology (VIM) [88] and the Guide to the Expression of Uncertainty in Measurement (GUM) as well as machine learning (2.2), followed by a short summary (2.3).

2.1. Metrology

Metrology is the science of measurement. To enable the inspection of products or deciding whether a product's quality characteristics lie within the specifications, such as tolerance limits, manufacturing relies on the ability to accurately evaluate a product's or process's properties. An accurate and trustworthy evaluation of the quality characteristics is ensured by proving the capability of the inspection processes in use. While attributive inspection can only assign nominal properties that have no magnitude (VIM 1.30), e.g., by performing classification, segmentation, or detection tasks [199], measurements provide quantitative information [214]. Thus, quantitative properties are reported as a measured quantity value together with a measurement uncertainty that characterizes the dispersion of values that could reasonably be attributed to the measurand, e.g., via a coverage interval with a stated probability [104,68]. For measurement processes used for quality control, the capability of the measurement process is directly related to the measurement uncertainty and evaluated by comparing the uncertainty of the measurement with the specifications of the quality characteristic considered.

In the following chapter, the core concepts of metrology as defined in VIM and GUM [52] for conducting measurements are introduced.

A measurement is defined as the process of experimentally obtaining one or more quantity values that can reasonably be attributed to a measurand (VIM 2.1). A measurand (VIM 2.3) is the specific quantity to be measured, such as the length of a rod or the temperature of a liquid. To conduct a measurement, the measurand must be identified and an appropriate measurement principle (VIM 2.4) and measurement method (VIM 2.5) have to be chosen. For the measurement method, the VIM distinguishes between direct measurements, where the measurand is obtained directly from the measurement device, and indirect measurements, where the measurand is derived from other quantities that affect the measurand. Based on that, the measurement instrument has to be chosen that can provide indications of the quantity values (VIM 1.19). The quantity values consist of a number and reference, together expressing the magnitude of the quantity (VIM 1.1, e.g., "1 meter" or "277 °C"). Therefore, the selected measurement instrument must be calibrated (VIM 2.39) to establish a relationship between the indications provided by the measurement system and the corresponding values realized by a reference (e.g., the speed of light c or the temperature of boiling water). Calibration ensures that the measurement indications are traceable (VIM 2.41), meaning they are linked to a reference (*VIM 1.1 - NOTE 2*) through a documented and unbroken chain of calibrations, and can be compared with each other (e.g., from different calibrated caliper gauges or thermometers).

In modern manufacturing, this view of metrology extends beyond the inspection of isolated parts or processes. Recent work on integrated metrology [6] emphasizes that measurement activities are inherently distributed across the manufacturing system, encompassing not only the product and process but also the manufacturing equipment itself. Sensors embedded in machine tools, robots, or additive systems continuously collect traceable data, forming a closed loop that links equipment condition, process state, and product quality. This integration turns measurement into a system-level capability, enhancing precision, adaptability, and productivity in manufacturing.

An Integral part of a measurement is the statement of the measurement uncertainty (VIM 2.26), a non-negative parameter that characterizes the dispersion of quantity values reasonably attributed to the measurand. It expresses the limits of knowledge associated with the conducted measurements.

The general procedure to quantify the uncertainty associated with a measurement is described by GUM. However, GUM does not solve the individual challenges of deriving a valid measurement model and imposes assumptions about the input data used to quantify the measurement uncertainty.

The results of a measurement are also described by their accuracy (VIM 2.13), defined as the closeness of agreement between a measured quantity value and a true quantity value of the measurand, though accuracy itself is qualitative. Results are further characterized by their precision (VIM 2.15), which refers to the closeness of agreement between measured values obtained by repeated measurements under specified conditions.

Other important characteristics of a measurement include repeatability (VIM 2.21), which is the closeness of agreement between results obtained under the same conditions, and reproducibility (VIM 2.22), which describes the agreement of results under different conditions, such as with different operators or instruments.

A measurement can only be conducted if the measurand can be described in terms of acquirable indications or input quantities with a measurement model. Following the VIM's definition, a measurement model can also incorporate ML based methods. At the same time, a trustworthy and traceable evaluation of the measurement uncertainty relies on a proper understanding of the factors influencing the measurement process. A suitable measurement model must be derived typically in the form of an analytical mathematical function of the input indications or quantities. However, typically not all influencing factors and their interactions can be modeled limiting the scope of metrology to those applications that are properly understood.

Traditional metrology often faces challenges when the underlying physical relationships are only partially known or too complex to model analytically. Measurement models typically rely on simplifying assumptions to remain mathematically tractable, which can limit their validity when confronted with dynamic processes, nonlinear dependencies, or high-dimensional data. ML, in contrast, can derive such relationships directly from empirical data, uncovering patterns and dependencies without requiring explicit analytical formulations. This makes ML a powerful tool for addressing complex measurement and quality control tasks, as demonstrated in numerous applications such as machine vision and sensor data analysis [21].

Nevertheless, a coherent integration of ML within the conceptual and terminological framework of metrology is still lacking, leaving a gap between data-driven modeling and established metrological principles [172].

2.2. Machine learning

Generally speaking, ML is a process through which computer systems are trained to identify patterns in data and improve performance on a given task based on that data, without explicit programming [168]. It is a broad field with extensive and established literature, e.g., the deep learning textbook by Goodfellow et al. [72]. This literature is forming the foundation of this subchapter, which provides a brief overview and introduces relevant structures.

As a first structure, ML methods can be categorized based on how they learn: supervised learning, unsupervised learning and reinforcement learning.

Beyond these core categories, two complementary approaches have gained importance. Transfer Learning enables the reuse of previously trained models in new but related scenarios, improving performance while reducing training effort [215]. Physics-informed ML (PIML), in contrast, integrates known physical laws or constraints directly into model training, ensuring physically consistent predictions even with limited data. Together, transfer learning and PIML extend conventional learning paradigms by enhancing both data efficiency and model reliability in industrial and scientific applications [127].

A key aspect of applying ML in manufacturing is the *data modality*—the type or form of data the model processes [7]. These modalities often cluster by dimensionality:

- *1D data* (e.g., time-series sensor signals) where the temporal aspect (e.g., periodic measurements) is integral.
- *2D data* (e.g., photographs or infrared images) commonly encountered in imaging tasks.
- *3D data* (e.g., point clouds or volumetric scans) found in optical 3D measurements or xCT scans.

By examining published work and aligning it with data modalities (1D, 2D, 3D), the number of papers that applied each ML method is illustrated in Fig. 1. The data basis is publicly available [182].

From these insights, six model types emerged as most prominent in the recent past. In the following, they will be presented in theory, while examples can be found in chapters 4–10.

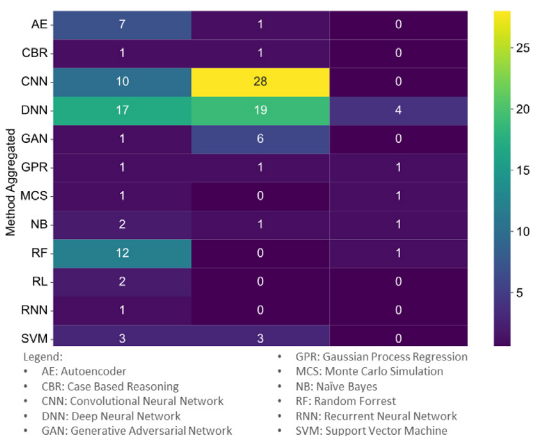

Fig. 1. Frequency of ML methods applied to different data modalities [182].

Random Forests (RFs), introduced in [17], are a composition of decision trees—simple models that recursively split data based on feature thresholds and form branch-like prediction paths. By combining multiple such trees, each trained on distinct data subsets, Random Forests achieve better generalization and reduce overfitting compared to a single decision tree.

Support Vector Machines (SVMs) are classical supervised methods that aim to find an optimal separating hyperplane in high-dimensional space [32]. While deep networks have gained popularity in recent years, SVMs remain a strong choice for smaller datasets or well-structured classification tasks.

Deep Neural Networks (DNNs)—often deep multilayer perceptrons (MLP)—underpin modern ML [171]. Early networks, such as Rosenblatt's perceptron (1958), were inspired by the way biological neurons “fire” upon exceeding a threshold. While the perceptron could only solve linear problems, adding nonlinear activation functions and stacking layers enabled DNNs to approximate more complex functions. This *data-driven* nature sets them apart from analytical approaches, as DNNs learn model parameters from labeled data. Specialized variants like Convolutional Neural Networks further extend DNN capabilities for image-like data.

Convolutional Neural Networks (CNNs) are a specialized class of deep networks tailored for analyzing grid-like data, notably images or volumetric scans. Pioneered by LeCun et al. [105] and later refined by Krizhevsky et al. [101], CNNs utilize convolution filters that capture local patterns (e.g., edges or corners) and pool them hierarchically, leading to robust feature extraction with fewer parameters than fully connected networks. Beyond standard 2D images, CNNs also excel in point-cloud-based tasks for 3D data [25].

Autoencoders (AEs) operate as unsupervised networks designed to learn compact latent representations by reconstructing their inputs [83]. They excel at dimensionality reduction, denoising, and outlier detection. Once trained, the compressed latent space can serve downstream tasks such as classification or anomaly detection, reducing computational load while maintaining informative features.

Generative Adversarial Networks (GANs) draw on two neural networks—commonly known as the generator and the discriminator—which engage in a competitive training loop. The generator aims to produce realistic synthetic samples, while the discriminator attempts to distinguish real data from the generator's output. Introduced by Goodfellow et al. [73], GANs have since become powerful tools for creating high-quality synthetic data and have proven especially useful in tackling challenges such as data imbalance and data augmentation [242].

It is important to emphasize that the models presented are a look into the past. Given the rapid pace of ML, there can be a significant lag between peer-reviewed papers and technologies used in practice. Looking beyond the field of metrology shows trends suggesting that, in the coming years, transformer architectures and LLMs—including multimodal variants—might have a significant impact.

To evaluate the performance of ML models, ML relies on statistical metrics that are conceptually distinct from those in metrology. For classification tasks, common metrics include precision, recall, RMSE, MAE, MSE, RAAE, and the F1-score, which assess a model's predictive correctness against labeled data [155]. For regression, the R^2 score is often used to measure how well predictions approximate actual continuous values [155]. Unlike metrological accuracy and precision, which concern the closeness of a measurement to a true physical value, these ML metrics quantify a model's performance on a dataset, underscoring the different evaluation frameworks of the two fields.

Given ML's data-driven nature, rigorous data management is essential for reproducibility and repeatability. Unlike analytic models, ML is fit via statistical optimization, making curated, traceable datasets critical. Metrology standards such as those presented by VDA Volume 5.3 [200] show how poor data management undermines measurement validity. The FAIR (Findable, Accessible, Interoperable, Reusable) and FACT (Findability, Accessibility, Completeness, Timeliness) principles provide a framework to ensure data quality across the model lifecycle, from training to deployment.

Nevertheless, even when grounded in sound data governance, ML solutions can encounter several pitfalls:

- *Generalization*: Overfitting hurts real-world performance; use cross-validation, careful tuning, and diverse data to improve out-of-sample results.
- *Natural Stochasticity*: Processes vary (materials, conditions, wear); model uncertainty or use probabilistic methods to handle noise [94].
- *Uncertainty Quantification*: Predictions carry uncertainty; Methods such as Monte Carlo dropout [58] or Bayesian neural networks [94,138] allow practitioners to estimate confidence intervals, give confidence estimates but lack industrial standardization.
- *Reproducibility*: Reproducing model outcomes requires disciplined version control of data, code, and experimental settings. In scientific and industrial environments alike, even small changes—such as minor software updates or sensor calibration shifts—can alter results. Maintaining detailed logs and following established best practices safeguard the reproducibility of ML-driven manufacturing processes [75].
- *Explainability*: Black-box models limit trust; explainable AI (e.g., attention, shapley additive explanations (SHAP), local interpretable model-agnostic explanations (LIME)) makes decisions more interpretable for diagnosing deviations and defending quality calls [77].

These pitfalls also occur in classic metrological applications. Yet, in traditional metrology, the pitfalls are often human in nature—stemming from misinterpretation, procedural errors, or incomplete understanding—since there is no learning component in the process itself. However, the established guidelines and strict procedural limitations aim to mitigate them.

2.3. Intermediate summary

In summary, metrology provides the rigorous foundation needed for reliable quantitative assessments, while ML excels in adapting to complex or incompletely understood systems. Combining these strengths opens new paths for advanced applications in manufacturing. However, to fully harness ML's capabilities, issues such as traceability, reproducibility, and standardized uncertainty quantification require careful consideration. The following framework (see chapter 3) offers a structured approach to classify and comprehend ML within metrological processes, analyzing the current landscape and providing practical insights that may guide future applications.

3. Introduction to the data flow framework

A key aspect of integrating ML into metrology is understanding how data flows through measurement processes in manufacturing and how ML can be effectively utilized at different stages. Consequently, a data flow framework is developed which is based on a literature review.

The developed data flow framework is shown in Fig. 2 and explained in the following: In the *manufacturing context*, data is collected through measurements. The measurements depend on *measurement parameters* and generate *raw data*. The *raw data* is processed to determine a *quantity value of the measurand*, which is subsequently synthesized into a *measurement result*. These results drive informed *decisions* and corrective actions on the shop floor. Besides the measurement pipeline, data can also be provided by sources in the machine itself resulting in *process data*. The primary purpose of this data is typically to monitor the machine's condition rather than to directly ensure product quality. However, this process data can nevertheless also be used to predict quantity values of a measurand or to make a decision.

All ML approaches rely on a data pipeline that begins with data sources and ends with feeding predictions back into the process. The start and end points of this pipeline can occur at various stages of the measurement process shown in the framework. Additionally, supervised ML approaches require labeled data for training, introducing a separate data flow for model development.

Based on this reasoning, the scope of Chapters 4–9 is illustrated in Fig. 2 and further specified as follows:

- *Chapter 4 (Setup and Parametrization)* elaborates on the usage of ML to support and optimize the preparation of a measurement, e.g., by predicting the best device, strategy, parameters or calibration for a given measurement task.
- *Chapter 5 (ML-Enhanced Measurement)* covers applications where raw sensor data is processed to yield a quantity value, or where a quantity value is refined into a measurement result.
- *Chapter 6 (Virtual Measurements)* includes work where manufacturing process data is used to directly predict a measurement result, from which the quality of a produced part can be derived.
- *Chapter 7 (Classification and Inspection)* focuses on approaches where raw data is used to make a direct decision (e.g., 'pass/fail'), bypassing the formal generation of a measurand.
- *Chapter 8 (Generating Insights)* contains all publications that use the results to either provide direct feedback into the manufacturing process or to generate explanations of process behavior.
- *Chapter 9 (Uncertainty Assessment and Risk Evaluation)* focuses on the uncertainty assessment when using machine learning and the underlying goal of risk assessment in decision making.

