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TOWARDS REPRODUCIBLE MACHINE LEARNING-BASED PROCESS MONITORING AND QUALITY PREDICTION RESEARCH FOR ADDITIVE MANUFACTURING

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ABSTRACT

Machine learning (ML)-based monitoring systems have been extensively developed to enhance the print quality of additive manufacturing (AM). In-situ and in-process data acquired using sensors can be used to train ML models that detect process anomalies, predict part quality, and adjust process parameters. However, the reproducibility of the proposed AM monitoring systems has not been investigated. There has not been a method to evaluate and improve reproducibility in the joint domain of AM and ML. Consequently, some crucial information for reproducing the research is usually missing from the publications; thus, systems reproduced based on the publications often cannot achieve the claimed performance. This paper establishes the definition of reproducibility in this domain, proposes a reproducibility investigation pipeline, and composes a reproducibility checklist. A research is reproducible if a performance comparable to the original research can be obtained when reproduced by a different team using a different experiment setup. The reproducibility investigation pipeline sequentially guides the readers through all the necessary reproduction steps, during which the reproducibility checklist will help extract the reproducibility information from the publication. A case study that reproduced a vision-based warping detection system demonstrated the usage and validated the efficacy of the proposed pipeline and checklist. It has been observed that the reproducibility checklist can help the authors verify that all the information critical to reproducibility is provided in the publications. The investigation pipeline can help identify the missing reproducibility information, which should be acquired from the original authors to achieve the claimed performance.

Keywords: additive manufacturing; machine learning; reproducibility; process monitoring; quality prediction.

1. INTRODUCTION

Additive manufacturing (AM) has significantly transformed the design and manufacturing industries as it enables fast prototyping and mass customization [1, 2]. AM also promotes sustainability by reducing material waste and recycling from end-of-life components [3, 4]. With recent research advancements, AM has been widely adopted in various sectors such as healthcare, aerospace, and construction [5]. Despite the promising features, AM processes are developing technologies that still lack reliability [6]. The physics behind rapid phase changes such as grain growth in AM has not been fully understood [7]. Besides, various defects that compromise part quality are likely to occur during the manufacturing process [6]. As a result, a batch of AM parts might have different levels of conformity even though the same design and process parameters are selected.

Machine learning (ML)-based process monitoring and quality prediction in AM (PQ-AM) have been extensively researched to overcome the reliability issue [8]. Inspired by cybermanufacturing, sensors including digital cameras and accelerometers are deployed to collect data from the AM system during or after the manufacturing process [9]. Using ML, the salient representations embedded in the collected data are extracted and correlated with the associated labels such as the defect type and part quality.

Although PQ-AM systems offer abundant potential to improve the reliability of AM processes, the reproducibility of the reported works has not been investigated. The reproducibility of scientific research characterizes its ability to be reproduced by others for the same results [10]. In the manufacturing domain, researchers contribute to the community mainly by publishing their work to show the feasibility and effectiveness of their proposed methodologies or systems. Critical information that fulfills reproducibility requirements in a publication allows the

readers to reproduce the proposed method and thus helps increase the impact and trustability of the authors. Besides, surveys conducted by Pineau et al. [11] revealed that papers with high reproducibility levels are more likely to be accepted.

ML-based PQ-AM is an interdisciplinary field that involves both AM and ML domain knowledge, which increases the difficulty of ensuring reproducibility. Apart from providing sufficient information about the AM and monitoring technologies, information about the dataset and model must be clearly presented [11]. Additional critical reproducibility information encompasses but is not limited to feature extraction, data preprocessing, ML algorithms, and model evaluation [11-13]. In fact, most ML-based monitoring research in manufacturing faces reproducibility challenges due to their interdisciplinarity, including machine fault diagnostics and production line scheduling. To the best of our knowledge, there has not been a reproducibility guideline or checklist for process or condition monitoring systems employing both ML and engineering domain knowledge.

This paper proposes a pipeline that systematically investigates the reproducibility of in-process and in-situ PQ-AM (IIPQ-AM) systems using the CRoss Industry Standard Process (CRISP) methodology, which is a process model for data mining projects [14]. An IIPQ-AM system reproducibility checklist is also proposed to guide the authors through the fulfillment of the reproducibility requirements. A case study that reproduces a vision-based fused filament fabrication (FFF) warping detection system was conducted to validate the reproducibility checklist. The contributions of this paper are:

- Defined the reproducibility of ML-based IIPQ-AM systems.
- Designed an IIPQ-AM reproducibility investigation pipeline that investigates the reproducibility of systems proposed by others based on the CRISP methodology.
- Proposed an IIPQ-AM reproducibility checklist to help authors achieve high reproducibility for their original systems.
- Implemented a case study to demonstrate and validate the reproducibility investigation pipeline and checklist.

The remainder of this paper is organized as follows. Section 2 reviews the existing reproducibility research of AM and ML, and then defines the reproducibility of IIPQ-AM. Section 3 elaborates on the reproducibility investigation pipeline and reproducibility checklist. Section 4 reproduces an IIPQ-AM system using the proposed method. Section 5 highlights the remarks of this research.

2. BACKGROUND

Reproducibility is a crucial measure of the transparency and authenticity of a published work. Although reproducibility definitions and rules have been established, the lack of reproducibility in scientific research is becoming a serious challenge for scientific discovery. A reproducibility survey conducted by Baker [15] was distributed to multiple domains such as chemistry and physics, and responses from 1576

researchers were obtained. It revealed that more than 60% of the respondents experienced failure when reproducing others' results, although 66% of them claimed that reproducibility procedures have been established in their laboratories. Lack of reproducibility was also revealed by surveys in biomedical [16], cancer biology [17], and psychology [18] domains.

Reproducibility, repeatability, and replicability have been defined and investigated for AM and ML, respectively. The three terminologies all aim to produce the same results or methods as the original research but are under different conditions (Table 1). For AM, repeatability means achieving the same precision while manufacturing the same part by the same operator and with the same equipment. In contrast, reproducibility concerns a different operator and different equipment [19]. Pineau et al. [11] adopted the definitions of ML reproducibility and replicability, which represent producing the same results using the same model with the same and different data, respectively. Association for Computing Machinery (ACM) [20] differentiates the reproducibility, repeatability, and replicability of artifacts according to the group and experiment setup. Adapted from AM and ML domains, the definitions of these three terminologies for IIPQ-AM are established and provided in Table 1.

Table 1: Definitions of reproducibility, repeatability, and replicability in relevant domains.

