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CRITICAL REVIEW

Machine condition monitoring for defect detection in fused deposition modelling process: a review

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Abstract

Additive manufacturing (AM), also known as 3D printing (3DP), refers to manufacturing technologies that build up the desired geometries by adding materials layer by layer. Common meltable and fusible materials such as polymers, metals, and ceramics could be used in 3DP processes. During decades of development, products made by 3DP can now achieve stringent industrial standards at comparable costs compared to those traditionally manufactured. Improving 3DP technologies is required to make them more competitive and acceptable than their counterparts. However, achieving this is challenging since the quality of printing products is still heavily dependent on many cost-driven factors. Inadequate quality, impaired functionality, and reduced service life are three main consequences of 3DP's failures. To effectively detect and mitigate defects and failures of 3DP products, machine condition monitoring (MCM) technologies have been used to monitor 3D printing processes. With the help of those dedicated algorithms, it could also prevent failures from occurrence by alerting operators to take appropriate actions accordingly. This study systematically reviews the MCM technologies used in a typical 3DP process—the fused deposition modelling (FDM), identifying their advantages and disadvantages. The mentioned MCM technologies include but are not limited to traditional MCM (sensors only), aided with analytical and artificial intelligence (AI) tools. The MCM techniques focus on the defects of the 3DP process. The detection and identification of those defects are investigated. Furthermore, research trends on developing MCM technologies, including challenges and opportunities, are identified for improving the FDM process. This review highlights the developed methodologies of MCM that are applied to FDM processes to detect and identify abnormalities such as defects and failures. The evaluations of defects are elaborated to deepen the comprehension of the essence of the defects, including their cause, severity, and effect. A detailed deliberation about identifying the critical components for the successful application of 3DP MCM systems was done. Finally, this review indicates the technical barriers that need to be overcome to enhance the performance of monitoring, detection, and prediction by MCM and associated technologies.

Keywords Additive manufacturing (AM) · 3D printing (3DP) · Fused deposition modelling (FDM) · Machine condition monitoring (MCM) · Defects and failures

1 Introduction

3D printing (3DP) is an emerging advanced manufacturing technology invented in the early 1990s. It was initially named Rep-Rap but is often termed as 3DP, AM, or rapid prototyping (RP) [1]. Traditional subtractive manufacturing technologies remove parts from an existing stock of materials to achieve the desired geometry, whereas the 3DP technologies create the product by adding materials layer by layer to an empty platform. Its layer-by-layer manufacturing process makes it more eco-friendly as the ratio of material usage and wastage is higher than that of traditional manufacturing. In the meantime, meltable and fusible materials used in 3DP processes have higher recyclability compared to the dominant steel materials that are often used in traditional manufacturing. The polymer-based fused deposition modelling (FDM), also known as fused filament fabrication (FFF), is the most widely used and economical technology among diverse types of 3DP technologies. The FDM method

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features the benefits of low cost, low material waste, simple operation, environmentally friendly, etc. [1, 2]. Commonly used polymers in FDM include ABS, PLA, and PET/PETG. Apart from FDM, other popular 3DP technologies include stereolithography (SLA), selective laser melting (SLM), and electron beam melting (EBM) [3], which utilise other materials such as metal, resin, and ceramic [1].

As a new trend in the manufacturing process, 3DP is becoming popular and known in many fields, such as medical [4], biomedical [5], construction [6], aerospace [7], tissue engineering [8], and reverse engineering [9]. The market value of 3D printing was 7.3 billion, which took 0.06% of global manufacturing in 2019 [10], and the value increased to 15.1 billion in 2022 [11] due to the COVID-19 pandemic and subsequent economic crisis impact on traditional manufacturing. Nevertheless, it is still a niche compared to those traditional manufacturing technologies. High failure rates and potential product deficiencies are the primary hindrances for current 3DP technologies to reach their full potential and become competitive enough when facing traditional manufacturing technologies. Common failures of 3DP products, like printing misalignment, could result in increased production costs or even the abortion of products. The defects, such as rough surface finish, material porosity, and body cracks, could occur during the 3D printing process, leading to product malfunctioning and potential danger in operation. The 3D printing d/f causes a large amount of filament waste. A survey from Filamentive [12] indicated that 10% of filaments are wasted, and 80.98% of the wasted filaments are due to failed prints. This necessitates the improvement of the reliability and consistency of 3DP processes. Plastic waste from 3D printing in the UK was evaluated to be 1.5 Mkg/year [13]. The waste in filaments weakens the sustainable nature of 3D printing. It is critical to control and reduce the defects and failures for strengthening the 3DP competitiveness as sustainability is one of the primary benefits of 3DP technology.