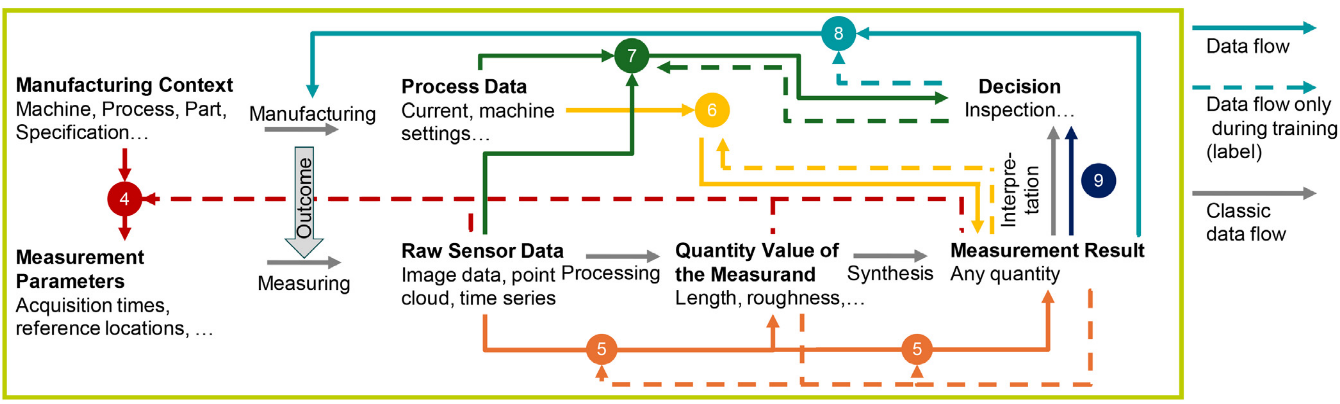

Fig. 2. Data flow from a manufacturing and metrology perspective as context framework. ML models may be applied in and/or between different steps depending on the use case.

Revisiting the example of ML in xCT from the introduction, raw sensor data is processed as input to predict a measurement result. As a result, it is allocated to chapter 5. Although this approach allows for a more rigorous distinction of ML approaches, the allocation of a single paper is not always uniquely possible as it can blend together multiple data flows, e.g., in a multi-stage approach.

4. Setup and parametrization

This chapter examines how ML supports metrology in the setup and parametrization of measurement systems. It revisits the long-standing practical questions (i) what to measure with, (ii) where to measure, (iii) how to set the instrument, and (iv) how to maintain calibration, and shows how data-driven learning now supports or automates each of them. The emphasis is a shift from fixed rules and hand-tuned heuristics to learned mappings and policies trained on experimental data and simulation.

Fig. 3 summarizes the resulting data-to-decision flow, and Table 1 provides a compact map of the literature covered in this chapter.

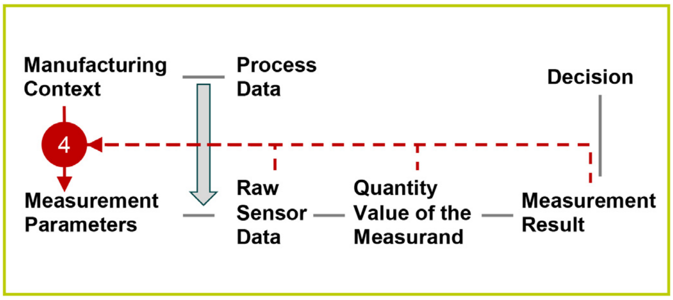

Fig. 3. Integration of machine learning-supported measurement system setup and parameterization within the data flow framework.

Table 1
Overview of references in chapter 4.

Chapter	
ML-based choice of measurement system	**CMM:** Lin and Liu [110]; Lin and Liu [111]; Kucharski et al. [102]; Kincaid and Pollock [96] **CT/ X-Ray:** Wang et al. [211]; Schneider et al. [174]
ML-based elaboration of measurement strategy	**CMM:** Cheng et al. [26]; Mian et al. [128]; Koch et al. [98]; Ghazouali et al. [48]; Li et al. [112] **Other:** Moro [134]; Zhou et al. [241]
ML-based choice of operating parameters	**CMM:** Urbas et al. [198]; Mian et al. [129] **CT/ X-Ray:** Giedl-Wagner et al. [70]; Schild et al. [169]; Blum et al. [12] **Other:** Plock et al. [146]; Farnes et al. [159]; Wright and Yang [219]
ML-based determination of calibration parameters	**CMM:** Kugunavar et al. [103]; Thai and Nguyen [192]; Zang [233] **Other:** Tang et al. [186]; Eastwood et al. [45]

4.1. ML-based choice of measurement system

In the context of ML-based choice of measurement system, Lin and Liu [110] address the problem by developing a system based on feed-forward neural networks (FNN). The study defines key attributes, including measurement accuracy and axis ranges, as well as decision categories representing different coordinate measurement machine (CMM) models. A training set is created by pairing these attributes with decisions, and an FNN model is trained to classify input specifications into suitable models. The system transforms user-provided measurement requirements into binary input patterns, enabling the network to infer the best-matching CMM model. In 2020, the same authors refined their approach by using decision trees instead of FNN in order to reduce the amount of data needed for making appropriate choices for suitable CMMs [111].

A more recent publication broadens the scope by exploring multiple ML approaches for incorporating tactile and non-tactile CMMs into the decision process. Here, Kucharski et al. [102] propose a decision-making support system for selecting measurement techniques in surface metrology. The study utilizes a dataset of 1143 measurements collected from various surfaces using tactile and optical systems. The authors employ Monte Carlo simulations to estimate uncertainties and use six different ML models, such as random forest, to predict the appropriate measurement system based on input parameters like material type, surface texture parameters, and uncertainties. A 10-fold cross-validation is applied for model training and validation with random forest, achieving the highest accuracy (98.63%) in choosing the best fitting measurement system.

Kincaid and Pollock [96] propose a language-model-assisted virtual assistant that leverages an ontology of instrument capabilities, attributes, and relationships to guide test engineers. A domain-specific language (DSL) maps natural-language (speech or text) requirements into structured queries over criteria like measurement ranges, capabilities, and software compatibility. The assistant supports context-aware, multi-stage refinements, narrowing options iteratively for complex needs. This approach scales expert knowledge to non-experts and keeps humans in the loop; however, its effectiveness hinges on ontology coverage and maintenance and clear governance of updates.

4.2. ML-based elaboration of measurement strategy

Here, the goal is to define a measurement strategy i.e., choose sampling points, probe paths, and viewpoints, so that coverage, accuracy, and cycle time are balanced under system and standards constraints. We group the works by their primary objective: coverage maximization, error/stability minimization, and cycle-time reduction, across tactile, optical, and X-ray modalities.

Focusing on tactile sampling and path planning, Moro [134] selects informative surface points using Gaussian-process regression (GPR) and multi-layer perceptrons (MLPs). The learned surrogate focuses on surface behavior relevant to the tolerance, trimming typical ISO-grid sampling from thousands of points to 20−50 while maintaining conformance assessment. Tolerance-aware surrogates convert oversampling into information-efficient sampling by ensuring that the surrogate adequately covers critical edge regions of the surface, thereby avoiding systematic bias in the conformance assessment.

Cheng et al. [26] plan probe paths without CAD by mounting two cameras to observe the measuring volume and using a convolutional neural network (CNN) to detect primitives (cylinders, holes, slots, steps). Detected features anchor the probe path, which is guided directly from camera feedback, avoiding complex calibrations and enabling setup on previously unseen parts. Such CAD-less setup boosts flexibility; however, robustness hinges on lighting/occlusion handling and reliable camera-to-CMM referencing.

Mian et al. [128] focused on sampling plans for measuring roundness of cylinders using tactile CMMs. They build an experimental design varying point distribution, step width, number of paths, and evaluation algorithms, then fit support-vector regression (SVR) and decision trees to jointly predict cylindricity error and measurement time. Afterward, practitioners can pick sampling plans that meet accuracy targets within cycle-time limits. Such simple response-surface models give fast, transparent trade-off curves; however, generalizability when moving to not learned geometries can be a problem.

Further, approaches for optical view or pose planning and coverage can be found. Koch et al. [98] enumerate kinematically feasible camera poses (via simulation) for robot-mounted optical CMMs, then train reinforcement learning (RL) agents to choose pose sequences that maximize visible surface coverage for the

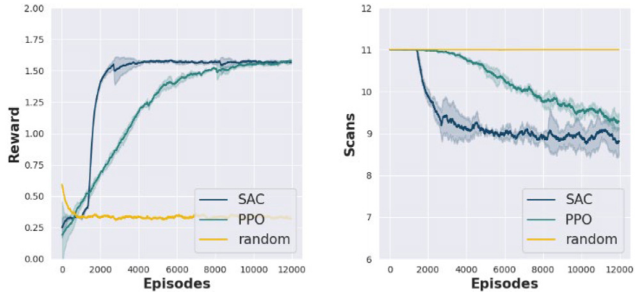

Fig. 4. Achieved visible surface coverage, reward and number of used camera poses in an optical view planning and coverage problem based on RL. The approach allows an autonomous, part-adaptive inspection setup [47].

specific part. Reported results (see Fig. 4) indicate ca. 90% coverage with ca. 9 camera poses on average across RL agents, yielding autonomous, part-adaptive setups. However, although coverage is a necessary condition, it is not sufficient for achieving accuracy. Error-aware scoring should also be incorporated into the autonomous setup.

Ghazouali et al. [48] target pose-dependent error rather than coverage planning. Here, a polynomial regression model trained on calibration-board data predicts reprojection error from a pose; a genetic algorithm then selects viewpoints that minimize this error, and the selected poses are applied to product measurements. This shifts from “seeing more” to “seeing stably.” However, the approach needs a representative calibration-board dataset spanning the operational pose space and ignores measurand characteristics like reflections.

Li et al. [112] perform pre-scan coverage prediction for structured-light scanners using a voxel encoder-decoder with a channel attention approach. Inputs combine geometric descriptors, scanner parameters, and a physics-based projector simulation. The network outputs likely coverage maps. Validation against real scans outperforms visibility-only baselines and supports automated in-line inspection. Here, the authors show that blending physics priors with learning improves autonomous measurements, especially when dealing with glossy or concave parts.

For wafer map sampling and measurement point extraction in the semiconductor industry, Zhou et al. [241] identify and cluster candidate measurement points with K-means and employ Monte Carlo sampling to select sites, reducing engineering time and human intervention while improving consistency. For repetitive layouts, such cluster-then-sample approaches give robust selections. However, the chosen cluster granularity has a big impact on the results.

Additionally, approaches regarding XCT trajectory optimizations can be found. Wang et al. [211] train RL agents offline on synthetic shapes to pick informative angles during circular scans, adapting in real time. When informativeness is non-uniform, this improves reconstruction quality versus equidistant sampling. RL enables online adaptivity; however, success depends on simulator-to-reality alignment.

Schneider et al. [174] define a CNN-based detectability index quantifying each projection’s contribution to feature/defect visibility in a region of interest, then solve an integer optimization to choose a compact subset of projections. Synthetic studies show reconstructions using ca. 4% of the projections required by traditional methods with limited information loss. The authors demonstrate how beneficial ROI-focused inspection can be for time-efficient measurements.

4.3. ML-based choice of operating parameters

Beyond deciding where and what to measure, practitioners must set the instrument, i.e., choose operating parameters that govern image quality, speed, and safety. In our review, several publications are identified that address the parameterization of tactile CMMs, optical CMMs, and CT systems.

One of the first approaches utilizing ML to automate the parametrization of CT measurements can be found in [70]. The authors use supervised learning to predict optimal values for voltage, current, and exposure time for the measuring of metal cylinders. The trained networks effectively predicted optimal parameters. However, due to the data set, the approach is only able to predict parameters for comparable metal cylinders.

A case-based reasoning (CBR) assistant for CT can be found in Schild et al. [169]. The CBR system is designed to help users choose optimal scan parameters for industrial CT by leveraging historical data and knowledge. For this, an extensive database of CT measurements is required. Decision trees extract generalized rules from this data to recommend scan parameters, enabling suggestions even for previously unseen parts. CBR scales institutional know-how with traceability, but its recommendations hinge on disciplined metadata and sufficient case-based coverage.

A concept for reducing the need for extensive databases for finding optimal CT parameters is presented by Blum et al. [12]. The concept proposes to train RL agents in CT simulations to reduce reliance on real scans. The simulator pipeline is validated, but full RL policy results are deferred. Reinforcement-learning approaches offer global exploration and online adaptivity, yet their success depends on simulator fidelity and robust sim-to-real transfer.

Mian et al. [129] focusing tactile CMM parameter optimization.

The authors tested different scanning speeds and point/line spacings, then used ranking and decision tools (Grey Relational Analysis, Principal Component Analysis and Fuzzy Logic) to pick settings that keep measurement error low while keeping the scan time short. The approach allows a clear, explainable balance between speed and accuracy and works well in audited settings, but it needs a lot of data and doesn’t adapt on its own.

4.4. ML-based determination of calibration parameters

Calibration links a measurement system’s indications to reference standards so deviations can be detected and corrected. Beyond manual procedures and fixed schedules, ML can propose calibration intervals, assist or automate calibration steps, and learn error fields for software compensation, reducing cost and downtime while safeguarding traceability.

In this context, Kugunavar et al. [103] use supervised learning on probe usage metrics (points taken, travel distance, tip size), workpiece hardness, ambient conditions, and stylus qualification status to recommend when a tactile CMM probe should be re-qualified. The data-driven schedule helps balance cost, uptime, and accuracy; however, the authors note dataset limitations and suggest incorporating additional influencing factors to improve reliability.

Tang et al. [186] propose a semi-automatic hand-eye calibration process for laser profilometers integrated into robotic measurement systems. The authors generate calibration postures automatically and use a CNN-based circle detector on laser profiles. A brief manual pre-calibration seeds the hand-eye transform; the system then auto-samples the workspace, fits sphere centers by least squares, and reduces human effort while improving accuracy. The approach is validated on industrial robots and automated fiber-placement machines. The approach highlights strong coverage with less operator time, but depends on robust target detection and safe posture generation.

Thai and Nguyen [192] propose a parametric error modeling with ML-aided compensation for tactile CMM. They model 21 axis errors (positioning, straightness, pitch, yaw, roll) using a hole-plate measured in multiple positions. An FNN interpolates errors across the working volume so that the learned field feeds software compensation, significantly improving accuracy. Parametric error models with ML interpolation increase CMM accuracy, but must be verified regularly to ensure that no drifts are concealed by software compensation.

Eastwood et al. [45] present a hybrid ML approach to improve camera calibration by refining machine vision-based feature localization using a CNN. The network is trained on synthetic ground-truth to improve sub-pixel feature localization in the calibration pipeline, cutting reprojection error by roughly 50% under ideal conditions and remaining robust under adverse imaging. A CNN for feature localization significantly reduces the reprojection, but the possible synthetic-to-real gaps and unseen situations within the training dataset can hinder the accuracy.