Domain	Reproducibility	Repeatability	Replicability
AM [19]	Same precision	Same precision	Not defined
	Different operator	Same operator	
	Different equipment	Same equipment	
ML [11]	Same result	Not defined	Same result
	Same data		Different data
	Same model		Same model
Artifact [20]	Same result	Same result	Same result
	Different group	Same group	Different group
	Different experiment setup	Same experiment setup	Same experiment setup
IIPQ-AM	Comparable performance	Comparable performance	Comparable performance
	Different group	Same group	Different group
	Different experiment setup	Same experiment setup	Same experiment setup

The reproducibility in AM usually concerns the ability to manufacture a part with certain desired characteristics (e.g., structure and properties). Kim et al. [21] defined producibility, repeatability, and reproducibility in AM with respect to the information elements of AM digital thread. Producibility concerns basic and fundamental information required to build a part. Repeatability incorporates information elements of the process such as system-dependent and system-independent components. Repeatability guides the completion of the same AM process without any consideration of resulting characteristics. Part reproducibility extends the information thread to include elements of structure and/or property and ensures that the manufactured part meets these requirements. The terms repeatability and reproducibility also extend to AM

techniques of quality inspection and part evaluation that are used to generate data for IIPQ-AM. In a related work, Seo et al. [22] termed repeatability as process repeatability and reproducibility as part reproducibility to present a quality assurance framework in AM. Cacace et al. [23] tested the repeatability (e.g., consecutive measurements) and reproducibility (e.g., measurements after system disassembly) for an X-ray Computed Tomography system. Gunay et al. [24] defined reproducibility in AM as the ability to produce parts under the same conditions. In their work, reproducibility was closely related to dimensional accuracy, but this could change depending on the AM application. Similarly, Petrovic et al. [25] pointed out the lack of part reproducibility in AM and linked it to insufficient quality and testing standards.

ML reproducibility faces unique challenges arising from both the data and model involved. Raff [26] independently implemented the ML algorithms proposed in 255 manuscripts, in which 63.5% of the manuscripts were considered reproducible. However, this study adopted several reproducibility criteria that are less stringent than the ones proposed in other reproducibility studies [16-18]. To help improve the reproducibility of ML research, Pineau et al. [11] proposed an ML reproducibility checklist that lists reproducibility key points with respect to the model, dataset, code, experimental results, and theoretical claim of a paper. Filling up the reproducibility checklist has been incorporated as a submission requirement for the Conference on Neural Information Processing Systems (NeurIPS) since 2018. Moreover, Reproducibility Challenges have been held since 2018 in prestigious ML conferences, including the International Conference on Learning Representations (ICLR) and NeurIPS [11, 27]. Attendees of this event attempt to reproduce the results of the papers accepted by the conferences and report their attempts. Reproducibility Challenges have been attracting thousands of participants all over the world and raising awareness of ML reproducibility.

This paper focuses on the reproducibility of IIPQ-AM systems, which is a joint domain of AM and ML. An IIPQ-AM system typically consists of four elements:

- 1) **Manufacturing system:** The manufacturing system encompasses the manufacturing process technology, the associated hardware, and the printing material(s). The hardware and materials could be off-the-shelf, or custom-designed for a given system.
- 2) **Sensing system:** The sensing system represents the sensing or monitoring technology, associated hardware, and its configuration.
- 3) **Dataset:** Data collected from the manufacturing system, along with the transformation techniques applied to obtain the data for ML.
- 4) **Model:** The proposed ML model, including its hyperparameters, training methods, and model selection techniques.

Adapted from the existing reproducibility definitions in AM and ML, the definition of reproducibility for IIPQ-AM systems

is proposed: To fulfill the reproducibility requirements, an IIPQ-AM system should be reproduced (Table 1):

- **With different experiment setup:** The experiment setup of the original manufacturing and sensing system might not be suitable or readily available for the specific reproduction purpose. Information about the experiment setup should be clearly conveyed for the readers to understand and develop their own system.
- **By a different team:** The reproduction procedure is taken by a team where the original team that proposed the system is not involved. This new team might lack information or expertise while reproducing the system.
- **To obtain comparable performance:** Reproduction of IIPQ-AM systems faces the challenges of reproducing both the hardware and software systems. Instead of aiming at achieving the claimed performance, it is more realistic to achieve a performance that is comparable to the original systems.

Although the number of IIPQ-AM publications increases rapidly, the reproducibility of the research works has not been investigated and regulated. Thus, this domain urgently needs a method for authors and readers to verify the reproducibility of a research. The following sections will analyze IIPQ-AM systems, propose a reproducibility investigation pipeline accompanied by a checklist, and evaluate the proposed method.

3. METHODOLOGY

This section analyzes IIPQ-AM systems and designs the reproducibility investigation pipeline and checklist. First, an IIPQ-AM reproducibility investigation pipeline is established based on CRISP. Thereafter, an IIPQ-AM reproducibility checklist is composed to evaluate the reproducibility of each phase in the investigation pipeline. The objective of this pipeline and checklist is to establish a method that helps the authors and readers check if the manuscript provides the necessary information to reproduce the system. Dictated by the special objective, this method must include all critical reproducibility requirements, while not overwhelming the readers with too many details. Therefore, this method must reach a balance between comprehensiveness and concision.

3.1. IIPQ-AM Reproducibility Investigation Pipeline

The CRISP methodology is utilized to investigate IIPQ-AM systems and design the reproducibility investigation pipeline for IIPQ-AM publications. The CRISP methodology is a widely recognized data mining process model, consisting of six phases that can be applied to different business contexts including AM (Figure 1) [14]. Therefore, the replication and reproduction of any IIPQ-AM system can be modeled using CRISP. This subsection proposes a reproducibility investigation pipeline that segregates the reproduction efforts into six phases based on CRISP (Figure 2). The purpose of this pipeline is to guide the reproduction of an IIPQ-AM system and investigate its reproducibility.