Critical steps to deal with defects or failures during the 3DP processes are to detect, identify, and mitigate. As a widely used technique in many industrial production sectors, machine condition monitoring (MCM) helps ensure product quality, making it an ideal approach to improve the 3DP processes.

An established MCM system receives digital or image data from different kinds of sensors. The data is extracted and analysed, demonstrating the corresponding properties of monitored data. The operator can understand the condition and provide prompt reaction if any abnormality is observed. The advanced MCM system could predict the defects. However, the development of MCM for 3DP processes is still ongoing. An efficient, standardised, and modularised MCM system can help the 3DP processes expand in scale and popularity to achieve mass production. Hence, this review is dedicated to gauging the maturity of this approach in terms of its feasibility in 3DP processes.

Adapting the existing industrial monitoring system to the 3DP processes directly is not easy because any obtained data during the 3DP processes by existing MCM systems cannot be directly interpreted into useful information. Correctively interpreting the obtained data requires comprehensive monitoring schemes, dedicated processing algorithms, and careful consideration of contextual physical applications. Artificial intelligence (AI) is a type of data processing algorithm that can learn from historically processed data to properly extract and classify the obtained data and thus correlate them with potential 3DP failures. However, the validity of the obtained data (in-situ and real-time) is the key to successfully implementing a dedicated 3DP monitoring system. Despite the challenges, published research focused on realising in-situ and real-time monitoring techniques for 3DP, especially for the FDM process. Carrying out the FDM process is cheaper and simpler than other AM processes [14].

Many researchers are devoted to developing methods to eliminate defects and failures (d/f) in the 3DP process utilising MCM technology. As a cutting-edge technology, there is no industrial standard or a developed general protocol on the application of MCM for failure detection and elimination yet. The majority of the studies reviewed in this review used their unique method due to limited access to the technology. Despite the intricate nature of various d/f occurrences, there may be a pattern that underlies the mechanism upon which d/f occurs. Based on this pattern, an MCM method that was designed specifically for one type of d/f can also be applicable to other types of d/fs. Systematic review and arrangement of the developed MCM methods enable a generalised MCM framework compatible with all the common types of d/f. This review also provides effective access to a vast amount of the available MCM methods and their corresponding catalogue of d/fs, which could help researchers and industrial practitioners.

Due to the differences in the nature of various types, the cause, severity, and representations are also different, which necessitates the study of the defects and results in the FDM process. The developed MCM implementations on FDM are collected and organised by the type of defects analysed and their respective results.

To the authors' knowledge, there has not been a review on the topic yet. To fill in the research gaps, this review summarises the monitoring techniques of 3DP processes, especially the FDM process, for d/f detection and identification and the different methods used to mitigate the specific type of FDM d/f. Due to the differences in the nature of various types, the cause, severity, and representations are also different, which necessitates the study of the defects and results in the FDM process. The developed MCM implementations on FDM are collected and organised by the type of defects analysed

and their respective results. Based on the monitoring results, evaluating the subtle differences in applying different mitigating methods and their performances can help ensure the quality of FDM printed products by effectively mitigating or eliminating the cause of d/f.