El Ghazouali et al. [48] present an ML-based approach for optimizing the calibration of a machine vision system in close-range photogrammetry. A polynomial regression is learned, mapping from camera pose to reprojection error. Then, a particle swarm optimization is used to select grid poses that minimize error while covering the full field of view and respecting geometry constraints. Simulations and experiments show improved accuracy and repeatability. However, a reliable pose error model and clear geometry boundary conditions are crucial.

Zang [233] trains regression models on calibration runs, environmental factors, and scanner metrics to predict optimal settings on the fly, outperforming traditional manual, object-based methods in accuracy, efficiency, and adaptability. Such dynamic ML calibration is very effective in changing environments but requires continuous telemetry and transparent protection mechanisms for traceability.

4.5. Intermediate summary

Across measurement system selection, measurement strategy, operating parameters, and calibration, recent work follows a common loop: (i) model how choices affect measurement quality (coverage, error, detectability, time, cost), (ii) optimize under physical and standards constraints, and (iii) validate against metrological criteria. In practice, modeling can use learned surrogates (regression, deep networks, learned indices) trained on shop-floor data and, where available, simulation/digital twins, enabling prediction before execution and policy search at design time or online. The problems are multi-objective and constrained: reinforcement learning or evolutionary search can be used when spaces are large/non-convex; supervised ranking/regression suffices when local quality is predictable. Overall, this section shows the application of new methods to established problems. The decisions treated here set the operating point and data-generating process for subsequent measurements.

5. Machine learning enhanced measurements

In this chapter, applications where ML is mainly embedded into core measurement setups and procedures, i.e., enhancing or optimizing their capabilities, are presented. These setups focus on ML used to extract and quantify measurands from raw sensor data including integrated measurements, e.g., for automation. Predominantly, the use of ML is reflected in the data analysis starting from raw sensor data up to the step of obtaining quantified measurement results as outlined in Fig. 5, while the equipment and parameters used remain unchanged after training the ML model. The literature review identified three pillars of ML for enhanced measurements: Preprocessing, cleaning and augmentation of raw sensor data (5.1), Feature extraction and quantification (5.2), and Dimensionality reduction and feature definition (5.3). The discussion also covers hybrid approaches that integrate traditional methods with ML to obtain measurement results, such as in Object and Pose Detection. References mentioned in this chapter are listed in Table 2 for the three subsections categorized according to the predominantly used ML method. Explicit achievements of the referenced works are only highlighted if this is meaningfully possible in a short summary, given the complexity of methods and results.

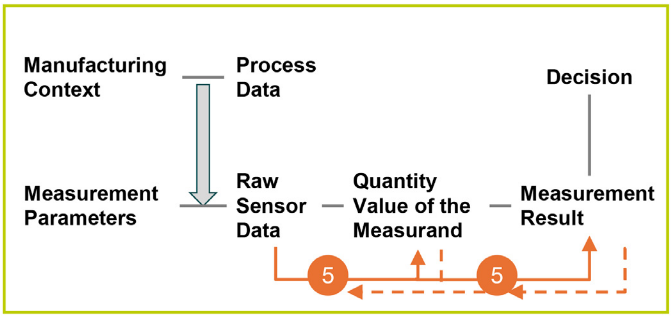

Fig. 5. The machine learning approaches described in this chapter according to the data flow framework.

Table 2
References related to ML enhanced measurement categorized into preprocessing.

Chapter	
Preprocessing, cleaning, and augmentation	**ANN**:Montes Dorantes et al. [132] **AE**: Vincent et al. [202], Hahn et al. [81] **CNN**: Wang et al. [206], Alonso et al. [4] Zhang et al. [235], Tsamos et al. [196], Novitom et al. [140], Bellens et al. [10], Ren et al. [157], Yang et al. [229], Mizutani et al. [131] **GAN:** Eastwood et al. [46], Moriz et al. [133], Sampath et al. [166] **GPR:** Yin et al. [231], Maculotti et al. [114,115] **SVM:** Podulka et al. [147]
Feature extraction and quantification	**ANN**:Ming et al. [130], Ren et al. [158], Cruz et al. [36] **CNN**: Bellens et al. [11,141], Wolfschläger et al. [218], Tatzel and León [190], Jiang et al. [89], Chen et al. [27], Yin et al. [230], Wan et al. [213], Huang et al. [86], Zhang et al. [236], Choudhari et al. [29], Xie et al. [222,223], Zhu et al. [243], Wang et al. [210], Nguyen et al. [139], Qi et al. [150], Cui et al. [37], Hinz et al. [84], Rawal et al. [156] **Regression:** Bedrosian et al. [9], Bonato et al. [13] **Clustering:** Chen et al. [27] **RNN:** Kong and Yu [100] **Transformer:** Wen et al. [216]
Dimensionality reduction and feature definition	**AE**: Maggipinto et al. [118], Proteau et al. [149] **GAN:** Qie et al. [151], Schmitt et al. [172], Schmitt et al. [173]

5.1. Preprocessing, cleaning, and augmentation

ML, especially DL, has powerful filtering characteristics. Salient illustrations are algorithms learning the difference between the actual signal and disturbances that are not expressible as closed mathematical formulations or Convolution-based methods that incorporate band-pass characteristics. Hence, preprocessing acquired data is a self-evident field of application. Fig. 6 summarizes an approach where images acquired using fringe light projection and stereo vision are corrected for speckle noise using a CNN, outperforming non-learning methods by reducing RMS from

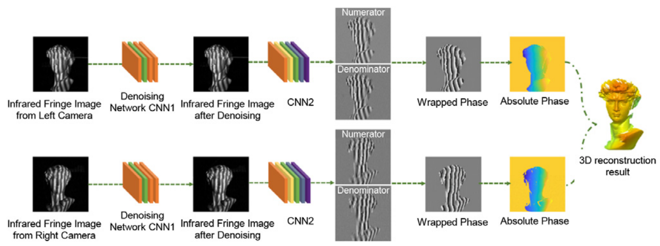

Fig. 6. The 3D reconstruction step is performed with traditional methods. Removal of speckle noise using a denoising CNN and extraction of phase using a second CNN in a stereo vision system presented in [68].

120 µm to 80 µm [206]. Alonso et al. [4] employ a U-Net based architecture to denoise data coming from a laser- and camera-based triangulation setup to measure surface flatness in metal sheet processing, introducing a 15% reduction of surface reconstruction error. Mizutani et al. investigate a DNN approach for estimating the center of beam intensity in a triangulation-based displacement measurement setup [131]. A clear influence of activation function and kernel size in convolutional layers is stated. Finally, the feasibility of subpixel peak detection is shown but with a remaining disclaimer on the further necessity to evaluate measurement uncertainty. These are only a few examples of methods being used among others, e.g., ANFIS [132] or Autoencoders [202].

Zhang et al. [235] employ CNNs for removing aliasing effects and noise fringe-derived height maps in a PBF-LB/M process, ultimately lowering the errors in the process by 40%.

Hahn et al. [81] employ Autoencoders to distill 100 kHz signals of welding processes into compact embeddings, which enable classification into quality predictions of the weld using LSTM networks. Podulka et al. [147] propose to use ML to choose optimal digital filters reducing high-frequency noise in contactless topography measurements with white-light interferometry. In their case study, SVM showed effective filter choice in 98.7% of cases.

Much research on deep learning-based pre-processing of data concentrates on the field of industrial xCT tomography. Fig. 7 shows the qualitative evaluation of a denoising and deblurring approach at BAM by Tsamos et al. [196]. The method, again based on CNNs, is trained with synthetic, artifact-free data generated by xCT simulations.

While other works focus on the removal of specific artifacts, e.g. ring artifacts [140], another example of data augmentation in CT can be found in [10]. The authors use ML to interpolate missing sinograms in CT measurements, ultimately reducing the needed scan time by removing projection angles and artificially creating the not scanned information. Results show a 6x speed up with keeping dimensional-metrology and pore-inspection fidelity.

While aforementioned methods rely on synthetic data for training an ML-based algorithm, also learning-based approaches to augmenting or artificially generating data exist. As suggested by their name, generative ML methods are suitable approaches. As examples, Eastwood et al. [46] present a method based on a progressively growing GAN to create synthetic surface texture data encoded in grayscale images, achieving up to 96% accuracy on unseen data in validation studies. Moriz et al. [133] use an approach based on CycleGAN to

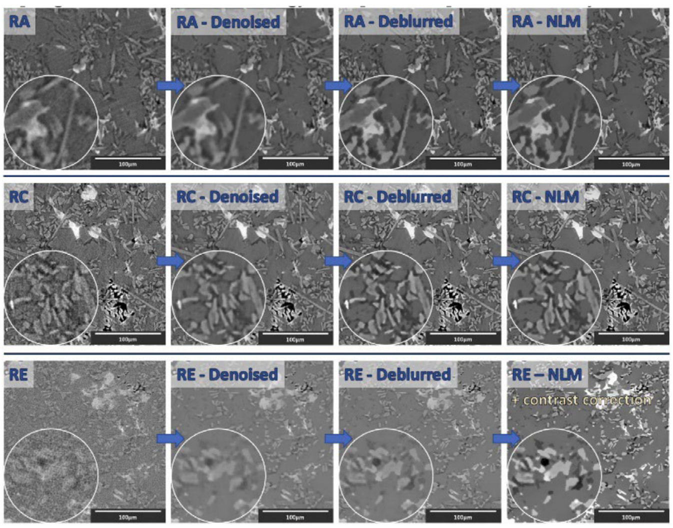

Fig. 7. Sequential denoising, deblurring, and non-local means filtering using a CNN trained on synthetic data on xCT volume slices developed in [196] at BAM. The increase of contrast among different materials, fundamental to further metrological evaluation, can clearly be seen.

augment small datasets, showcased on pore detection in xCT volumes and detection of surface defects on sheared edges of fine-blanked parts, showing visually convincing results. Sampath et al. mix GAN-based synthetic data with real training data in magnetic particle inspection to improve the classification accuracy (defect/non-defect) in terms of F1 score [166].

Another class of approaches considered pre-processing is fusing data from multiple sensors to a common dataset. Ren et al. [157] present a three-staged method to fuse tactile data acquired by a CMM and photometric stereo data to reconstruct complex surfaces. The second stage leverages a U-Net-like structure to fuse the normal maps. Yin et al. [231] tackle a similar data fusion approach (CMM and laser scanner) but rely on Gaussian Process regression (GPR), also known as Kriging. The approach enables the reduction of tactile sampling by approximately a factor of 10 while maintaining similar performance in terms of RMS.

5.2. Feature extraction and quantification

The use of ML can also be attractive to use cases that address metrologically already established characteristics (e.g., porosity) which hitherto have been determined by classical algorithms. This applies if learning-based approaches are more robust to noise and variations in the input data, less tedious and sensitive to parametrize or better capable of generalizing. Thereby, the enhanced feature extraction capabilities of ML are employed to provide either abstract features as an intermediate step when modeling the desired measurand or by modeling the measurands directly by means of an ML-based measurement model.

Many works in this field perform segmentation, and again xCT has a strong focus. Furthermore, many approaches are based on the U-Net structure. In [11], the results of a method for ML-based porosity segmentation in xCT measurements of polymer additive manufacturing parts are presented which maintain good performance in contrast to conventional Otsu thresholding over decreasing scan quality from 1572 gradually down to 99 projections. Applications of deep learning based xCT segmentation can also be found in the domain of electronics, e.g., applied in [141], to detect and subsequently analyze buried features in semiconductor packages. They evaluate different algorithm types, i.e., based on V-Net, nnU-net, and Cascaded Anisotropic CNN.

Wolfschläger et al. [218] also use a U-Net based structure to segment tears on images of sheared edges of fine-blanked parts. Based on the segmented tears, the quality characteristics cut-off height can be evaluated. The approach is able to adequately compete with a fine-tuned, traditional image processing algorithm without extensive tuning and achieves a MAE below 1px, corresponding to 7.5 µm in the dimensional domain.

Surface topography has already been another focus of ML methods in metrology for many years, even before the recent ML era. For example, Tatzel and León [190] present a CNN-based algorithm estimating the roughness of laser cut edges based on 2D RGB-images and achieving a mean error between 3.2 µm and 4.8 µm compared to 3D reference data. Ren et al. [158] show another strategy to reduce the effort in surface characterization by allowing for sparse sampling and subsequent inference of the dense surface by a neural network.

Yin et al. present an approach to move surface topography measurements in-situ in additive manufacturing processes based on camera images [230]. By training a CNN with reference data focus variation microscopy, indirect measurements with an error of 17% compared to ground truth have been achieved.

Indirect measurements are also very common in improving kinematic accuracy, such that ML based techniques emerge. Kong and Yu [100] use a recurrent neural network (RNN) on the residuals of an analytical model for kinematic compensation of an industrial robot based on measurements taken with a standard laser scanner and suitable artifact to further reduce the kinematic error by 30%. ML is also being employed at various stages in machine tool calibration and compensation, e.g., thermal error modeling, for which the reader is referred to the review in [60].

ML is also employed to enable measurements under adverse imaging conditions. Wan et al. [213] perform single-shot 3D measurement of highly reflective objects using a multi-stage DL approach. The authors achieve errors in the order of 50 µm for both center distance and sphere radius on a 100 mm (distance)/30 mm (radius) artifact. An example for compensating distortion is shown in [86].

In [130], a physics-informed neural network is incorporated in a terahertz wavelength measurement system for nondestructive testing of optical thin films. The mathematically inverse relation between optical scattering and the parameters of interest is solved using ML such that the measurement can be carried out with a single frequency. A further application for nondestructive testing can be found [9]. The authors utilize ANN and continuous wavelet transformation to classify ultrasonic signals with respect to fiber orientation. The model achieves an MAE of 7.7°.

Zhang et al. [236] use an object detection approach based on YOLOv5 to automatically quantify the defect size of weld seams in CT measurements. After identification, a minimal bounding box covering the defect is calculated and translated to a physical length unit. The results are consistent with manual measurements within 0.1 mm. Choudhari et al. [29] propose in-process shaft diameter measurements using retrofitted cameras. The authors utilize a YOLOv2 model for real-time segmentation. Errors in the regime of 0.5 mm are achieved for work pieces with approx. 20 mm in diameter and mainly attributed to the imaging system.

In the previous examples, the main data modalities consisted of statistical features, 2D images, or 3D voxel volumes. Especially when using integrated measurements, e.g., for automation and automated inspection, point clouds and their analysis become highly relevant. The first eminent task is the detection and extraction of specific objects within the point cloud. For example, DL can be used to classify rivet regions and mark corresponding points in point clouds acquired by a mobile 3D scanner, which are then evaluated in a conventional way to determine the rivet flush, a geometric characteristic relevant to aerodynamics using the Rivet Region Classification Network developed in [223]. Another, similar example is the detection of bonding regions of gold wires in 3D scans of integrated circuits [222]. Zhu et al. [243] compare point clouds generated from a nominal CAD and acquired by 3D laser triangulation camera using a domain adaptation network called PointDAN outperforming other approaches in an automotive toy case [152].