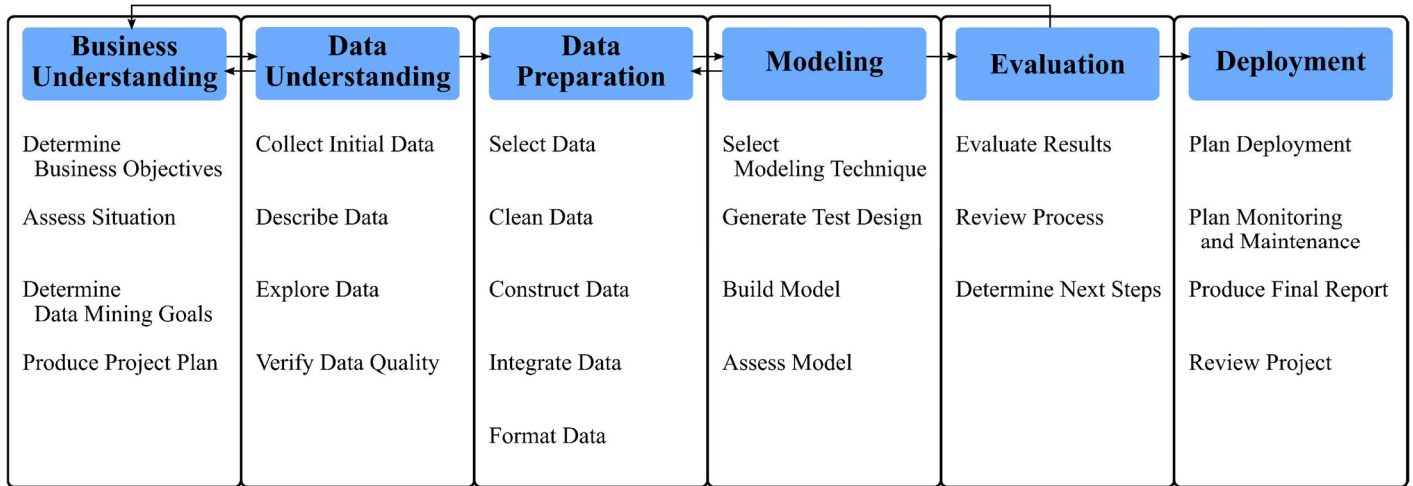


Figure 1: Phases of the CRISP process model (adapted from [14]).

Business Understanding. In the business understanding phase, the focus is to investigate the project objectives and requirements from a business perspective. The investigation results are then utilized to formulate a data mining project and a preliminary project plan. For an IIPQ-AM system, business understanding involves the investigation of the manufacturing system and the modeling purpose (Figure 2a). The manufacturing system, including the AM machine and materials, must be introduced to illustrate the manufacturing assets as building blocks of the system. The modeling purpose such as process anomaly detection and control must be discussed to illustrate the capability of the system. Besides, the physical phenomena being monitored must be discussed to bridge the manufacturing and sensing systems.

Data Understanding. The data understanding phase concerns initial data collection and analysis, where preliminary insights of the data are extracted and potential data quality challenges are identified. In this pipeline, data understanding focuses on the sensing system and raw datasets (Figure 2b). Before the physical phenomena are captured by the sensors, various supporting apparatus can be utilized to filter out undesirable signals or signify the target signals. Different sensors are deployed according to the physical phenomena being monitored. Note that the same sensing system can yield datasets with different quality and characteristics. For example, different sensor calibrations and settings will lead to different data quality. Data biases might be introduced to the dataset during the experimental design phase. Lastly, the raw datasets acquired using the sensing system must be elaborated, including the data formats, modality, and statistics.

Data Handling. We use data handling to represent this phase to cover most data transformation techniques, including data preparation and data preprocessing (Figure 2c). Data preparation techniques leverage engineering domain expertise to

transform and align raw datasets. Data preprocessing techniques transform the data into a suitable form for machine learning to improve the learning performance [13]. The final datasets fed into the ML models are obtained after applying the transformations.

Modeling. The modeling phase involves selecting the modeling techniques, training the ML models, and preliminarily testing the models (Figure 2d). For the modeling phase of IIPQ-AM, candidate ML algorithms are first selected according to the modeling task and data modality. A hyperparameter search technique is then determined to search for the optimal hyperparameters for each candidate ML algorithm. Afterward, a batch of ML models is trained according to the selected ML algorithms and hyperparameter search technique using the designated infrastructure.

Evaluation. Evaluation encompasses the assessments of the previous steps and the results (Figure 2e). In this pipeline, some appropriate metrics must be defined to evaluate the ML models according to the modeling task. A model selection strategy helps select the optimal model using the metrics. Thereafter, the optimal performance of the IIPQ-AM system is obtained during the evaluation phase.

Deployment. In this phase, the ML model is being deployed to make decisions and guide future AM activities (Figure 2f). It is crucial to understand the hardware and software requirements to deploy the IIPQ-AM system. Failure to meet the requirements would compromise the model performance and/or cause interoperability issues.

3.2. IIPQ-AM Reproducibility Checklist

This section presents the IIPQ-AM reproducibility checklist in detail. Each reproducibility is elaborated with definitions, discussions, and examples.