The structure of this review is organised as follows: Section 2 elaborates on the research methodology of the review. Section 3 provides an overview of current 3DP technologies with an emphasis on the FDM. Section 4 summarises the commonly used 3DP d/f and the numerical tools, including data collection devices and analysing algorithms for studying 3DP d/f. Section 5 reviews methodologies of d/f detection, identification, and the corresponding steps of those methodologies. Section 6 discusses critical features of the monitored data for d/f detection and identification and the criteria for choosing the proper algorithms for FDM d/f studies. At last, Section 7 concludes the conducted works and outlook for future work in this area.

2 Research methodology

The article aims to collect state-of-the-art articles about studies related to machine condition monitoring (MCM) applied in 3D printing, specifically, the fused deposition modelling (FDM) technology. The research starts with collecting related to two major keywords (FDM and MCM). The keywords expanded during the search, and the research question was iterated and specified during the research, with the corresponding keyword filtering on article titles.

The sources of literature searching include search engines (Google Scholar, Sci-hub), major databases in the engineering field (Engineering Village, Scopus, etc.), and e-library access provided by Western Sydney University. Another source is the reference list of articles that were searched, which provides a large number of highly related literatures. Besides the keyword selection, the collected articles were recapitulated to ensure the quality of the review. The review focuses on selecting articles of methodology development published within the last 5 years from the start of the review process. The year requirements for theoretical articles and those considered to have contributed significantly to the review may be waived. The quality of searched articles is focused. The articles from Q1 journals from SJR are priorly considered. Other articles with convincible arguments, methodical means, and contributory results are also included in the consideration. Furthermore, the study of MCM on other 3DP technologies rather than FDM may also be considered in the review, with their potential applicability to FDM.

The keywords for different categories used in this review are listed in Table 1.

Table 1 Keyword filtering list for literature searching

Defects in FDM printed samples						
Attributes	d/f	Function	Data extraction technique	Data processing technique	Monitored object	AM technology
In-situ	Defect	Detection	Image analysis	Convolutional neural networks (CNN)	Surface	Fused deposition modelling (FDM)
Automatic	Abnormality	Monitoring	Image entropy	Computer vision (CV)	Nozzle/extruder	3D printing
Real-time	Failures	Prediction	Laser scanning	Deep learning (DL)	Printed part	Fused filament fabrication (FFF)
Online	Warpage	Compensation/correction	Point cloud	Machine learning (ML)		AM (additive manufacturing)
In process	Dimensional accuracy	Condition monitoring		Supervised learning (SL)		
	Surface roughness			Unsupervised learning (UL)		
MCM techniques applied for FDM processes						
Scope	Object of scope		Parameters		AM technology	
Investigations	Mechanical properties		Printing settings		Fused deposition modelling (FDM)	
Effects	Tensile strength		Raster angle		3D printing	
Parametric study	Dimensional accuracy		Filling pattern		Fused filament fabrication (FFF)	
Optimisation	Warpage		Filling percentage		AM (additive manufacturing)	
			Layer thickness			
			Print speed			
			Filament temperature			

3 Overview of FDM technology

Ever since the 3DP technologies were invented, numerous studies have been devoted to excavating the potential of 3DP by establishing theoretical frameworks and their connections with other fields of industry. Shahrubudin et al. [15] introduced several types of bonding mechanisms, filament materials, and applications of 3DP. Gao et al. [16] summarised seven common types of AM processes, as shown in Table 2 [16]. The summarisation is according to material handling mechanisms, filament types, power sources, highlights, and challenges in process operation and printing quality. A general framework of AM is also shown in Fig. 1 [16], which covers the steps of AM fabrication from design to the product, the applications, and impacts on other fields.