A recurrent measurement task, extending object detection, is 6D pose estimation with varying input types, which is also intensively studied outside the metrology domain. Low-cost RGBD cameras have emerged as attractive equipment. Wang et al. [210] show an end-to-end approach to determine 6D pose from RGBD data considering possible occlusions with four substeps: Object localization, incomplete 3D shape recovery, multimodal feature fusion, and final 6D pose prediction. Further, approaches solely using RGB images can be found. Rawal evaluates the capabilities of two different NN approaches for use in a flexible spraying robot for the coating of aircraft components [156]. NVIDIA, namely Wen et al. [216] even present a foundation model for 6D pose estimation and object tracking on standard RGB images. The model combines a multitude of very advanced ML techniques, including LLMs to generate synthetic data. As input, a CAD model or a small number of reference images is required. Nguyen et al. [139] report research on using deep learning on 3D point clouds of automotive wiring harnesses to achieve automated inspection, i.e., checking whether the correct components have been assembled to the correct place. Their work is based on PointNet++ [150] and incorporated synthetic data, but also concludes that the consideration domain gaps between synthetic and real point clouds is a challenge to consider in such industrial applications.

5.3. Dimensionality reduction and feature definition

Based on the ideas that compressing high-dimensional data, such as images or point clouds, to a lower dimensionality will lead to an extraction of information and that the purpose of measurement is to acquire relevant information, ML methods containing inherent or explicit dimensionality reductions can be leveraged. Often the representation of lowest dimension in deep learning is denoted as the latent space, which provides abstract features learned implicitly when training an ML model.

An obvious approach are Autoencoders, as exemplarily outlined in [118] in the semiconductor context. A priori, the latent space is abstract and unrelated to any interpretation. Proteau et al. [149] show that a classifying variational Autoencoder architecture can be leveraged to perform dimensionality reduction on handcrafted data features obtained from vibration and current measurements during machining. The approach outperforms traditional Principal Component Analysis by achieving 99.24% classification accuracy.

Qie et al. [151] also address interpretability but from the perspective of tolerancing. They employ a Wasserstein GAN architecture to generate samples exposing typical defects from manufacturing which are traditionally described by GD&T methods. Subsequently, tolerancing can be extended or moved to the latent space by defining the features of interest using the dimensionality reduction inherent to the model.

Schmitt et al. [172] introduce a framework based on GANs, namely an adversarial latent autoencoder using a StyleGAN generator, which is explicitly targeted at metrological interpretability of a continuous latent space. The approach allows for interpreting, extracting, and evaluating measurands that were implicitly learned in the latent space during semi-supervised training of the architecture. Fig. 8 shows that quantity values ζ measured in the latent space correlate with quality characteristic *filling degree* b_B of the cross-sectional images of hem flange bonds within an error of below 1 mm. The authors claim that the framework is suitable for measuring surface quantities and dimensional quantities, and that a full metrological interpretability compatible with the VIM can be achieved in the future [173].

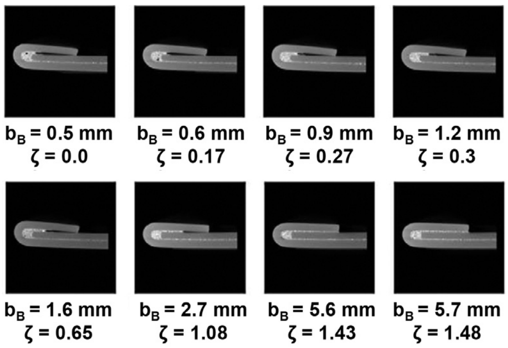

Fig. 8. Measured and interpretable latent space representation extracted from cross-sectional images of hem flange bonds using an approach based on adversarial latent autoencoders [173].

5.4. Intermediate summary

The literature indicates ML is already widely integrated into today's industrial and scientific metrology. Numerous realized systems embed learning algorithms in fringe-projection, laser-triangulation, and xCT pipelines, yielding lower noise, more reliable feature extraction and even six-degree-of-freedom pose estimation without changes to the hardware. While the literature encompasses a diverse set of model classes, e.g., autoencoders, Gaussian processes, point-cloud networks, and GAN-based data generators, CNNs have established themselves as the dominant paradigm. Their locality and weight-sharing properties are well suited for high-dimensional grid-like metrological data such as 2-D imagery, volumetric xCT slices, or dense or sparse point clouds. New concepts from computer-science research are now transferred to metrology. Yet, the growing dependence on synthetic data, domain adaptation, and transfer learning introduces a critical challenge: ensuring that models retain accuracy when confronted with the subtle, device-specific variations of real measurement environments.

6. Virtual measurement

VM can be understood as the virtual representation of a measurement process that is implemented in a manufacturing process, having the goal of estimating the product-related quality based on manufacturing process data [191]. It was initially introduced as a means of indirectly acquiring a physical quantity through modeling when direct physical measurement using sensors was not feasible or possible (e.g., in a harsh environment). Therefore, the application of VM is a special case of an indirect measurement, where the measurement process is virtually represented by a model which does not (only) consider the factors that are directly influencing the measurement, but also the manufacturing process parameters that are assumed to have an influence on the product quality.

This virtual representation of a measurement process can be, for example, achieved by the utilization of an ML model, which is used to predict the measurement result based on manufacturing process data. A key application of VM is to address the visibility gap that arises during industrial processes where quality inspections are conducted based on random sampling. Hence, in classical, physical quality inspection, the assessment of the quality is not available for all produced parts. Since manufacturing process data is usually available for all produced parts and can then be used for quality prediction, VM can be employed to enhance process observability for parts that are not physically inspected (e.g., due to time, money or environmental restrictions).

To allow for the integration of VM in a production line and to establish a VM system, both process data and measurement results must be collected and stored in a database as a preliminary requirement. These data are then used to derive a model that represents the dependencies between manufacturing process data and measurement results. Once the VM model is trained, it can be used for inferencing to predict the measuring result and thus the quality of the produced parts using the manufacturing process data only. In the overarching framework of this publication, VM are integrated as shown in Fig. 9.

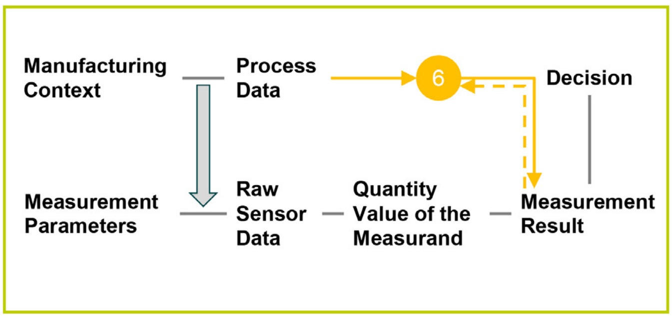

Fig. 9. Placing of Virtual Measurements in the overall framework.

The ML-based prediction of measurement results based on manufacturing process data has been addressed in different studies in the past. Dreyfus et al. [43] review VM within Industry 4.0, but their work is limited to applications that explicitly consider the term *virtual metrology*, excluding other relevant work. Tercan et al. [191] present the most relevant review on ML-based predictive quality, which can be considered as a more generic concept that not only includes the prediction of measurement results, but also attributive quality assessment, i.e., classification.

The considered applications of VM in the manufacturing environment presented here are categorized based on the manufacturing technologies outlined in DIN 8580 [40]. These categories include primary shaping, forming, cutting, coating, joining, and changing material properties. Moreover, VM applications in multi-stage manufacturing processes are discussed. In Table 3, a summary of the VM-related work considered in this study is given, as an overview over different applications. In the following, the VM applications are described in more detail, following the same structure as given in Table 3.

Table 3
Focus of VM-related work in the different domains.

Domain	Focus – Prediction of:
Primary Shaping	Part lengths and widths (Ke & Huang; Cramer et al. Wang et al.) [93, 34;207]; Deviation from nominal form (Zhu et al., Zanini et al. *) [234,244]; material properties, such as solids concentration (SC) and melt flow index (MFI) (De Mattos et al.) [39]
Forming	Form Deviations (Mayr et al.) [123]; diameters/ radii, sheet thicknesses (Wang et al.; Ma et al.) [209,121]; mechanical properties (Hartl et al.) [80]
Cutting	Quality characteristics, such as diameters, surface roughness (Cruz et al.; Du et al.; Tieng et al.; Suthar et al.; Gentner et al.) [36,44,194,187,67]; form deviations (Maggipinto et al.) [119]
Coating	Coating thickness (Ferreira et al.; Wu et al., Genta et al.*) [56,221,66]
Joining	Technical or mechanical properties, such as shear strength (Li et al.) [113]; weld quality, coaxiality (Müller et al.; Wu et al.) [137,220]
Changing Material Properties	Material properties, such as hardness (Ch et al.; Tian et al.) [28,193]
Multi-Stage Manufacturing Processes	geometrical properties (Papananias et al.; Cramer et al.; Wang et al.; Song & Huo) [142,33,208,179]; battery state-of-health (Rohkohl et al.; Turetskyy et al.) [161,197]; general frameworks (Dreyfus et al.; Witt et al.) [43,217]
Non domain specific	Digital image correlation (Yang et al.) [228]

* Statistical Methods/Non ML.

6.1. Primary shaping

Primary shaping encompasses processes like casting, molding, and additive manufacturing. The application of VM shows potential for the manufacturer to efficiently monitor quality both when a high number of parts is produced in a short time and only a few samples can be tested physically, e.g., in injection molding, and when processes take a long time and should be adjusted to avoid the production of defective parts, e.g., in additive manufacturing.

For injection molding, Ke et al. [93] employ ANN to predict geometric quality characteristics based on pressure profiles from the molding machine. Similarly, Cramer et al. [34] propose a VM system utilizing Bayesian neural networks (BNNs) trained on process settings to predict geometric quality characteristics.

In additive manufacturing, in-line measurement techniques, such as cameras or laser scanners, are usually used to capture real-time information about the workpiece and can be leveraged by VM. Zhu et al. [244] focus on constructing deviations from the nominal STL representation of a part using VM, contributing significantly to process understanding and control.

For high-density polyethylene (HDPE) production, de Mattos et al. [39] use an ANN to replace the physical measurement of the solids concentration and the melt flow index. The study shows that the VM approach can be used to accurately predict variables in an industrial loop slurry reactor. Beyond these applications in primary shaping, Wang et al. [207] explore a less conventional application of VM by predicting quality characteristics in yarn spinning. Their work highlights the potential for novel network architectures and data preprocessing techniques to enhance the capabilities of VM in diverse production domains.

6.2. Forming

In forming, VM is used to predict whether the produced parts are manufactured in a way that they have the desired shape based on the machine and process parameters in the forming process.

Due to the collection of time series data in the forming process, CNN are used in several applications for the VM prediction. Mayr et al. [123] use CNN to address the challenge of predicting leg length during hairpin bending for electric motors. Their approach exploits the temporal correlations present in data collected from a CNC bending machine, with a focus on axis torques as key indicators. Another application is introduced by Wang et al. [209], who explore the use of CNNs for predicting inner tube diameters in tube rolling. Their study employs a dataset combining process settings and time series torque data to develop adaptive predictive models that can generalize across different tube sizes, fostering a more versatile and robust framework. In a study published by Rocha-Jacomé et al. [160], combined approaches using different ML models for the application of VM are introduced. They both use a Long Short-Term Memory (LSTM) and an Autoregressive Integrated Moving Average (ARIMA) approach for the prediction of a curvature radius in a bending process based on time series data. Both models are used to predict the outcome of the production process and enable the operators to adjust and correct the control of the bending machine within an industrial environment in real time.

Besides the prediction of the workpiece's shapes, other applications focus on material properties. Hartl et al. [80], for instance, apply an ML model to investigate the relationship between mechanical properties and electrical properties in a rolling process. In this study, VM was integrated within the ML-assisted solving of the complex underlying system of differential equations and used to optimize rolling schedules for improving the quality of desired properties of the produced aluminum sheets.

6.3. Cutting

In different studies, the (physical) measurement of quality characteristics, such as diameters or surface roughness is replaced by VM approaches.

One representative study is introduced by Cruz et al. [36], who pioneered VM for estimating hole diameter and surface roughness in a composite titanium-aluminum alloy, showcasing its potential in precision metal manufacturing. Their approach utilizes multi-sensor data and an ANN for prediction. Another application using ANN for predicting well diameter and position in aerospace engine casing manufacturing is introduced by Tieng et al. [194]. Their work addresses challenges associated with component deformation in large parts and demonstrates the adaptability of ANN in cutting processes. Whereas ANN shows sufficient results in the previously mentioned works, Schorr et al. [175] investigate that random forests outperform ANN, support vector regression, and others in terms of minimizing mean absolute error (MAE) within a drilling process. For their prediction, they use torque data with statistical feature extraction to predict concentricity and diameter. They further extend their research in 2021 by incorporating deep learning models like CNN [176]. However, the performance of deep learning models does not surpass that of shallow ML models with feature extraction.

A more recent study by Du et al. [44] investigates predicting roughness, profile, and roundness deviations from process vibration data during the turning of steel workpieces. Their VM system demonstrates real-time quality monitoring capabilities for turning applications with varying diameters. In another recent study, Maggipinto et al. [119] demonstrate a VM system for etching, utilizing optical emission spectroscopy to detect etch depth.

A more domain specific application for plasma etching and Chemical mechanical polishing (CMP) is introduced by Suthar et al. [184], focusing on batch-based datasets and feature extraction from process data. In their proposed feature-based VM, a partial least squares variant outperforms linear regression and ARIMA methods for both processes. Another study regarding plasma etching across different factory machines is introduced by Gentner et al. [67] using a domain-adversarial neural network for predicting layer thickness and critical dimensions. This work represents a significant step towards establishing a universal VM framework for similar processes.

6.4. Coating

Coating techniques, as defined by DIN 8580 [40], are employed to modify or enhance surface properties of workpieces through methods like painting, electroplating, or thermal spraying. Within this field, VM is mainly used for the prediction of coating thickness. Ferreira et al. [56] employ a method that simplifies time series data into mean values. This study establishes the foundation for applying VM for efficient predictive techniques in manufacturing. In a different study, Susto [183] analyze a large dataset (>6000 samples) encompassing CVD thickness and various machine parameters. They implement advanced pre-processing and dimensionality reduction techniques to extract relevant features from the process data. Their findings indicate that, while an ANN model yields the most accurate predictions compared to their least angle regression (LARS) method, the LARS method's lower computational complexity makes it more suitable for environments with frequent changes. Building upon this progress, Wu et al. [221] present a comprehensive approach using a CNN to extract features from the multivariate timeseries data. These features are then used within a Gaussian process regression model, showcasing a sophisticated integration of deep learning and regression techniques for predicting coating thickness.

6.5. Joining

For ultrasonic welding, Li et al. [113] propose a comprehensive VM method, combining failure load in a shear test and weld quality levels as quality characteristics. They employ a unique preprocessing technique alongside an ANN and a random forest model to analyze welding data. In a different study on this application, Müller et al. [137] use an ensemble model approach based on random forests to predict different quality characteristics. The predictions are based on welding machine sensor data. It is investigated that both the phase within the production process and the quality of the considered quality characteristic have an influence on the prediction result.