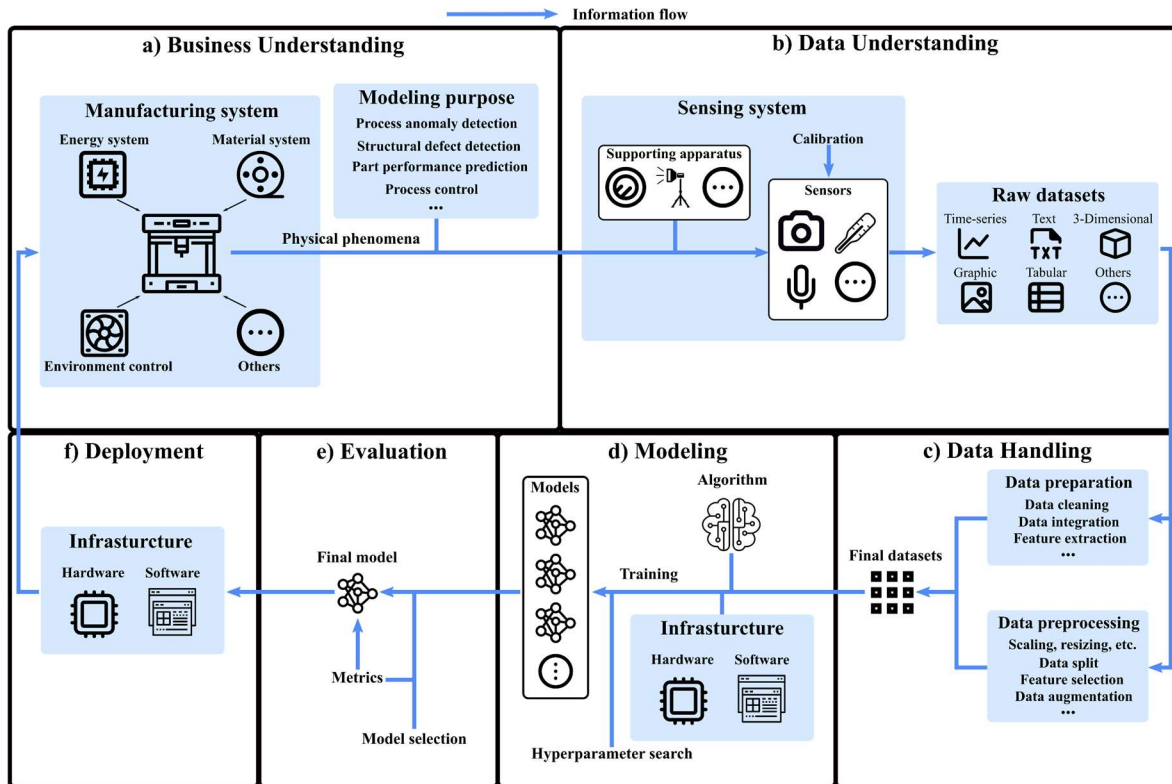


Figure 2: IIPQ-AM reproducibility investigation pipeline based on CRISP.

3.2.1. Business Understanding

Special notes on the AM system: Much of the IIPQ-AM research is expected to involve a well-known AM technology such as the seven standardized AM process techniques by ASTM [28]. A manufacturing system in AM consists of the AM technology under focus and the associated components of its printing setup including the materials used to print parts. In their introduction to AM technologies, Gibson et al. [29] provided a description of major process technologies and associated manufacturers of AM systems. The manufacturing system in this study represents concise information that is critical for setting up a system to reproduce parts for a specific AM process technology. In some applications, a customized manufacturing system can lead to additional information critical for reproducibility. In this regard, an AM system can be represented by different subsystems such as material feeding, energy supply, part handling or positioning, and environment control among others. Material feeding system supports layer-wise addition of feedstock according to the process plan. All AM technologies are dependent on energy (direct or indirect) to carry out the build process. Handling system dynamically supports the substrate or under-build part for the deposition process. environment control system ensures specific conditions in the build environment for certain applications. The customization-specific system-level information is needed to reproduce parts across laboratories or production shops as indicated by the relevant section in the checklist.

RQ1. Is the manufacturing system encompassing process technology and associated hardware component(s) reported?

Explanation: Since a majority of the systems are expected to be original off-the-shelf AM machines with standard process technologies from suppliers such as Optomac, EOS, Renishaw, Desktop Metal, 3D Systems, and similar companies, the first question concerns the model details and description of the base manufacturing or printing system. If this information is clearly provided, it could help the researchers find detailed descriptions of the system from original suppliers aiding the reproducibility of the manufacturing system.

RQ2. If applicable, is customization of the manufacturing system reported?

Explanation: In some research and development scenarios, it is expected that the printing setup is customized by integrating designated components into the base manufacturing system. The second question under manufacturing systems in the reproducibility checklist concerns such customized systems where the individual components are either resourced from different suppliers or developed in-house. As a result, specific information on these components (e.g., energy, material feeding, part handling, cooling, and environmental control) should be elaborated accordingly. The scope of customization also extends to materials and process technology.

RQ3. Are characteristics of the material system reported?

Explanation: Finally, the characteristics of the material system used to fabricate the test specimen are also included in this section of the reproducibility checklist as the last question.

In this regard, material name, grade, and associated specifications need to be provided.

RQ4. Is the modeling purpose discussed?

Explanation: This question reveals the modeling task of the IIPQ-AM system. Typical modeling tasks include AM process anomaly detection, structural defect detection, part performance prediction, and process control. Discussing the modeling purpose helps justify the selections of the sensing system configurations, data handling techniques, and ML models.

RQ5. Are the physical phenomena being captured by the sensing system introduced?

Explanation: This question bridges the manufacturing and sensing systems. In IIPQ-AM, the input data captured by the sensing system are fed into the ML model to perform the prediction task. A sensing system captures the physical phenomena occurring in the AM system, which contains important information about the modeling task. Physical phenomena include both the AM process concern (e.g., melt pool and thermal gradient) and the signal (acoustic emission, vibration, and infrared light) being captured.

3.2.2. Data Understanding

Special notes on the sensing system: Given the focus on ML-driven AM research, we separate the sensors from base AM systems as these are critical to generating the data that drives such applications. AM has a rich ecosystem of sensors, thanks to complex multi-phase and multi-physics process phenomena. In their review on condition monitoring of metal AM, Zhu et al. [9] categorized AM sensing technology based on the signals captured during the process. These include optical, thermal, acoustic, and vibration sensors with optical and acoustic types as the most frequent in AM. In order to reproduce ML-driven AM research, the information on sensors integrated into AM systems is critical, as highlighted by the reproducibility checklist. The critical information to reproduce the sensing system has been divided into sensing technology, sensor type, sensor specifications, sensor deployment settings, and sensor usage details as indicated in the reproducibility checklist.

RQ6. Are sensor type(s) and specification(s) provided?

Explanation: The sensor specification information must be provided to decide which sensors should be deployed while reproducing the system. The selection of similar sensors ensures that data are acquired with similar fidelity, which increases the success rate of the reproduction. Typical sensor types in AM include optical cameras, infrared cameras, photodiodes, pyrometers, acoustic emission sensors, microphones, ultrasonic transducers, and accelerometers [9]. If off-the-shelf sensors are deployed in the original system, their serial numbers can usually reveal the sensor specifications. When it is not available, a set of specifications necessary for sensor selection should be presented to obtain similar data fidelity. For example, to describe the basic specifications of a high-speed camera, its resolution, pixel size, frame rate, and exposure time range should be provided.

RQ7. Are the sensor settings or calibration details discussed?

Explanation: Information regarding how the sensors are tuned and calibrated to adapt to the sensing task must be

provided. Within the specifications, the sensors can be tuned or calibrated to capture the specific signals of interest. Taking a high-speed camera as an example, the sampling rate should be calibrated to align with the manufacturing process. Overly high or low sampling rates will result in redundant or missing information, respectively. The resolution of a camera should be calibrated according to the size of the region of interest (ROI). Overly large or small resolutions will result in both noises and missing information. Other typical settings and calibrations include zooming, brightness, sampling rate, contrast ratio, shutter speed, and focal length.

RQ8. Are the sensor deployment details discussed?

Explanation: The physical setup of the sensing system must be elaborated, including where and how the sensor is attached to the manufacturing system, as well as the setup of the supporting apparatus. For example, the location, angle, and field of view of a camera must be provided. The location, angle, and light intensity of any light sources should be discussed. If any filters are deployed, their locations and functions must be illustrated.