The revolution of 3DP technologies also brings about the innovation of business models to the industrial market. Rayna and Striukova [17] studied how 3DP could change business model innovation by investigating the features of 3DP technologies and how those features become the key to opening new business opportunities. The filament used in 3DP processes refers to a wide range of materials that could be used in AM technologies. They can be deconstructed into small particles and then fused into new geometry. Polymer filaments are the most frequently used in extrusion processes

Table 2 Classification of AM process [16]

Categories	Technologies	Printed "ink"	Power Source	Strengths/downsides
Material extrusion	Fused deposition modelling (FDM) Contour crafting	Thermoplastics ceramic slurries, metal pastes	Thermal energy	• Inexpensive extrusion machine • Multi-material printing • Limited part resolution • Poor surface finish
Powder bed fusion	Selective laser sintering (SLS) Direct metal laser sintering (DMLS) Selective laser melting (SLM) Electron beam melting (EBM)	Polyamides/polymers Atomised metal powders (17-4 PH stainless steel, cobalt chromium titanium Ti6Al-4V), ceramic powders	High-powered laser beam Electron beam	• High Accuracy and Details • Fully dense parts • High specific strength & stiffness • Powder handling & recycling • Support and anchor structure • Fully dense parts • High specific strength and stiffness
Vat photopolymerisation	Stereolithography (SLA)	Photopolymers, ceramics (alumina, zirconia, PZT)	Ultraviolet laser	• High building speed • Good part resolution • Overcuring, scanned line shape • Excessive cost for supplies and materials
Material jetting	Polyjet/inkjet printing	Photopolymers, waxes	Thermal energy/photocuring	• Multi-material printing • High surface finish • Low-strength material
Binder jetting	Indirect inkjet printing (binder 3DP)	Polymer powders (plaster, resin), ceramic powders, metal powders	Thermal energy	• Full-colour object printing • Require infiltration during post-processing • Wide material selection • High porosities on finished parts
Sheet lamination	Laminated object manufacturing (LOM)	Plastic films, metallic sheets, ceramic tapes	Laser beam	• High surface finish • Low material, machine, process cost • Decubing issues
Directed energy deposition	Laser-engineered net shaping (LENS) electronic beam welding (EBW)	Molten metal powders	Laser beam	• Repair of damaged /worn parts • Functionally graded material printing • Require post-processing machine