Further studies on welding are introduced by Zhou et al. [240], who focus on analyzing feature extraction methods specifically for VM in resistance spot welding, and Chang et al. [24], who address the need for real-time VM in resistance spot welding for the automotive industry. Zhou et al. [240] conclude that achieving accurate VM for resistance spot welding is feasible, although further research is needed to identify robust hyperparameters.

Moreover, in the study by Chang et al. [24], the importance of robust and relevant features for accurate VM prediction when using

CNN and LSTM is emphasized. Two further applications to predict geometry features were identified: Mu et al. [136] propose a VM approach for predicting bead geometry features in arc-wire manufacturing. Using an MLP regressor, the geometry is predicted based on different welding signals. In a different application in aero-engine assembly, Wu et al. [220] introduce the utilization of VM for predicting coaxiality. Their research focuses on the integration of a spatially embedded transformer model for 3D point cloud data to predict the coaxiality of the assembled aeroengines.

6.6. Changing material properties

Processes like heat treatment and surface hardening, which alter a material's mechanical, thermal, or chemical characteristics, are encompassed by changing material properties. Ch et al. [28] investigate predicting hardness in the upsetting process. Their work highlights a synergistic approach combining finite element (FE) simulation and VM to enhance the precision and control of material property changes. FE simulation offers a detailed understanding of the material's mechanical behavior under various conditions, providing insights into factors influencing hardness. The VM aspect, implemented concurrently, facilitates the data-driven development of robust algorithms for real-time hardness prediction.

Gilbert Chandra et al. [71] use a LSTM-based approach to predict three key characteristics in hot tests of liquid rocket engines, based on ten process-related parameters that are available as time-series data. Tian et al. [193] use an ANN to predict catalyst activity parameters in polyethylene reaction processes. The VM model approach for catalyst activity prediction is based on input data which are determined by mechanical properties and hand selected, and clustered using k-means clustering.

6.7. Multi-stage manufacturing processes

While the previously mentioned applications of VM focus on specific manufacturing technologies, a growing body of research explores methodological advancements in VM applicable across various processes. Since most production processes are rather a sequence of different process steps than one isolated manufacturing process, the application of VM to *multi-stage manufacturing processes* enables a holistic perspective for the whole production process.

In this context, Dreyfus et al. [43] present a conceptual framework addressing challenges in VM for multi-stage manufacturing. They propose three VM architecture types (serial, hub, and cascading) suitable for such scenarios. To enable the application of VM in multi-stage manufacturing processes, Witt et al. [217] develop a product-centered process-independent meta-model for production and quality data. This meta-model allows for structured data collection in VM applications, and its functionality is shown based on a multi-stage industrial additive manufacturing process. In an application, Papananias et al. [142] use a typical metalworking process as an example, where a blank is first produced (joining/shaping) followed by a cutting/coating process to achieve the final product.

Turetskyy et al. [197] explore multi-stage battery manufacturing, utilizing ML models (ANN, random forest, Lasso-Lar's regression) to predict maximum capacity, self-discharge rate, and state of health for lithium-ion batteries. Moreover, Rohkohl et al. [161] develop a non-destructive testing method for weld seams of battery cells where a CNN allows to predict size, orientation, and location of defects based on eddy current measurements and compared to respectively trained on xCT reference data. Cramer et al. [33] investigate the impact of feature extraction and hyperparameter optimization on VM in a multi-stage halogen bulb production process. They emphasize the importance of feature engineering alongside the choice of regression method. Wang et al. [208] focus on the application of VM in a multi-stage manufacturing processes by combining multi-scale convolutional neural network with control gates for feature extraction and designing a multi-layer multi-gate mixture-of-experts multi-task model for quality prediction. In a case study, they apply their methodology to a two-step production process of inertial navigation products.

6.8. Intermediate summary

Most current VM applications concentrate on specific techniques, with cutting processes being the most common. Research has mainly focused on predicting geometric quality characteristics, while fewer studies address material properties. A smaller number of works propose more generic frameworks for predicting measurement results from production data, either by aligning prediction quality assessment with established production standards or by extending VM to multi-stage processes, which are typical in manufacturing.

The work presented here targets prediction of part quality based on defined quality characteristics derived from manufacturing process data. VM models are typically developed using regression or time series analysis, while attributive testing treats inspection as a classification task, determining whether requirements are met or, in case of defects, which error occurred (cf. chapter 7).

The VM approach can be expanded to follow established principles from metrology, where every (physical) measurement process needs to be made traceable. By providing information about the uncertainty, the trust in the model prediction in terms of a VM can be increased [34]. However, there are certain challenges associated with the uncertainty determination, specifically for ML models, which are elaborated in chapter 9. A different approach to generate trust in a VM model, which is usually a black box, is to apply techniques from the field of *Explainable AI* [177]. Overall, the developments in the field of VM are striving towards making the prediction more trustworthy to ensure the application of VM models is associated with low risk.

7. Classification and inspection

Classification and inspection are fundamental to manufacturing quality assurance. Inspection distinguishes between conforming and non-conforming parts, a task often realized in ML through classification algorithms [30]. Classification can be based on previously extracted measurands, acting as a decision step after a formal measurement, which outputs as yields a quantified physical property (the measurand) [88]. Alternatively, it can operate directly on raw sensor data, bypassing the generation of the quantity of a measurand. In this latter case, the classification model acts as a surrogate for the measurement process, which becomes effectively embedded within a black box, making the model's accuracy directly influence the reliability of the final decision. This case is the focus of this chapter as can be seen by the data flow in Fig. 10. Raw sensor data of a product or process measurement is used to make a decision, such as a part being in specification or out of specification.

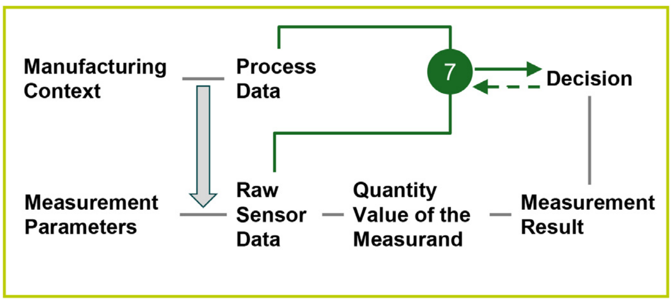

Fig. 10. Data flow in classification-based inspection processes using machine learning.

Sometimes, the classification task is formulated as an anomaly detection task, where only one class is required. One should be aware that anomaly detection can extend also to implicitly evaluating metrological quantities, e.g., by detecting objects of incorrect dimensions [90]. When training the model data from past decisions are used as labels.

This chapter reviews classification methods in inspection, structured following Pfeifer [144]: Inspection tasks are divided into three categories. The first is material testing, which aims to determine material properties such as hardness and elasticity and to assess macrostructures like cracks or microstructures. The second is functional testing, which focuses on verifying the entire product's functionality and is typically conducted at the end of the process chain. The third and most prevalent is geometric testing, which involves assessing features such as the form, size, and position of geometric elements, as well as the surface condition of workpieces. This classification is extended by categorizing inspection approaches according to the nature of the input data: one-dimensional timeseries data, two-dimensional images, and three-dimensional volumetric data. This dual perspective enables a systematic and practice-oriented categorization of inspection approaches and provides the basis for identifying recurring patterns and shared themes across a wide range of application domains. Table 4 shows an overview of the analyzed work in the state of the art categorized by the inspection task and the input data. The most relevant work is presented in detail in the next subchapters.

7.1. Application in material testing

In the context of powder bed fusion of metal with laser beam (PBF-LB/M), Eschner et al. [49] propose a method for classifying part density based on structure-borne acoustic emissions. These one-dimensional signals are transformed into spectrograms using a short-time Fourier transform and serve as input to an MLP. The model classifies parts into three density classes, achieving an F1-score of up to 88%, which enables non-contact, in-process quality assessment without relying on optical measurements. Zouhri et al. [246] propose an ML approach for layer-wise quality monitoring in PBF-LB/M, processing signals recorded by a pyrometer during the build process. These raw signals are analyzed through statistical feature extraction and the parts are classified into density categories by SVM, MLP, and 1D-CNN models, achieving classification accuracies exceeding 94%. Building on this, Zouhri et al. [245] refine the methodology by focusing exclusively on optimized statistical feature extraction and SVM classification, further improving model robustness and interpretability. This process is presented in Fig. 11. Together, both studies demonstrate the feasibility of partial real-time predictive quality classification in additive manufacturing based solely on pyrometer-based process data.

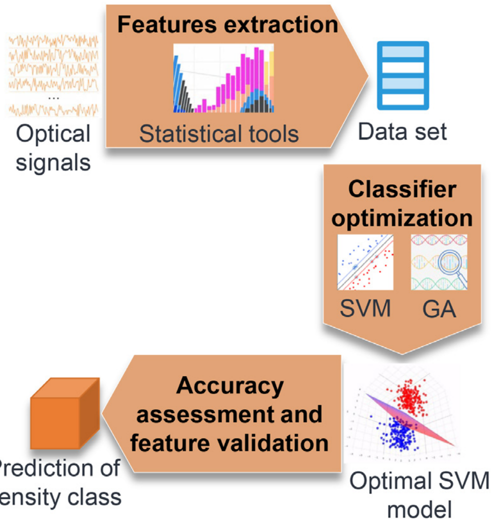

Fig. 11. Visualization of the quality prediction in Zouhri et al.'s [245].

Beside acoustic and thermal signals, image-based analysis is common. Roux et al. [162] develop a deep learning-based method for in-process quality classification. The system analyzes layer-by-layer electron-optical (ELO) images acquired during the build process to classify each layer as normal, porous, or bulging. Five CNN are evaluated, with SqueezeNet achieving a classification accuracy of 95.1%.

Tao et al. use XCT for supervised learning of ML algorithms for in-situ melt pool monitoring. By combining physics-informed melt pool feature engineering, a one-to-many approach enabling the incorporation of the full thermal history, and a random forest model, superior predictive accuracy of keyhole pores was established [188]. Moreover, geometric deviations were successfully predicted by integrating a CNN and a Transformer encoder [187].

Bonato et al. [14] detect spatter-induced defects in laser beam fusion using long-exposure optical monitoring. A random forest model extracts features from images of each layer and classifies regions prone to lack-of-fusion defects. Validated against CT data, the ML model achieves an F1-score exceeding 85% for defects larger than 90 µm.

Beyond two-dimensional imaging, volumetric data reveals the precise morphology and volume of internal material defects, providing a more accurate characterization than planar views. For instance, Xu et al. [225] apply a modified U-Net model for segmenting pores and cracks in XCT scans of metal additive manufacturing parts. Their method enables contactless defect classification directly from raw volumetric input, yielding a mean Intersection over Union (mIoU) of 84.83% and a pixel accuracy of 98.87% across diverse XCT datasets.

Table 4
Overview of references in chapter 7.

Chapter	Input data dimensions	References
Application in material testing	1 D (signals / time-series)	Eschner et al. [49]; Zouhri et al. [246]; Zouhri et al. [245]
	2 D (images)	Fang et al. [54]; Bonato et al. [14]
	3 D (volumetric / point cloud)	Xu et al. [225]
Applications in functional testing	1 D (signals / time-series)	Cassoli et al. [23]; Rydzi et al. [163]; Wagner et al. [203]; Qiu et al. [154]; Deleruyelle et al. [38]; Wang et al. [208]; Proteau et al. [149]
	2 D (images)	Börold et al. [19]; Zhu et al. [243]
Applications in geometric feature testing	2 D (images / topographic maps)	El Ghadoui et al. [47]; Maculotti et al. [116]; Medina et al. [125]; Fan & Qiu [55]; Sampath et al. [167]; Wang et al. [204]; Zhang et al. [238]; Staar et al. [180]; Alcaire et al. [3]; Qin [153]; Xin et al. [224]; Wang et al. [205]; Zhang et al. [237]; Mainsah & Ndumu [120];
	3 D (volumetric / point cloud)	Zhang et al. [239]; Xu et al. [226];

7.2. Applications in functional testing

ML models are particularly amenable to functional testing scenarios where the relationship between process variables and product performance is non-linear or too complex for threshold-based logic. Specifically, ML excels in functions characterized by high-dimensional signal data, rapid cycle times, and complex assembly relationships. Functions involving part recognition and sorting benefit from ML's ability to handle visual variance. For example, Börold et al. [19] present a method for improving the identification and verification of unmarked automotive parts. The proposed system uses synthetic images (generated from 3D scans) as training data for a CNN, significantly reducing manual annotation efforts, increasing process reliability, and achieving high accuracy in part classification, even in challenging cases with slight color deviations or mirrored parts.

Another commonly used input in functional testing is in-process data. When product functionality depends on the correct interaction of multiple components, graph-based or predictive models are most effective. Cassoli et al. [23] show that complex assembly lines are amenable to Graph Neural Networks (GNNs) to classify defective products in an automotive assembly line. Therefore, raw process data, such as line, station and feature relationships are encoded as knowledge graphs and a GNN model with GraphSAGE layers classifies products based on graph representations. This method is then shown to outperform tabular baselines like MLP and random forest in F1-score and ROC-AUC, despite strong data imbalances. Wagner et al. [203] demonstrate a virtual in-line inspection for fuel injectors using ANNs. Based solely on production data from sensors and machine signals, their ANN shows strong results in early defect detection.

Functions that generate high-speed waveform data are ideal for real-time ML classification. In this context, Deleruyelle et al. [38] combine NNs with clustering (DBSCAN) to classify functional, damaged, and nearly broken RFID chips in high-throughput production. Classification is performed directly on raw waveform data during chip personalization, enabling real-time inspection without generating explicit measurands. Stamer et al. [181] apply data fusion to PCB remanufacturing. This process is particularly amenable to ML because the "functional health" of the product is embedded in the transient current signatures or waveforms, which ML can classify faster and more accurately than manual signal analysis.

7.3. Applications in geometric and surface quality assessment

ML in this domain addresses two conceptually different but complementary objectives: the characterization of geometric features (e.g., measuring dimensions or roughness) and the detection of surface defects (e.g., identifying cracks or anomalies). While feature testing focuses on quantifying design intent, defect detection ensures topological integrity. In practice, many ML-based systems are designed to handle both tasks, leveraging similar data sources and architectures to provide a comprehensive quality assessment.

The following research highlights these applications, showing a strong focus on image-based surface inspection. For instance, El Ghadoui et al. [47] apply Faster R-CNN to classify surface roughness from camera images in machined steel, enabling real-time inspection without contact and up to 99% accuracy in metal cutting. Fan and Qiu [55] implement a RepConv-enhanced CNN with a novel loss function to detect surface defects in injection-molded plastic and classify the defect type. The system enables real-time inspection of raw camera images with an inference time of 6.1 ms and achieves a 0.960 F1-score, without requiring prior generation of the measurand.

Zhang et al. [238] present an automated in-process monitoring system for soft tooling injection molding that utilizes computer vision and deep learning. Their two-branch neural network model employs DeepLabv3 for defect detection and YOLOv5 (a pretrained algorithm based on CNN) for dimensional measurements, integrating data from CCD and thermal cameras for comprehensive quality assessment.