RQ9. Are the data modalities, formats, and types introduced?

Explanation: The modalities, formats, and types of raw and final datasets should be introduced. For example, the datasets can be tabular, graphics, 3-dimensional, time-series, and textual. Even if two datasets are both tabular, they might have different formats (e.g., .csv, .txt, and .xlsx). The data types of the variables should also be discussed. For example, variables can be categorized into nominal, ordinal, discrete, and continuous. Clear descriptions of the data formats and types will increase the compatibility while reproducing the systems.

RQ10. Are the relevant statistics provided?

Explanation: The statistics of the raw and the final datasets such as data quantity, number of input variables, and number of classes should be discussed if applicable. Data are the foundation of ML-based modeling and should be clearly presented. The statistics should be provided for the raw data, data after each transformation, and the final dataset. This question informs the status of the datasets as they through transformations. It also helps reveal potential data imbalance and scarcity issues, which compromise the training and testing of ML models.

RQ11. Are the experimental design settings for data acquisition introduced?

Explanation: The values of the experimental parameters used to design the experiments for data acquisition must be presented, including the fixed and variable parameters. The experimental parameters can be categorized into part design parameters and AM process parameters. The part design parameters include the geometry, materials, orientation, and configuration of the part. Different AM processes involve different process parameters to be introduced. For example, typical process parameters for FFF include the print bed temperature, nozzle temperature, print speed, layer height, and infill percentage [30]. The sampling method of data acquisition must also be discussed. Together with the statistics of the raw data, this question ensures that the raw data can be reproduced using similar experimental parameters and sampling methods.

3.2.3. Data Handling

RQ12. Are the data preparation techniques discussed, if any?

Explanation: This question concerns the techniques that leverage engineering domain expertise to transform and align raw datasets (e.g., data cleaning, feature extraction, data integration, and data registration). Unlike the ML domain which primarily focuses on data preprocessing, data preparation plays a vital role in industrial ML applications where data are acquired from multiple complex sources. For example, time- and frequency-domain features frequently used in signal processing can be extracted from the raw time-series data as representative features. Texture and contour features developed by computer vision can be extracted from images as representative features. Data from different sources must be registered and integrated at appropriate scales and rates using industrial expertise before training ML models. These data preparation methods, if utilized, must be provided to highlight what domain expertise is required to transform and align the datasets.

RQ13. Are the data preprocessing techniques discussed, if any?

Explanation: This question concerns the techniques that transform the data into a suitable form for machine learning and that improve the learning performance must be discussed (e.g., scaling, resizing, data split, sliding window, feature selection, and data augmentation). This question focuses purely on the data preprocessing techniques from the ML domain. Any techniques that are utilized to preprocess the datasets to obtain the final input and output data for ML should be presented.

RQ14. Is there a link to a downloadable version of the dataset?

Explanation: A downloadable version of the dataset will significantly reduce the effort of reproduction. The number of experiments to reproduce the system can be reduced using knowledge transfer if the original dataset is available.

3.2.4. Modeling

RQ15. Is there a clear description of the machine learning algorithm?

Explanation: This question concerns the descriptions of the ML algorithm, which do not include the specific hyperparameters and training methods of the final model. The descriptions of the ML algorithm include the algorithm type (e.g., diffusion models and transformers), type of learning task (e.g., regression, classification, clustering, supervised, semi-supervised, and unsupervised), and specialization (e.g., multifidelity, multiscale, multimodal, and multiobjective). This question establishes a fundamental understanding of the ML algorithm before the elaboration of the trained models.

RQ16. Are the details of the model described?

Explanation: The structure/architecture of the final model(s) must be exhibited. For example, the number of hidden layers, the number of neurons in each layer, and associated information of DNNs should be provided. Also, computational complexity should be discussed. This is to ensure that the readers can reproduce the architecture of the model(s) proposed in the original paper.

RQ17. Are the details of model training described?

Explanation: The methods and settings of the ML training procedure must be presented. First, the optimizer must be discussed to reveal which optimization method is chosen, how the learning rate is adjusted, and how the early stopping scheme is scheduled, if applicable. Second, the special machine learning strategy, if any, must be elaborated, including transfer learning, active learning, ensemble learning, and federated learning. This is to ensure that the readers can obtain the same trained models as the original paper.

RQ18. If applicable, are hyperparameter search and selection procedures explained?

Explanation: This question concerns the process of how hyperparameters are determined for the selected model(s) (e.g., randomized search and Bayesian optimization). Hyperparameter search and selection is a critical process in ML that may induce randomness and data leakage, which compromises the generalizability of the selected model. It also helps ensure that the best models are selected from each candidate ML algorithm for comparison to show the advantages of the proposed method. Apart from enhancing the trustworthiness, this question ensures that the readers can select the same ML model as the original paper.

RQ19. Is the final trained model shared?

Explanation: A downloadable version of the model will significantly increase the success rate of reproduction. The readers can investigate the model architecture and performance by accessing the model.

RQ20. Is the code open access or provided?

Explanation: A downloadable version of the code will significantly reduce the effort of reproduction. To reproduce the work, the readers will not need to implement the ML architecture, training procedure, and hyperparameter search if the code is provided.

3.2.5. Evaluation

RQ21. Are the methods and metrics of model selection illustrated?

Explanation: The methods (e.g., cross-validation) and metrics (e.g., accuracy and F1-score) to evaluate the model performance should be discussed. The suitability of the evaluation methods and metrics with respect to the dataset, ML model, and application task should be demonstrated. This question ensures that the readers understand and utilize the same evaluation strategies as the original paper.

3.2.6. Deployment

RQ22. Is the computational hardware described?

Explanation: The computational resources and infrastructure must be provided to inform the readers of the computational power the authors utilized to train the model(s).

RQ23. Is the computational software described?

Explanation: The specifications of dependencies such as the packages and virtual environments used to obtain the proposed models must be introduced for the reproduction. The models obtained from different computational environments can be

different even if the same ML architecture, training procedure, and hyperparameter search are deployed.

4. CASE STUDY

This section conducts a case study that implemented the investigation pipeline and filled the reproducibility checklist while reproducing a published IIPQ-AM system [31] (Figure 3). First, the published system was reproduced using the proposed pipeline, during which the missing information on the checklist was identified. Afterward, the authors of the publication were contacted to gather the missing information, with which the system was reproduced again. The checklist was iteratively updated through communication to fulfill all reproducibility requirements. Finally, the effectiveness of the proposed method was analyzed by comparing the performances of the original system, the reproduced system with published information only, and the reproduced system with complete reproducibility information obtained from the original authors.