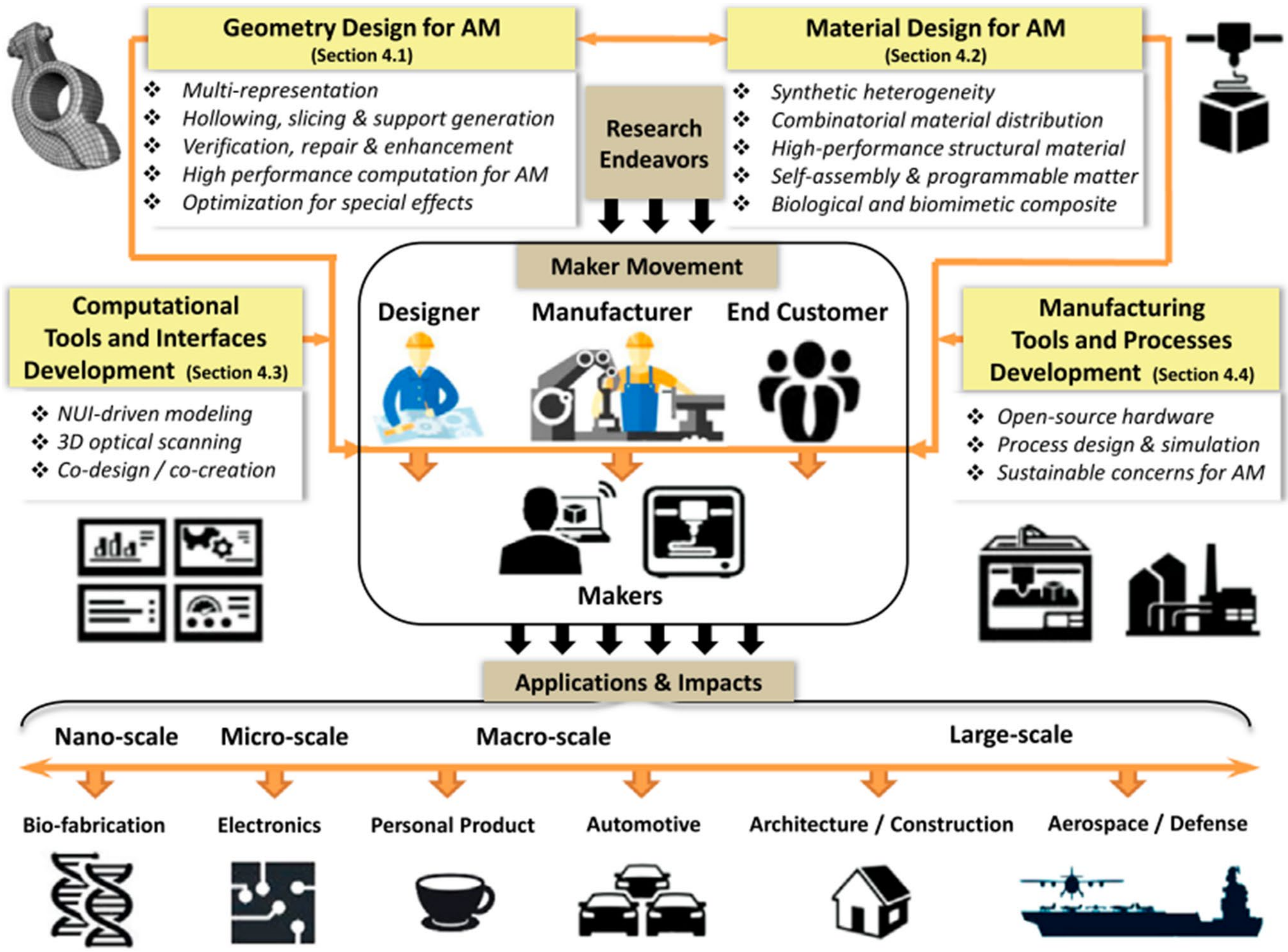


Fig. 1 Web framework of AM [16]

like FDM since polymers offer a wide range of selection (Fig. 2 [18]) at low cost (Table 3 [19]).

The convenience of filament recycling makes the 3DP process more competitive than the traditional manufacturing processes. Mikula et al. [20] reviewed the investigations on the feasibility of reusing wasted polymer filament in 3DP processes. They also established the filament recycling scheme based on the studies of filament recycling, as shown in Fig. 3. The performance of recycled ABS filaments that were continuously used in FDM processes and found their overall strength was not heavily affected even when recycled multiple times [21].

The quality of those filaments using recycled plastics depends on many combined factors, including the recycling process, stock material impurities, and the environment wherein the recycling process is carried out. It is important to evaluate and validate the recycled materials by comparing the properties with corresponding virgin materials to determine their feasibility. For example, in the study conducted by Mohammed et al. [22], a noticeable increase in ductility was observed on 100% recycled ABS (r-ABS) as a result of enhanced thermal stability after recycling. However, the tensile strength of the 100% r-ABS was decreased with a range between 13 and 49% because of the material degradation. Similar results have also been noticed in the studies of other recycled filaments, such as PLA (r-PLA), whose tensile strength and Young's modulus are reduced by 32.5% and 29%, respectively, compared to the non-recycled PLA. They also found an interesting phenomenon of a strengthened tensile property and Young's modulus (89% and 26% higher than the virgin PLA, respectively) [23].

Compositing recycled filaments is one way to unlock the great potential of their application. Giani et al. [24] studied the relation between the portion of added carbon fibre, recycled carbon fibres (rCF), and virgin carbon fibres (vCF) on PLA filaments. All added carbon fibres can enhance Young's modulus to a certain extent. The rCF performed better than vCF, which may caused by an improved bond at the interface between the PLA matrix and the partially oxidised surface of rCF. The enhanced bond facilitates a more