Addressing the challenge of limited defective samples, Staar et al. [180] propose a method for industrial surface inspection using anomaly detection with CNNs. Their approach uses deep metric learning with triplet networks, where the CNN learns a similarity metric for surface textures. This method trains with non-defective samples to create a prototype of normal features, providing a general solution for quality inspection by comparing new measurements against this prototype to detect anomalies. Examples of such anomalies are presented in Fig. 12. For validation the authors use a public image data set of the German Association for Pattern Recognition (DAGM).

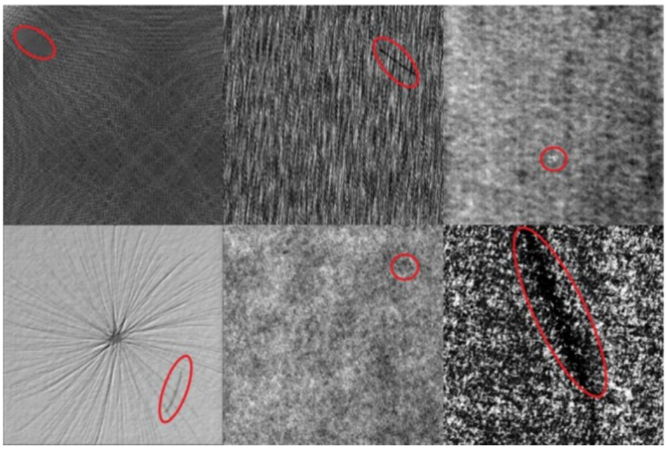

Fig. 12. Anomaly detection based on [180]. Red ellipsis highlight anomaly detected in the gray image.

Zhang et al. [237] use the VMA-UNet to automatically segment images of laser cladding coatings into cladding and dilution zones and extract geometric features such width and height directly from pixel-level predictions. Achieving over 95% mIOU when segmenting coating area, and over 98% mean relative agreement of automatically measured coating morphology features with respect to manual reference measurements, the method enables non-contact classification in post-process quality assessment.

While the previous examples utilize optical intensity data, ML is equally applicable to topographic data, where pixel values represent surface heights. Although mathematically similar to 2D images in their grid-like structure, these height maps provide direct geometric information. Furthermore, some applications move beyond grid-based representations to utilize true 3D data structures, such as point clouds. For instance, Mainsah and Ndumu [120] expand the use of ANNs to categorize surface roughness based on topographic data sampled down to 32×32 patches with 4 quantized height levels. The surface data is recorded by a stylus-based surface profilometer. Zhang et al. [239] develop 3D-SWiM, a 3D vision-based method for measuring seam width in composite fiber layup. The system estimates seam width in fiber layup by analyzing point clouds through region growing, edge detection, and PSO-optimized B-spline fitting. Applied in aerospace manufacturing, the method enables real-time inspections with sub-0.1 mm errors.

7.4. Intermediate summary

As illustrated by the various examples, the integration of deep learning models is becoming increasingly prevalent in classification tasks. Among input types, 2D image data is most prevalent, owing to the affordability and ease of integration of camera systems, and the fact that many defects are surface-visible and well captured by standard imaging. Furthermore, 2D data is computationally efficient and supported by a mature deep learning ecosystem. At the same time, a growing number of studies incorporate process-integrated sensor data, enabling real-time inspection of quality characteristics that are not directly visible or accessible post-production. This approach reduces reliance on destructive testing and supports early fault prediction and preventive action, thereby enhancing process stability and efficiency. In parallel, real-time quality control systems are increasingly adopted, as they enhance process transparency and enable timely, data-driven interventions.

Reflecting the dominance of image-based inputs, CNNs are among the most widely used architectures in industrial inspection, particularly for defect detection and object or component classification on image data. Their success stems from their ability to learn hierarchical representations: early layers detect low-level features like edges, while deeper layers capture more complex patterns such as object parts or entire components. This makes them especially effective for analyzing RGB images, thermal scans, and other grid-structured data. CNNs also offer a favorable trade-off between performance and complexity, enabling reliable, real-time classification in high-throughput production environments.

8. Generating insights

Integrated within feedback loops, ML models enable real-time generation of actionable insights that improve process understanding and output quality. These insights fall into two categories: (i) feedback mechanisms that directly allow to adjust production parameters based on measurement data, and (ii) identification of key influencing factors through model interpretation techniques, which inform longer-term process adjustments. This interaction is shown in Fig. 13. It shows how contextual information is combined with live process data to condition the manufacturing process.

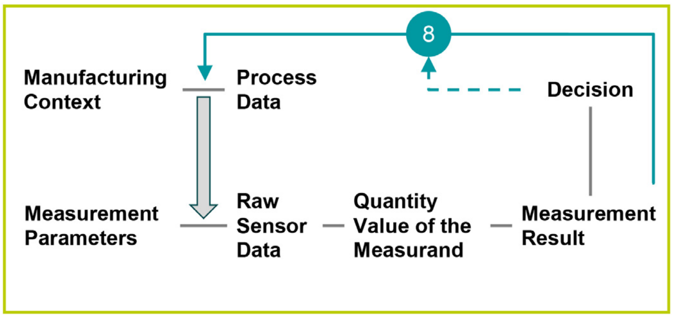

Fig. 13. Integration of machine learning in the measurement and manufacturing feedback loop in the overall framework.

8.1. Closing the loop: Feedback to the production process

Advancements in ML systems enable real-time generation of actionable insights from continuous sensor data, facilitating automated process adjustments without human intervention. Once trained on initial quality measurements, ML systems use continuous sensor data streams to dynamically control process parameters and reduce defect rates. A key advantage of ML-based systems lies in their temporal resolution: not only the speed of predictions but also the availability of continuous information between conventional sampling points. The following section groups key contributions according to manufacturing domains: primary shaping, forming, cutting, and joining, consistent with the structure of DIN 8580 [40]. In addition, mechanical assembly and multi-stage systems are included as separate categories. Assembly, though not part of the six core process categories in DIN 8580, is widely classified as a final-stage activity in production systems. Finally, multi-stage systems capture feedback spanning multiple processes and extend beyond the scope of single-domain classification. Table 5 provides a structured overview of the reviewed literature.

Table 5
Overview of literature addressing closed-loop ML applications by manufacturing domain.

Domain	Focus
Primary shaping	Melt-pool control (Baraldo et al., 2020) [8], layer defect detection (Angelone et al., 2020) [5], layer quality monitoring (Roux et al., 2021) [162], process quality prediction (Gülçür & Whiteside, 2021) [78]
Joining	Weld defect correction (Massaro et al., 2020) [122], quality assessment (Yang et al., 2018) [227]
Forming	Reducing operator workload (Škulj & Bračun, 2020) [178], dimensional control (Gauder et al., 2023) [62]
Cutting	Surface roughness optimization (Taga et al., 2016) [185], surface integrity (Chia-Yen & Tsung-Lun, 2019) [106], tool wear (Böttger et al., 2024; Gu et al., 2022) [20,76], milling optimization (Bott et al., 2024) [15],
Assembly	Assembly optimization (Schiller & Lanza, 2023) [170], fastening validation (Meiners et al., 2021) [126]
Multi-stage systems	Multi-stage cutting optimization (Ji et al., 2023) [91], trench depth control (Timoney et al., 2023) [195], system-level quality assessment (Kies et al., 2023) [95]

8.1.1. Primary shaping

In the context of additive manufacturing, systems leverage optical or thermal imaging and CNNs for inline defect detection and control, supporting in-situ adaptation of AM parameters. Baraldo et al. [8] present a closed-loop system for automated laser power control based on the melt pool image intensity to maintain uniform track height and minimize over-deposition at critical points. Utilizing an effective PI process control model, the system reduces height overshoots by 17%, particularly benefiting V-track corners prone to over-deposition due to the machine tool's deceleration and acceleration dynamics.

An alternative feedback system is proposed by Angelonea et al. [5] and employs a camera to capture images of the scanned layers, which are then rotated and segmented to separate the images for every sample. A novel dedicated convolutional neural network architecture is created to identify the presence or absence of different categories of defects, such as critical stripes in the powder bed affecting scanning surface quality, scanning surface quality degradation due to stripes in the powder bed, upraising areas/scan-lines due to bad melting conditions, and recoating defects.

Roux et al. [162] aim to automate quality assessment in the Electron Beam Melting process by analyzing electron-optical images (see Fig. 14). Various CNNs like AlexNet, DenseNet, ResNet, SqueezeNet, and VGG are employed to classify the layer quality into porous, bulging, and normal states. The pre-trained CNN achieves 95% accuracy with inference times under 0.01 s, enabling real-time monitoring within the layer printing cycle.

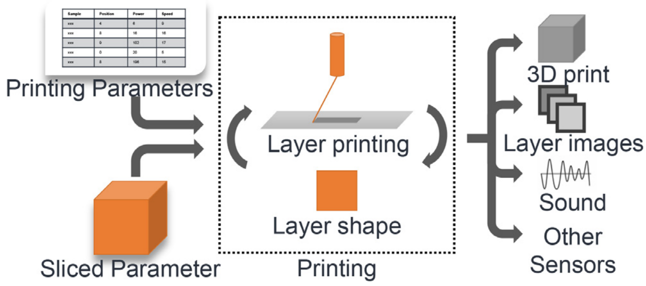

Fig. 14. Input and output data for ML-based layer quality monitoring in 3D printing. [162].

8.1.2. Joining

Joining applications integrate process monitoring signals (e.g., thermography, torque, geometry) with ML models to detect quality deviations and trigger corrective actions in real time. Massaro et al. [122] utilize infrared thermography to assess the structural homogeneity of welds. It employs image post-processing analyses like the K-Means algorithm, morphological image processing, and LSTM networks to identify and quantify welding inhomogeneities, such as cracks and defects. Experimental results indicate that the proposed method effectively highlights and quantifies defects and irregularities in welds, providing a substantial basis for improving welding processes through real-time monitoring and feedback. Similarly, Yang et al. [227] establish a welding detection system based on the 3D reconstruction technology for the arc welding robot. The shape from shading algorithm is used to reconstruct the welding seam's 3D shapes, and the curvature information is extracted as the feature vector of the welds. Furthermore, the SVM classification method is adopted to perform the evaluation task of welding quality, achieving 94% classification accuracy.

8.1.3. Forming

Feedback loops in forming processes employ surface metrology, sensor fusion, or regression models to adjust process settings and minimize dimensional or surface defects. With a focus on zero defect manufacturing, Gauder et al. [62] develop a control loop for micro gear hobbing by integrating an optical focus variation measurement system in the production chain. Based on these measurements, the developed software provides correction values to the hobbing process. The above control loop increases the dimensional quality of the micro gears which positively affects running behavior and acoustics. Škulj et al. [178] rely on ML to reduce the workload of forge operators responsible for the forging process. Based on the process temperature measurements, an ML algorithm autonomously decides a geometry measurement of a part, thereby reducing the workload of the operator.

8.1.4. Cutting

Closed-loop machining systems use sensor data, vision-based diagnostics, and sensors to monitor tool wear, surface integrity, and process states, enabling adaptive control of cutting parameters. Surface roughness in subtractive manufacturing is highly dependent on cutting parameters such as feed rate and cutting speed.

Böttger et al. [20] developed a sensor for turning operations that uses micromagnetic non-destructive testing and PCA-based regression to detect surface integrity issues such as White Layer formation in AISI 4140 steel. Integrated into the machining process, the sensor supports adjustment of process parameters. Bott et al. [15] take this further by proposing a general framework for real-time milling optimization. By aggregating signals from multiple machine components and applying ML to refine process parameters, their system enables continuous, use-case-independent performance adaptation. Collectively, these studies demonstrate a progression from surface monitoring to full-process integration, where ML enables increasingly autonomous control of machining quality and tool condition.

8.1.5. Assembly

In discrete assembly operations, often the terminal stage of production, ML enables in-line measurement systems to guide decisions such as part pairing, fastening validation, and functional optimization. Schiller and Lanza [170] introduce an adaptive assembly strategy for micro gears that closes the loop between in-line measurement and assembly control. Optical topography scans are used to predict functional properties, specifically NVH metrics, of potential gear pairings using an ML meta-model. This enables real-time optimization of assembly decisions by selecting gear combinations that reduce predicted functional deviations. The result is a direct transformation of component-level quality data into actionable control inputs for the assembly process. For mechanical fasteners, Meiners et al. [126] evaluate different ML and DL algorithms to investigate their effectiveness to discriminate between an in specification and out of specification fastening of the screw. The results show that a 1D-CNN model achieved an average accuracy of 86.81%. Fig. 15 shows the different error types and accompanying torque curves.

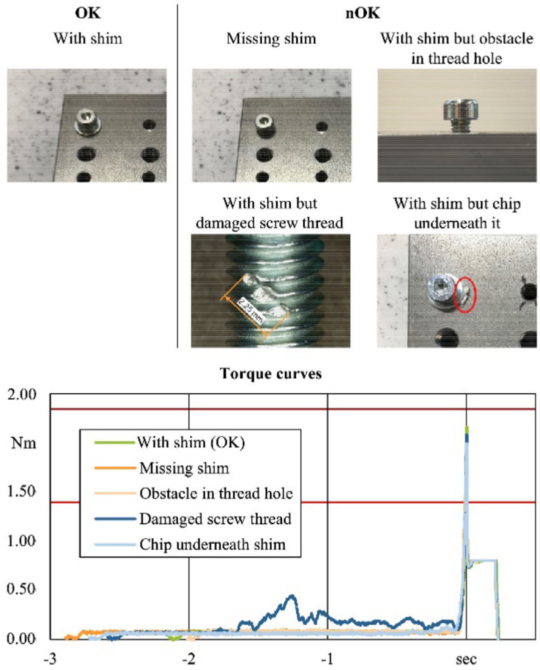

Fig. 15. Different error types in screw fastening experiments detected by 1D-CNN [126].

8.1.6. Multi-stage systems

In multi-stage production systems, ML integrates data from multiple process steps to enable cross-stage feedback, parameter tuning, and defect propagation analysis. Timoney et al. [195] develop a control strategy for Copper CMP, using ML models trained on e-test resistance to predict trench height from integrated metrology spectra. This approach outperforms conventional OCD-based control, particularly when measurement and test structures are spatially separated. ML-based feedback improved centering of both trench height and resistance, reducing baseline shifts across product variants and enabling robust multi-product control without additional setup overhead. At the broader system integration level, Kies et al. [95] propose a QA system for battery cell production that integrates inline and offline data acquisition with digital traceability to support process-level decision-making. Sensor data from multiple steps are aggregated and analyzed to inform virtual quality gates, which trigger adaptive interventions such as process parameter tuning or rejection of defective intermediates. By linking measurements to individual units via robust identifiers, this architecture enables real-time feedback loops that adjust manufacturing conditions based on learned quality correlations, thereby aligning closely with the definition of closed-loop control.