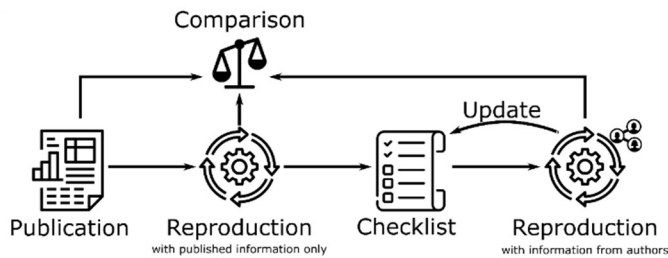


Figure 3: Implementation of the case study.

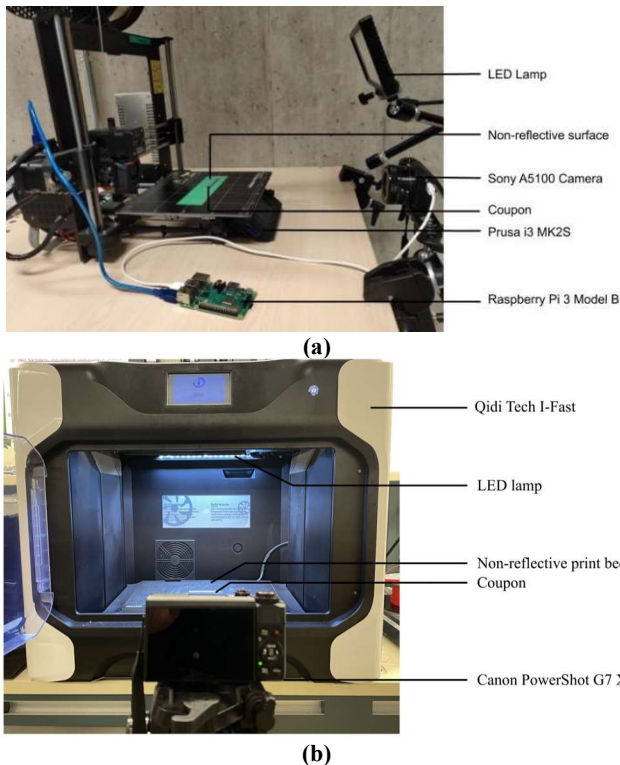


Figure 4: The experiment setup of the a) original (adapted from [30, 31]) and b) the reproduced IIPQ-AM systems.

4.1. Implementation

This case study reproduces an IIPQ-AM system that detects warping using a camera and a convolutional neural network (CNN) model during the FFF process (Figure 4a) [31]. The print is terminated to avoid material waste and machine damage once any warping is detected. This system is representative in this domain because 1) FFF is one of the most popular AM processes for recreation, production, and research; 2) Vision-based monitoring systems with cameras are widely deployed.

The reproduction goal of this case study was to reproduce a vision-based warpage detection system to terminate the print if warping occurs. The monitoring system was deployed for a Qidi Tech I-Fast FFF 3D printer at the Additive Design and Manufacturing Lab (ADML) (Figure 4b). The reproduced system was constructed using the instrument and resources available at ADML.

Table 2 records the reproduction process of the selected IIPQ-AM system. The reproducibility investigation pipeline was implemented phase-by-phase to reproduce the original system. The reproducibility questions of each phase were sequentially answered to investigate the reproducibility of the original work and to compose a reproduction plan for the reproduced system. If a reproducibility question is answered in the original paper, the users will check the associated box and record the answers. If a question is partially answered or not answered, the users will leave the box empty, record the available information, and identify the missing reproducibility information. With the available information, the users will design the reproduced system according to their goals and resources.

Table 2: The implementation of the reproducibility investigation pipeline and the reproducibility checklist.

<i>Business Understanding</i>	
<input checked="" type="checkbox"/>	RQ1. Is the manufacturing system encompassing process technology and associated hardware component(s) reported? The original AM machine was an off-the-shelf Prusa i3 MK2S FFF 3D printer. The system was reproduced for an off-the-shelf Qidi Tech I-Fast FFF 3D printer.
<input checked="" type="checkbox"/>	RQ2. If applicable, is customization of the manufacturing system reported? No customization was implemented for the original or reproduced systems.
<input checked="" type="checkbox"/>	RQ3. Are characteristics of the material system reported? Both the original and reproduced systems used white polylactic acid (PLA) filament with a diameter of 1.75 mm.
<input checked="" type="checkbox"/>	RQ4. Is the machine learning modeling purpose discussed? The modeling purpose is to detect warping during the FFF process to avoid material waste and machine damage.
<input checked="" type="checkbox"/>	RQ5. Are the physical phenomena being captured by the sensing system introduced? The physical phenomenon being monitored was the part geometry.
<i>Data Understanding</i>	
<input checked="" type="checkbox"/>	RQ6. Are sensor type(s) and specification(s) provided? The original and reproduced systems were equipped with a Sony A5100 digital camera and a Canon PowerShot G7 X digital camera, respectively.

<input type="checkbox"/> RQ7. Are the sensor settings or calibration details discussed? The sensor settings or calibration details are not discussed in the original paper. However, the example images exhibited in the original paper can reveal some calibration information. No special filters or modes were applied because the example images are regular RGB images. The camera was not specially calibrated except that the focal length was adjusted to focus on the part. Therefore, the camera of the reproduced system was also calibrated to focus on the part.
<input checked="" type="checkbox"/> RQ8. Are the sensor deployment details discussed? In the original system, the camera was fixed in front of the 3D printer at the same height as the print bed using a desk camera mount (Figure 4a). A non-reflective tape was stuck to the print bed to enhance the image quality. An LED lamp was deployed as the light source to increase the light intensity and remove the shadow. The reproduced system mounted the camera at the same height as the print bed using a tripod. A non-reflective print bed and an LED lamp were also deployed to replicate the original experiment setup (Figure 4b).
<input checked="" type="checkbox"/> RQ9. Are the data modalities, formats, and types introduced? The raw and final input data are RGB and grayscale images, respectively.
<input checked="" type="checkbox"/> RQ10. Are the relevant statistics provided? The raw dataset consists of 520 RGB images with red, green, and blue channels. The resolution of the raw images is 6000×4000 pixels (Figure 5). The dataset has two classes: images of parts without warping and images of parts with warping. There is no data imbalance in this dataset because each class has 260 examples. The final dataset is comprised of 520 grayscale images with one channel and a resolution of 100×100 pixels.
<input checked="" type="checkbox"/> RQ11. Are the experimental design settings for data acquisition introduced? In the original experiments, the printing processes of the rectangular coupons were monitored using the experiment setup in Figure 4a. An image was captured when the print was dwelled at the end of each layer. Warpage was created by manually peeling the part from the print bed at early layers. The warping angles kept increasing as the thermal stress built up through the subsequent layers. The reproduced system used the same approach to set up the experiment, create warping, and capture layer-wise images. The FFF process parameters provided in the original paper were selected for the reproduced system.
Data Handling
<input type="checkbox"/> RQ12. Are the data preparation techniques discussed, if any? The original system did not involve many data preparation techniques. The only noticeable data preparation is cropping the ROI, which is the corner of the part shown in Figure 5. However, the original paper did not discuss the method to identify and crop the ROI. Therefore, the images were cropped manually with the part corners at the center for the reproduced system (Figure 5).
<input type="checkbox"/> RQ13. Are the data preprocessing techniques discussed, if any? According to the original paper, the raw dataset was shuffled and split into a training and a test set of 416 and 104 images, respectively. Resizing and grayscaling were then applied to the cropped images. One-hot encoding was utilized to label images of different classes. Additionally, the training set was further split into a training and a validation set. However, the split ratio was not provided.
<input type="checkbox"/> RQ14. Is there a link to a downloadable version of the dataset? The dataset is not publicly available but is available upon request.