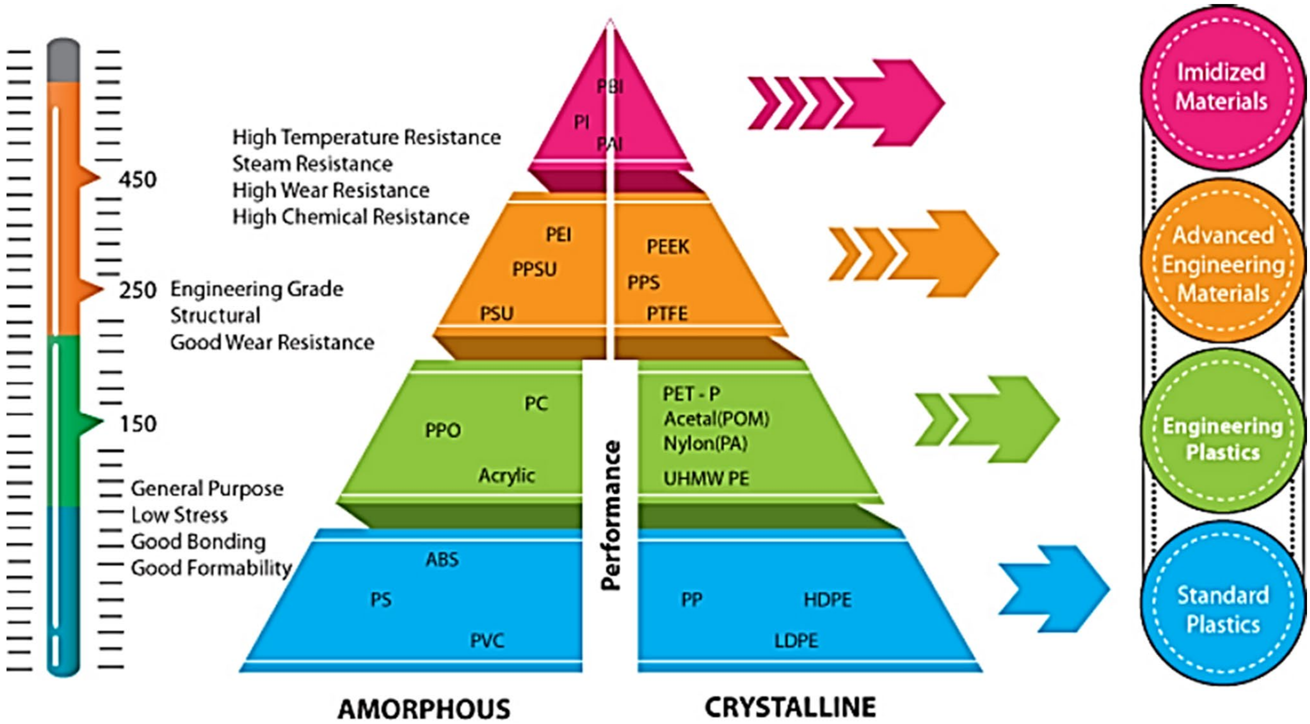
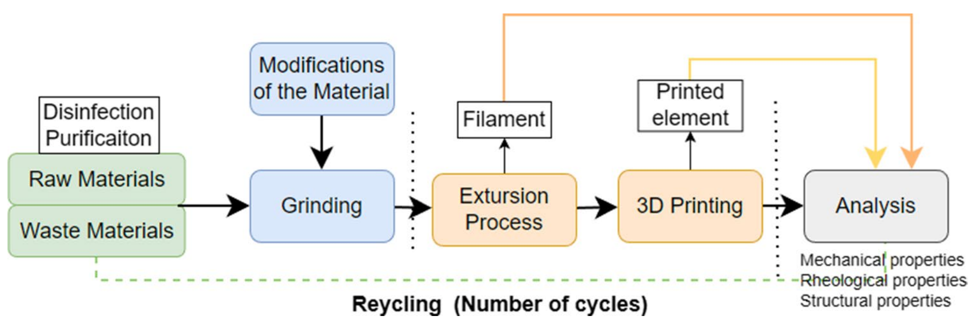


Fig. 2 Classification of thermoplastics [18]

Table 3 A cost list of polymer filaments [19]

Filament material	ABS	PLA	PC	PEEK	PEI	Nylon	HIPS
Cost per kg (USD)	17–25	15–25	30–70	400–700	140–200	30–70	20–60

Fig. 3 Flow chart of filament from waste materials in the 3DP process [20]



effective transfer of loads between the materials involved. The Young's modulus can be enhanced by up to 220% increase compared to neat PLA, with 10 wt% of rCF.