8.2. Identification of key influencing factors

Another aspect of these feedback systems is the identification of key influencing factors. By processing the data collected through sensors, manufacturers can pinpoint the causes of defects and predict failures across multiple scales, from millimeter-level deviations to microstructural anomalies. These insights are drawn either from intuitive relationships between monitoring data and final quality or from the node weights of advanced ML models. Two critical questions arise in this context: (i) How can influencing factors in ML models be revealed to explain model decisions? and (ii) How can ML techniques contribute to deeper insight generation through advanced pattern recognition? Addressing these questions is essential not only for generating insight with ML-based systems but also for operationalizing them as tools for continuous improvement rather than black-box decision engines.

A growing body of research focuses on how ML systems can support root-cause analysis and explainability by uncovering latent patterns and key influencing factors in manufacturing data. Klamert et al. [97] use Grad-CAM to interpret a VGG-16 model for in-situ curling failure detection in Selective Laser Sintering, showing that the CNN filters focus on physically meaningful regions. As shown in Fig. 16, the Grad-CAM heatmap highlights areas corresponding to visible curling in the thermal image. Similarly, Saadallah et al. [164] apply Grad-CAM to highlight important regions in torque-time signals used to classify screw fastening quality with a 1D-CNN. These methods help build trust in ML outputs by exposing model attention and decision bases.

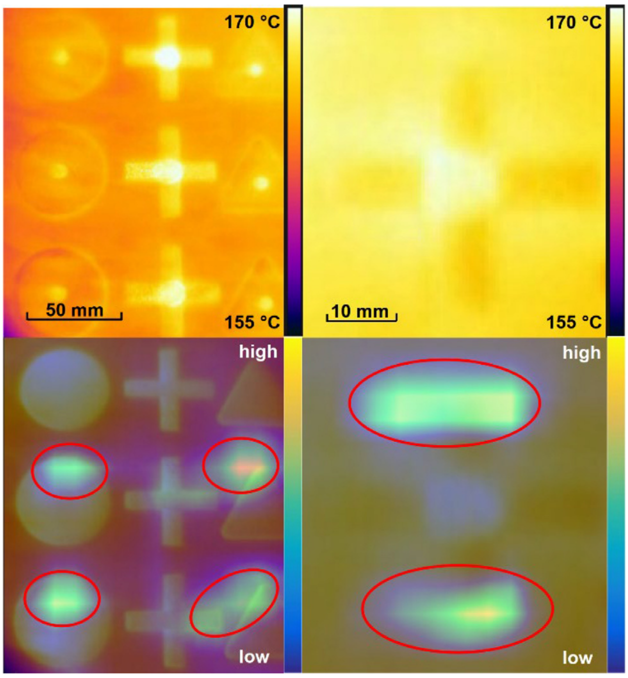

Fig. 16. Comparison of thermographic view and Grad-CAM heat map Top: Visible curling on the thermographic multi-geometry data set and the patch of the multi-geometry data set. Below: Related Grad-CAM heatmap of VGG-16, red circles indicate areas of high importance [97].

Other studies address the second question, focusing on the use of ML for uncovering new insights via advanced pattern recognition. Kogel–Hollacher et al. [99] demonstrate that seam quality in laser welding can be inferred from raw process emissions, enabling the discovery of latent influencing variables beyond binary defect labels. Wang et al. [212] show that surface preparation defects in optical metrology can be detected using a YOLOv7-based system, identifying defect classes that degrade 3D scan integrity. Gellrich et al. [64] use regression models to link process data in carbon fiber production to final fiber properties, revealing dominant upstream variables via feature importance analysis. Similarly, Lee and Tsai [106] apply variable selection and modeling techniques in TFT-LCD manufacturing to isolate key drivers of product quality variation, enabling targeted process optimization.

8.3. Intermediate summary

ML enables metrology systems to extract process-relevant information from high-dimensional sensor data, supporting both in-situ process control and predictive quality assurance. By learning correlations between process signatures and quality outcomes, ML models facilitate real-time parameter adjustment, reducing defects and rework. Virtual measurement extends this capability by replacing physical measurements with data-driven estimations, allowing quality predictions to be integrated directly into control logic.

Most implementations focus on closing short control loops, where sensor inputs drive immediate parameter updates. While effective for local optimization, this approach overlooks the potential of intermediate and longer feedback loops. These would link real-time monitoring data to operator guidance, design adaptation, or upstream decision-making. Preliminary studies [22,108] indicate the feasibility of such approaches, suggesting a pathway toward integrating design-for-quality within adaptive manufacturing workflows.

Many ML-based feedback systems remain constrained to isolated process steps or linear sequences. Looking ahead, research should address cross-stage integration, such as linking surface integrity metrics from machining to downstream assembly optimization or using early material characteristics to inform subsequent processing steps. Finally, embedding ML within digital twins would enable synchronized virtual-physical control, supporting real-time prediction and correction.

9. Uncertainty assessment and risk evaluation

The result of a measurement is only complete when accompanied by a statement of its uncertainty. In industrial quality assurance, the uncertainty is the foundation for conformity assessment, process control, and the validation of automated measurements. A valid uncertainty evaluation relies on the identification of all relevant sources of uncertainty, the quantification of the contribution of these sources, and a measurement model relating the sources to the measurand. For ML models, which often hide or lack traceable input-output relationships, there often is a lack of this understanding as a physical model could be used otherwise. As a result, uncertainty evaluation is challenging but at the same time critical to avoid misinterpretation and to demonstrate compliance with industrial standards.

GUM [52] is continually evolving to address new challenges, including the integration of ML models into measurement practices, where standardizing uncertainty evaluation for complex, data-driven systems remains an ongoing task. To comply with GUM, uncertainty evaluation must include:

- Explicitly define the measurand,
- Relate input quantities to the measurand through a model,
- Assign standard uncertainties (Type A or Type B) for all inputs, covering all relevant sources of uncertainty,
- Document all assumptions, inputs, and uncertainty sources for traceability, and
- Report results with a quantified uncertainty statement and associated confidence level.

Following the fundamental definition and concepts of uncertainty outlined in Section 2.1, GUM distinguishes between two evaluation methods for quantifying uncertainty contributions. Type A evaluation derives uncertainty components from statistical analysis of repeated observations (e.g., estimating the variance from a measurement series), whereas Type B evaluation derives uncertainty components from other information sources such as manufacturer specifications, calibration certificates/reports, prior data, or expert judgment.

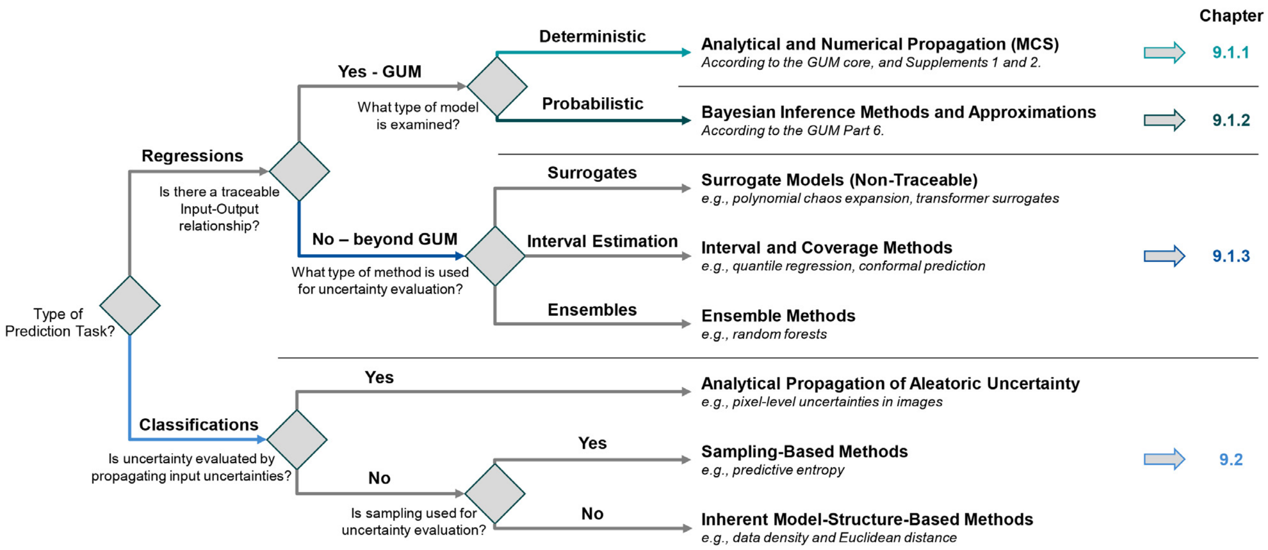

Fig. 17. Decision tree of handling uncertainty using machine learning.

Examples for analyzing all relevant sources of uncertainty in the context of ML models are given in the following: Zhang et al. [238] investigate the main contributors to measurement uncertainty in a neural network–based image segmentation system (YOLOv5) applied to dimensional inspection during injection molding. Two primary sources are considered: u_c, associated with the camera and environmental factors such as lighting conditions, and u_p, stemming from training data, including variability introduced by operators' annotations. These contributions are quantified by varying camera settings and repeatedly training the model.

Gallo et al. [57] provide another example of a GUM-compliant Type A uncertainty in an image-based system by measuring the rotational displacement of fastened railway clips. Their approach employs a YOLO—OBB neural network, where variations in camera positions and angles led to differing predictions for identical samples, highlighting these factors as key sources of uncertainty. The calibration uncertainty was estimated from the standard deviation of repeated measurements.

Uncertainty in the field of ML does not always follow the perspective of metrology but is commonly divided into aleatoric and epistemic components. Aleatoric uncertainty results from inherent variability in the data or system, such as measurement noise or sensor resolution. It is generally considered irreducible without adapting the system itself. In contrast, epistemic uncertainty arises from limited knowledge, e.g., due to non-representative data, model uncertainty, or insufficient training, and can be reduced through additional data collection or improved modeling approaches [87]. In practice, this distinction helps to guide method selection. Moreover, both data-related and model-induced uncertainties are considered jointly in the field of ML. As a result, the uncertainty is evaluated and handled differently compared to the field of metrology. In addition, in classification tasks the definition of uncertainty as stated in Section 2.1 is not applicable at all, as classification models assing nominal values rather than continuous measurement quantities. Instead, classification-specific metrics as introduced in Section 2.2 can be used. However, such metrics, although indicative of predictive reliability, are not traceable under GUM definitions.

To structure these diverse approaches and guide the reader, Fig. 17 presents a decision tree summarizing how uncertainty evaluation can be treated. It begins with GUM-compliant deterministic and probabilistic regression models, where uncertainty is evaluated according to established GUM principles. It then extends to methods beyond GUM, which are not yet formally covered by GUM but still fall under its fundamental concept of evaluating uncertainty, and finally concludes with classification tasks.

9.1. Uncertainty evaluation in regressions

9.1.1. Uncertainty evaluation in deterministic models

In addition to the general requirements mentioned, the original GUM Core document, as well as Supplements 1 and 2, demand a deterministic measurement model in the form $Y = f(X_1, X_2, \ldots, X_n)$ where Y is the measurand and X_i are the n input quantities, with the model f being deterministic.

The GUM Core [52] employs analytical uncertainty propagation based on the law of propagation of uncertainty, also known as the uncertainty propagation formula:

$$u_c(y) = \sqrt{\sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i} \cdot u(x_i) \right)^2}$$

Here, $u_c(y)$denotes the combined standard uncertainty of y, $u(x_i)$ the uncertainty of the input quantities, and $\frac{\partial f}{\partial x_i}$ each input's sensitivity coefficient, indicating how much a change in x_i affects the output.

The formula describes how known uncorrelated input uncertainties are propagated through the measurement model using sensitivity coefficients derived from the partial derivatives with respect to each input. For linear models, this propagation can be performed directly. However, for nonlinear models, the GUM requires a first-order Taylor series expansion of the measurement function around the best estimates of the input quantities. This linearization assumes that the function is differentiable and that higher-order terms are negligible.

Jungmann et al. [92] treat neural networks as deterministic, differentiable functions. In their method, uncertainty is propagated layer by layer through convolutional and pooling layers, incorporating weights, biases, and activation functions. The method's effectiveness is demonstrated on synthetic and real-world datasets from the semiconductor manufacturing industry, where a feedforward network is used to predict transistor parameters based on process and geometric features. Similarly, Lin et al. [109] use a differentiable ANN in the application of a nonlinear optical angle sensor and validate their results with an MCS.

Genta and Maculotti [65] investigate the measurement of small wear volumes on complex surfaces using machine vision by treating their measurement model as linear. They combine Type A and Type B components, such as coordinate measurements and pixel size uncertainties, with analytical propagation to provide traceable uncertainty estimates for wear volumes.

GUM Supplement 1 (S1) [53] extends the framework by introducing Monte Carlo simulation (MCS) for numerical uncertainty propagation. Unlike analytical propagation, MCS does not require differentiability or linearization. It estimates output uncertainty by sampling from the full input distributions, accommodating non-Gaussian inputs. According to the law of large numbers, the sample size must be sufficiently large to ensure statistical stability of the results. GUM S1 recommends one million samples for the 95% coverage interval, although this can require significant computational effort.

Gauder et al. [61] apply MCS to evaluate the uncertainty caused by systematic deviations in a simulated single-flank rolling test for micro gears. Their simulations are based on optical measurements from real micro gear production and validated against a high-precision test facility. To overcome the large sample size requirements for statistical stability by improving sampling efficiency, they use Latin Hypercube Sampling (LHS), which ensures uniform input coverage and accelerates convergence.

GUM Supplement 2 [50] extends the framework to multivariate models, formalizing both analytical and numerical approaches. For analytical propagation, this involves using Jacobian sensitivity matrices and covariance matrices. Habibi et al. [79] apply this method to assess perpendicularity measurements on mechanical parts using coordinate measuring machines. They derive a Jacobian sensitivity matrix J and an input covariance matrix M from a first-order Taylor expansion and compute the output variance as $u_c^2 = J \cdot M \cdot J^T$. The authors employ MCS and interlaboratory comparison to validate their analytical results. However, this example does not involve classic ML models.

9.1.2. Uncertainty evaluation in probabilistic models

The assumption of determinism underlying classical GUM is often incompatible with the probabilistic nature of many modern ML models. GUM Part 6 [74] extends the framework to support probabilistic models, explicitly addressing model inadequacy and parameter uncertainty as key sources of epistemic uncertainty.

This allows for Bayesian inference, which treats model parameters as random variables with prior distributions. Combining prior knowledge with observed data yields posterior distributions that reflect epistemic uncertainty and, when observation noise is modeled, also aleatoric uncertainty [63].

Bayesian linear regression exemplifies this by treating model parameters as probability distributions rather than fixed values. As a result, predictions become full probability distributions [142]. Papananias et al. [142] apply Bayesian linear regression to predict part quality in a multistage manufacturing process, utilizing in-process data such as on-machine probing coordinates and temperature readings. They employ Markov Chain Monte Carlo (MCMC) to approximate the joint posterior distribution and derive credible intervals that capture both aleatoric and epistemic uncertainty, providing interpretable uncertainty estimates for virtual metrology.