Modeling
<input checked="" type="checkbox"/> RQ15. Is there a clear description of the machine learning algorithm? The selected machine learning algorithm was CNN. The original paper clearly described the structure of a CNN model, including the convolutional layers, pooling layers, fully connected layers, and activation functions.
<input type="checkbox"/> RQ16. Are the details of the model described? The original paper clearly exhibited most of the hyperparameters of the final model, including the activation functions, dropout rate, number of hidden layers, number of hidden neurons in each layer, kernel sizes, stride, and activation functions. However, the initial learning rate was not discussed.
<input checked="" type="checkbox"/> RQ17. Are the details of model training described? Adam optimizer was used to train the CNN model for 50 epochs. An early stopping mechanism was implemented to terminate the training process when the validation loss converged. The same training method was implemented for the reproduced system.
<input type="checkbox"/> RQ18. If applicable, are hyperparameter search and selection procedures explained? The hyperparameter search and selection method was not discussed in the original paper. A self-defined hyperparameter optimization was implemented for the reproduced system.
<input type="checkbox"/> RQ19. Is the final trained model shared? No.
<input type="checkbox"/> RQ20. Is the code open access or provided? No.
Evaluation
<input checked="" type="checkbox"/> RQ21. Are the methods and metrics of model selection illustrated? The metric used to evaluate the model performance was classification accuracy, which was implemented for the reproduced system as well. The model selection method was not applicable as the original paper does not discuss the hyperparameter search for the proposed model.
Deployment
<input checked="" type="checkbox"/> RQ22. Is the computational hardware described? For both the original and the reproduced systems, the training and predictions of the networks were run in an Intel® Core™ i5-6300U CPU @ 2.40 GHz and 8GB memory running on Windows 10 64-bits. The Raspberry Pi in the original system controlled the camera to automatically take a picture once a layer was completed. In the reproduced system, the camera automatically took a picture at every minute.
<input type="checkbox"/> RQ23. Is the computational software described? The only information about the software is that the programming language was Python 3.6.

4.2. Results and Discussions

The selected IIPQ-AM system was first reproduced only with the available information from the original paper. The reproduced manufacturing and sensing systems were constructed as described in the business understanding and the data understanding phases (Table 2 and Figure 4). The only missing information about the two systems was the camera settings and calibration, which can be inferred from the example images in the original paper. Thereafter, experiments designed based on the original system were conducted to acquire the datasets for the

reproduced system (Figure 5). The experiments sequentially printed 30 coupons, which consisted of 15 coupons with no warping and 15 manually warped coupons. Each coupon has 20 layers and a print time of around 20 minutes. The camera started capturing images after the 6th minute of every print. Consequently, 225 images with warping and 225 images without warping were captured to train and test the ML model of the reproduced system. In the data handling phase, the data preparation and preprocessing techniques discussed in the original paper were implemented. Regarding the missing information, the cropping was centered at the part corner, and the train-validation split was set to 8:2 for the reproduced system. The ML models of the reproduced system were trained and evaluated according to the original paper. The missing information was the initial learning rate and the hyperparameter search method.

The models were trained in two ways: 1) The original hyperparameters and an initial learning rate of 0.01 (Figure 6a) and 2) A self-defined randomized hyperparameter search with self-defined hyperparameter ranges (Figure 6b). The former provided validation and test accuracies of 92.6% and 92.8%, respectively. The latter yielded an optimal model with validation and test accuracies of 95.1% and 94.9%, respectively. It can be seen that the original hyperparameters were not the optimal hyperparameters for the reproduced system. It was because the changes in the manufacturing and sensing systems imposed a domain shift on the distribution of the input image data. To address this, it is crucial to implement a hyperparameter search for the reproduced system to find the new optimal hyperparameters. Although the hyperparameter search information was missing in the original paper, the reproducers can define and conduct their self-defined hyperparameter search. However, the original hyperparameter search can be a valuable reference to determine the hyperparameters and the ranges to search. It helps increase the search efficiency and will probably lead to improved performance.

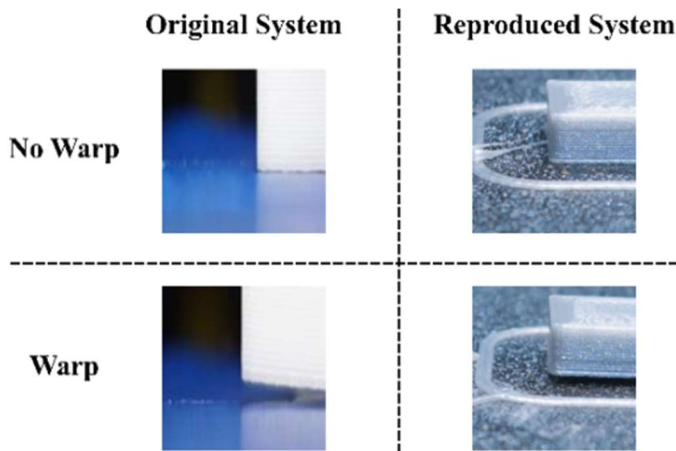


Figure 5: Examples of original and reproduced cropped images.