Besides carbon fibres, there are many other materials that can be used as composite materials. Plant fibres such as harakeke and hemp fibre can also help enhance tensile strength, and Young's modulus has 74% and 214% of PP filament, respectively [25]. The coffee dreg could also be considered a composite of recycled plastic composite as the dreg can fill up the voids within the filament [26].

However, some other properties may be weakened with the addition of composite material. It was observed that the ductility of recycled PE/PP (rPE/PP) by adding active carbon (AC) was increased by up to 8%, while Young's modulus was decreased with a significant 65% with recycled filament reaction to the AC addition unexpectedly [27].

It should be cautious with the portion added material in composites. In the study mentioned above [25], the tensile strength of the PP printed part increased with the added 10 wt% gypsums but decreased when increasing the gypsum portion and even lower than the neat PP, while the gypsum was increased to 50 wt%.

There are multiple process steps [28] that help understand the complete printing process of FDM. To start with, the desired geometry is created by appropriate CAD software and saved in STL format, which is then converted to G-code by slicing software such as Cura, OctoPrint, or ideaMaker. Some 3D printers have embedded slicing functions. The STL files can be directly sliced on those printers. The G-code is a computer programming language that is interpreted into a series of orders of motion trajectories and printing settings based on which 3D printers will operate.

Some printed parts need to be enhanced through post-processing to enhance their properties or make them better completeness in appearance. Dizon et al. [29] summarised that common post-processing in different polymer parts, such as cold welding and vapour smoothing, could help enhance the surface smoothness on printed ABS parts. Lyu and Lu [30] developed HA/TiO_2 coating to reduce the porosity on the printed part surface, which also enhances Young's modulus. Khosravani et al. [31] developed surface treatment on 3D-printed parts. The part is immersed in prepared acetone solution and controlled by fabricated equipment, which could control the progress of immersion. The post-processing of 3D-printed parts results in increased ductility, but Young's modulus is weakened as a cost.

However, the defects and failures that exist in the FDM printing process still hurdled its further growth in the market. They hindered the performance of this 3DP technology, and it is essential to comprehend the facts of defects and failures and seek methods to mitigate them.

4 Review of defects and failures generated during the FDM process

4.1 Common defects and failures during FDM processes

To understand the causes and effects of the defects and failures in the FDM process, it is necessary to correctly categorise those defects as it helps to determine the appropriate methods for defect mitigation. The impacts of defects generated during FDM processes cannot be ignored. Typical defects were summarised in Fig. 4 [32] and Table 4 [33].

Chen and Gabriel [34] categorised 3D printing process errors with a fishbone diagram shown in Fig. 5 and analysed the six fundamental sources of defects and their sub-factors.

Song and Telenko [35] provided a method to generalise the cause of defects in Table 5 by attributing the defect origins to provide a clear guideline for AM defect analysis. Currently, no standard principle is available for researchers to categorise the cause of defects.

The following content summarised several common defects that significantly affect printing quality and have been extensively discussed by other scholars. They are