GPR, or Kriging, offers a non-parametric Bayesian approach by modeling a posterior distribution over functions conditioned on observed data. It provides both point predictions and prediction variances, from which confidence intervals can be derived. GPR excels in interpolating sparse or irregular data but is computationally feasible mainly for small- to medium-scale problems. It is commonly employed as a surrogate model within localized regions [117].

BNNs extend Bayesian inference to deep learning by learning a posterior over network weights. Since the exact computation is generally intractable, approximation methods are widely used [63]. Heidary et al. [82] apply BNNs to evaluate measurement uncertainty in cylinder radius measurements obtained via non-contact articulating arms. One network captures aleatoric uncertainty by minimizing negative log-likelihood, while another models epistemic uncertainty in the network parameters. The aleatoric model outperforms classical geometric methods in accuracy, and the epistemic model effectively captures model-related uncertainty.

Variational Inference (VI) offers a scalable Bayesian technique for approximating otherwise intractable posteriors by optimizing a simpler distribution via Kullback–Leibler divergence minimization. It transforms Bayesian inference into a tractable, gradient-based optimization problem and is favored in large models like BNNs due to its computational efficiency [1,107]. Li et al. [107] apply VI within BNNs to evaluate uncertainty in multivariable regression for predicting creep rupture life of steel, titanium alloys, and nickel-based superalloys. Cramer et al. [35] extend VI to virtual measurements by probabilistically modeling the measurand and propagating uncertainty through the posterior parameter distribution. Their framework captures both aleatoric and epistemic uncertainty, adapting dynamically to input realizations.

While VI scales well, simpler heuristic approximations such as Monte Carlo (MC) Dropout have been proposed. MC Dropout retains stochasticity during inference by running multiple forward passes with dropout active. This simulates sampling and estimates epistemic uncertainty through the variation across predictions [1]. Dey et al. [42] apply MC Dropout to tool flank wear prediction during milling operations. After 50 passes, the resulting confidence intervals are sufficiently narrow and robust (compare Fig. 18).

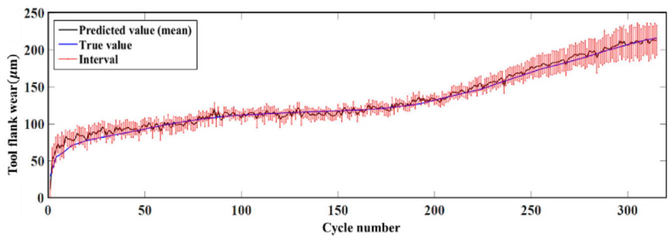

Fig. 18. Interval prediction results for tool flank wear, estimated from 50 MC Dropout forward passes per cycle number [42].

9.1.3. Beyond GUM

Although the GUM framework has been progressively expanded to include analytical, numerical, and probabilistic approaches, it does not formally encompass all methods currently used for uncertainty evaluation. Especially, many evaluation metrics commonly used in ML fall outside the formal GUM definition of uncertainty.

ML models are frequently employed as surrogates for physical measurements and computationally intensive simulations, enabling faster evaluations under uncertain inputs, albeit at the cost of reduced accuracy. These surrogate models are typically valid only within a limited region of the input space and require validation against trusted reference models or experimental ground truth [1]. Pitz et al. [145] present a Transformer-based surrogate for finite element simulations of continuous fiber composites produced via Fused Filament Fabrication. A CNN first infers spatial stiffness fields from DIC strain maps, providing point and predictive uncertainty estimates. Sampled realizations are then propagated through the Transformer using Quasi-Monte Carlo sampling, a more efficient variant of MCS based on structured, quasi-random sampling. In consequence, aleatoric uncertainty for 60 printed samples with four different layups were tested.

Polynomial Chaos Expansion (PCE) offers another surrogate modeling technique often used to replace computationally expensive finite element models (FEM). By approximating model outputs as weighted sums of orthogonal polynomials of the input variables, PCE enables efficient computation of statistical moments and sensitivity indices [189]. Tapia et al. [189] apply a generalized PCE to propagate uncertainty from process parameters in PBF-LB/M, achieving accurate approximations with far fewer simulations than Monte Carlo sampling. Additionally, Sobol indices are derived from the PCE coefficients to perform a global sensitivity analysis. Petrocchi et al. [143] use sparse PCE for uncertainty propagation in microwave transistor nonlinear models. Using only 30 LHS samples, they construct surrogates that match Monte Carlo results in accuracy while significantly reducing computational effort.

Quantile Regression (QR) and Conformal Prediction (CP) are distribution-free methods that construct prediction intervals and primarily capture aleatoric uncertainty. QR estimates conditional quantiles using an asymmetric pinball loss and captures heteroscedasticity, while CP provides formal marginal coverage under the assumption of sample exchangeability. QR directly estimates conditional bounds but can suffer from undercoverage and quantile crossing. Conformalized Quantile Regression (CQR) combines both approaches by calibrating QR-based intervals using CP's nonconformity scores to ensure coverage guarantees [2]. Akpabio and Savari [2] apply standard CP, normalized CP, and CQR to construct prediction intervals around estimates produced by EDGENet. The study predicts line edge roughness in semiconductor manufacturing based on synthetically generated scanning electron microscopy images. While CP ensures marginal coverage guarantees, normalized CP adapts interval widths using autoencoders. CQR addresses undercoverage and quantile crossing through calibration to enforce coverage guarantees, producing smoother and more stable intervals at the cost of increased computational effort.

Ensemble methods estimate uncertainty by training multiple instances of a model on different data subsets, feature sets, or parameter configurations. The variability in predictions serves as a proxy for epistemic uncertainty, while the ensemble mean provides a robust point estimate [63]. Unlike Bayesian methods, ensembles do not rely on posterior distributions and thus fall outside the probabilistic framework formalized in GUM Part 6. They are attractive when probabilistic inference is impractical or computationally expensive, though it limits traceability. Random forests are one such method combining a multitude of decision trees (see Section 2.2). Bott et al. [16] propose a predictive maintenance framework for estimating the remaining useful life of ball screw drives. Confidence intervals are constructed from ensemble variance, and accelerated degradation experiments are used for feature-based regression. RFs achieve high predictive accuracy (up to 91% R^2) and deliver tighter uncertainty bounds compared to gradient boosting and SVMs.

Deep Ensembles extend the ensemble concept by training multiple neural networks with different random initializations or training data subsets [85]. Hoffmann et al. [85] apply Deep Ensembles to reconstruct optical surface topographies from interferometric measurements of spheres and freeform surfaces. They train an ensemble of independently initialized U-Net architectures, capturing model uncertainty at both pixel and image levels and demonstrating robust performance across perfectly calibrated, miscalibrated, and noisy scenarios.

9.2. Uncertainty evaluation in classifications

In classification tasks, uncertainty evaluation does not follow traditional metrological definitions, as the result is not a continuous measurand. Still, predictive uncertainty remains essential, especially for decision-critical applications. Indicators like those introduced in chapter 2.2 can be used to get insights about the uncertainty of a model.

Deleruyelle et al. [38] apply a density-based clustering approach using DBSCAN to classify the functional state of high-frequency RFID devices from non-contact impedance measurements. DBSCAN relies on data density rather than probabilistic estimates, capturing epistemic uncertainty by identifying data points that lie outside high-density regions, inherently flags uncertain classifications without explicitly modeling prediction confidence. The authors validate their approach on real-world RFID production data with MSE as the central metric. Staar et al. [180] apply a CNN with triplet networks to detect surface anomalies in manufacturing. The model is trained to map defect-free samples into a compact feature space, where anomalies are detected based on the Euclidean distance to a prototype. Larger distances serve as a proxy for epistemic uncertainty without relying on probabilistic outputs. They use AUC (area under the curve) as a central metric.

Jungmann et al. [92] propose an analytical method to propagate pixel-level input uncertainties through CNNs in an image-based classification task. Handler-induced defect patterns are identified on semiconductor wafer maps and corresponding uncertainties, such as those from quantization or spatial resolution, are propagated through convolutional, pooling, and dense layers. This enables direct computation of class-wise output uncertainties alongside predicted probabilities. Their results on gray-scale defect maps show that increased input resolution reduces output uncertainty, as expected.

9.3. Risk assessment

Ultimately, measurement uncertainty in the domain of metrology provides an input to assess the risk of a decision taken in the operational domain, particularly in manufacturing [18]. Uncertainty in AI-enabled measurements feeds into risk assessment frameworks, where metrics such as statistical process control (SPC) classifications and risk priority numbers guide decision-making. Integrating both ensures robust quality control.

Conformance zones define the acceptable limits for product or process parameters and serve as threshold regions in risk assessment. Formalized in ISO 14253-1 [69] and GUM S6 [51], guard bands are introduced around tolerance limits, effectively reducing acceptance zones. The width of these guard bands is determined by the expanded measurement uncertainty in accordance with GUM principles (cf. Section 2.1).

Mueller et al. [135] provide a practical example by integrating ML predictions into SPC control charts to map predicted values into conformance zones (see Fig. 19), linking measurement uncertainty directly to discrete risk levels such as low or high risk. Their study illustrates how interpretable ML models can enable risk-based decisions in line with ISO 9001:2015 standards.

While the previous examples integrate uncertainty into existing SPC structures, Polzanski et al. [148] propose an inverse approach: starting with measurement uncertainty to derive conformance-like zones. They estimate Type B uncertainty in ML regression models

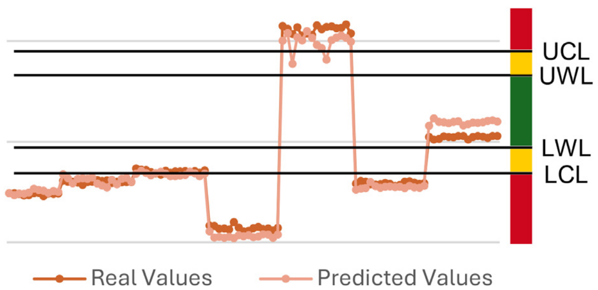

Fig. 19. Risk assessment via control chart on one critical product parameter [135].

based on maximum empirical L_1 loss, assuming a uniform distribution. Treating the model as a measuring instrument, they define uncertainty bounds around predictions, linking UE directly to structured, risk-based decision-making.

For quality prediction assessment, Schorr et al. [175] address the crucial aspect of the acceptance of ML in industry by proposing an evaluation framework based on established inspection standards like VDA5 and MSA. This framework evaluates ML models' predictive capability using indicators like cg, cgk, and %GGR. The German VDA 5.3 guideline [200] emphasizes modeling uncertainty and tolerance limits, defining α- and β-error rates for classifiers, ideally validated with real or simulated samples. High-risk tasks require rigorous validation, while low-risk tasks (RC1/RC2) may rely on error rates or expert review, supported by revalidation and monitoring.

The Japanese QA4AI guideline [31] views uncertainty as inherent, recommending confidence-based outputs, robustness tests, and model-internal indicators over strict formal methods. It highlights robustness, explainability, context-specific thresholds, and adaptive measures (e.g., human review, fail-safe), with ongoing monitoring and retraining to address data drift.

Both VDA 5.3 and QA4AI stress uncertainty evaluation but diverge: VDA permits simplified validation for low-risk tasks, while QA4AI prioritizes adaptability when traceability is limited.

9.4. Intermediate summary

Measurement uncertainty provides a structured basis for risk-based decision-making by linking model predictions to conformance criteria and process control. While traditionally grounded in formally quantified uncertainty, risk assessments may also rely on less formal estimates if their limitations are understood. In practice, two paradigms coexist: traceable metrological approaches and flexible, data-driven ML methods. Although differing in rigor, both support robust risk evaluation and require context-specific application. In regulated environments, compliance with standards such as GUM or ISO 14253-1 remains essential. Frameworks like VDA 5.3 and QA4AI illustrate how uncertainty can be operationalized through confidence thresholds, revalidation routines, or adaptive decision logic, embedding it as a structural component of risk modeling rather than merely a numerical output.

10. Conclusion and outlook

The integration of ML into manufacturing metrology accelerates the shift from static quality control to dynamic, data-driven process optimization. Advanced algorithms extract deeper insights from sensor data, improving measurement inference, automating inspection, and enabling intelligent feedback loops. This evolution brings the need for a unified framework that combines metrological rigor with ML flexibility. The field's future depends on how effectively these challenges are addressed, paving the way for intelligent and autonomous manufacturing.

At its core, ML enhances key measurement processes. Models like Convolutional Neural Networks excel in processing high-dimensional data for denoising and feature extraction, while synthetic data mitigates industrial data scarcity. Virtual measurements now predict quality characteristics from process parameters, reducing physical inspections. Beyond incremental improvements, ML offers transformative opportunities to advance metrology in several directions. The strongest impact emerges where conventional analytical models reach their limits—particularly in complex, high-dimensional, or dynamic measurement scenarios. In sensor-level data interpretation, CNNs and Autoencoders enable robust noise suppression and feature extraction beyond classical filtering methods. In calibration and setup, reinforcement learning and surrogate modeling can optimize parameter settings, alignments, and recalibration intervals based on data-driven performance indicators rather than fixed heuristics. Generative models such as GANs extend the concept of measurement itself, allowing virtual or indirect assessments where physical sensing is impractical.

However, the very challenges that ML can help overcome in metrology also pose difficulties for ML itself—first and foremost, limitations in data availability and quality. Furthermore, poor model generalization requires more adaptable architectures, while computational complexity restricts real-time applicability, emphasizing the need for efficient algorithms. Finally, consistent treatment of uncertainty, establishing interpretability and risk quantification remain essential for industrial trust and sound decision-making. This might be the most important aspect for realizing the full potential of ML-based metrology. Currently, a disconnect persists between the deterministic framework of traditional metrology and the probabilistic nature of ML. Most ML models treat input and training data as error-free, neglecting uncertainty in the reference data itself. This omission undermines metrological traceability and highlights the need for frameworks that integrate measurement uncertainty into training and inference. Hybrid, physics-informed networks are beginning to embed uncertainty models and traceability constraints directly into their loss functions. Robust domain-adaptation and calibrated uncertainty-quantification methods are emerging to ensure reliable transfer across instruments.

In this context, digital twins and virtual environments may play a vital role as a natural framework for integrating ML-enabled metrology. Digital twins allow the replication of manufacturing processes with metrological fidelity. By combining ML-based metrology with digital twins, manufacturers may be able to bridge the gap between measurements and decision-making models.

Progress in intelligent metrology will depend on unifying ML with established principles of uncertainty, calibration, and traceability. Expanding standards such as GUM to accommodate ML models, advancing explainable AI for transparency, and overcoming technical challenges in data scarcity, generalization, and efficiency are central to this effort. The long-term vision is the creation of hierarchical, uncertainty-aware manufacturing ecosystems where digital twins, predictive models, and metrological traceability converge to enable self-optimizing production.

CRediT authorship contribution statement

Gisela Lanza (1): Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Robert Schmitt (1):** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Wim Dewulf (1):** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Hans Hansen (1):** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Yang Zhang (2):** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benjamin Montavon:** Writing – original draft, Visualization, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Florian Stamer:** Writing – review & editing, Writing

– original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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