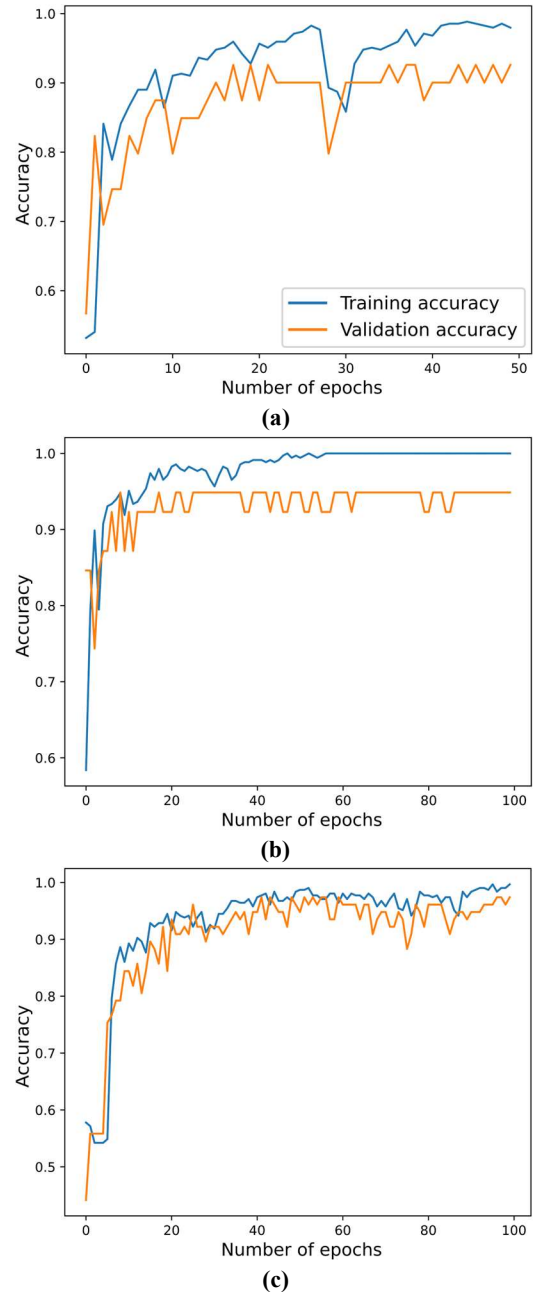


Figure 6: Accuracy curves of the reproduced CNN model when using a) The information available from the paper only and original hyperparameters; b) The information available from the paper only and a self-defined hyperparameter search; and c) Complete reproducibility information provided by the original authors and the original hyperparameter search.

The system was reproduced again with all the reproducibility information gathered from the original authors (Figure 6c). There was no special camera setting or calibration involved in the experiment except that the focal length must be adjusted to focus on the part. One experiment detail not revealed in the original paper was that non-reflective tapes of different colors were used to improve the representativeness of the

dataset. Besides, the original manual cropping only required that the part corners were included instead of centered to improve the robustness of the model. In reality, the corners cannot always be centered in the cropped image because the parts can have different positions and geometries. Therefore, data augmentation was applied to the reproduced dataset to approximate the above effects. The original train-validation split ratio was 8:2. Finally, the same hyperparameter search as the original system was conducted, including the search method (Bayesian optimization), tunable hyperparameters, and the search ranges. The optimal model had validation and test accuracies of 98.1% and 98.4%, respectively.

By obtaining and adopting the complete reproducibility information, the test performance of the reproduced system was increased from 94.9% to 98.4%, which was much closer to the 99.3% claimed in the original paper. The hyperparameter search became more efficient with the original search information. A model with higher test performance can be found using the same search resources and budgets. The newly added experiment design and data handling details successfully improved the generalizability of the model. The overfitting was reduced, leading to smaller discrepancies among the training, validation, and test accuracies.

This case study demonstrated that the reproducibility investigation pipeline can help enhance the performance of reproduced IIPQ-AM systems. The authors with the reproducibility checklist can make sure that all the reproducibility information is provided in their publications. The investigation pipeline can help the readers investigate the reproducibility of an IIPQ-AM research and guide them through the reproduction.

5. CONCLUSIONS

This paper proposed a reproducibility investigation pipeline and a reproducibility checklist for IIPQ-AM systems. Based on the CRISP methodology, the investigation pipeline was designed to guide the readers through the reproduction of an original IIPQ-AM system. During the reproduction, the proposed reproducibility check can help discover the missing reproducibility information. The checklist can also help the original authors ensure that they provide all the information necessary to reproduce the system in their publication. A case study was implemented to validate the proposed method by reproducing a vision-based warping detection system for an FFF 3D printer at ADML. Using the proposed pipeline and checklist, the test performance was improved from 94.9% to 98.4%, achieving a similar test performance to the original system.

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DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing interests.

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APPENDIX
REPRODUCIBILITY CHECKLIST

Additive manufacturing process monitoring and quality prediction systems
Jiarui Xie, Mutahar Safdar, Andrei Mircea, Yan Lu, Hyunwoong Ko, Zhuo Yang, Yaoyao Fiona
Zhao*
Version 1.0 – clean version

Business Understanding

- RQ1. Is the manufacturing system encompassing process technology and associated hardware component(s) reported?
- RQ2. If applicable, is customization of the manufacturing system reported?
- RQ3. Are characteristics of the material system reported?
- RQ4. Is the machine learning modeling purpose discussed?
- RQ5. Are the physical phenomena being captured by the sensing system introduced?

Data Understanding

- RQ6. Are sensor type(s) and specification(s) provided?
- RQ7. Are the sensor settings or calibration details discussed?
- RQ8. Are the sensor deployment details discussed?
- RQ9. Are the data modalities, formats, and types introduced?
- RQ10. Are the relevant statistics provided?
- RQ11. Are the experimental design settings for data acquisition introduced?

Data Handling

- RQ12. Are the data preparation techniques discussed, if any?
- RQ13. Are the data preprocessing techniques discussed, if any?
- RQ14. Is there a link to a downloadable version of the dataset?

Modeling

- RQ15. Is there a clear description of the machine learning algorithm?
- RQ16. Are the details of the model described?
- RQ17. Are the details of model training described?
- RQ18. If applicable, are hyperparameter search and selection procedures explained?
- RQ19. Is the final trained model shared?
- RQ20. Is the code open access or provided?

Evaluation

- RQ21. Are the methods and metrics of model selection illustrated?

Deployment

- RQ22. Is the computational hardware described?
- RQ23. Is the computational software described?