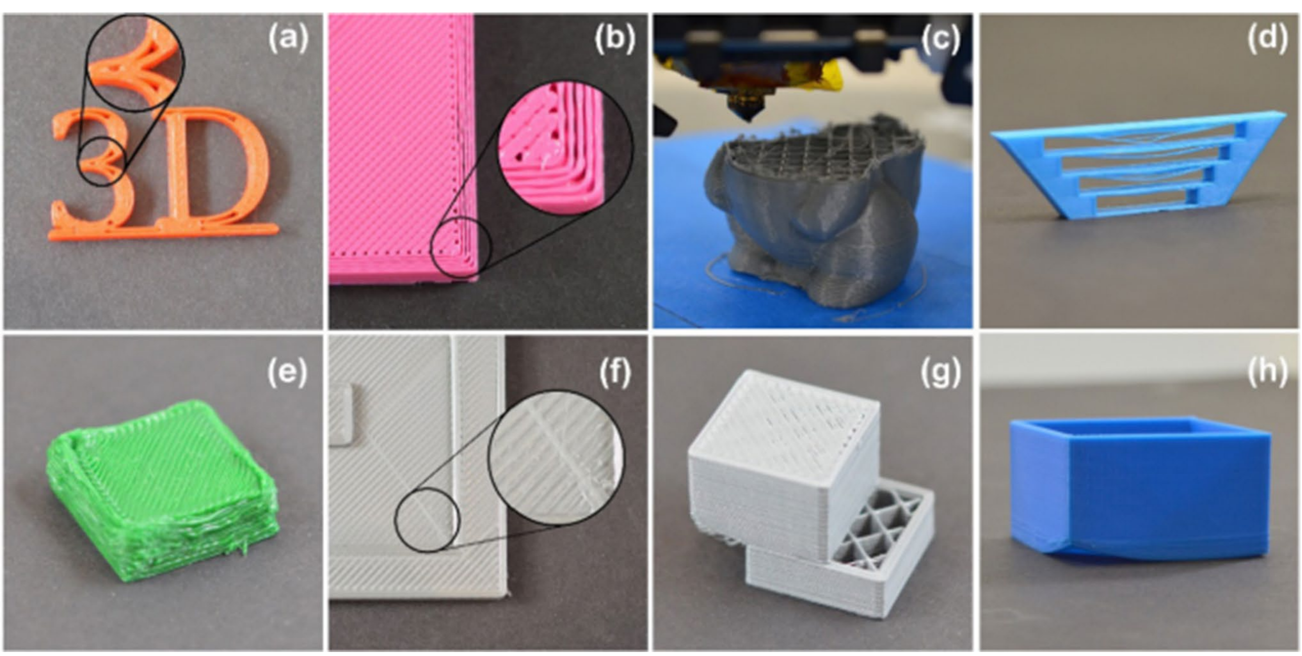
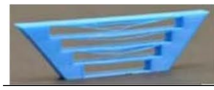
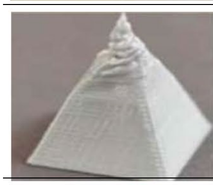
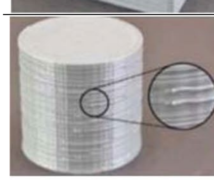
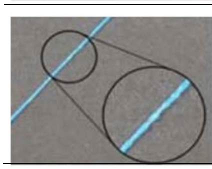
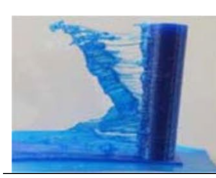


Fig. 4 Types of defects in material extrusion process. **a–c** Underfill defects: **a** gaps in thin walls, **b** under-extrusion, **c** uncompleted part; **d** poor bridging; **e**, **f** overfill defects: **e** over-extrusion, **f** scars on top surface; **g** layer shifting; **h** warping [32]

Table 4 Type of defects and corresponding causes [33]

Image of print	Type of defect	Causes
	Poor bridging	Lack of support provided for larger bridging regions of printed parts.
	Dimensional accuracy	Many common factors can cause this defect: thermal contraction, under or over-extrusion, filament quality, and first-layer nozzle misalignment.
	Gaps between infill and outline	Many common factors can cause this defect: thermal contraction, under or over-extrusion, filament quality, and first-layer nozzle misalignment.
	Layer separation and splitting	In this case, the infill is printed too fast, making it not have enough time to bond to the outline perimeters.
	Elastic deformation	This defect occurs when the layer height preselected is too large or when the printing temperature is too low. This is mostly caused by insufficient cooling or printing at too high of a temperature.
	Misalignments	This type of situation occurs when there is over-extrusion of printing material.
	Layer shifting	This kind of case arises when the tool head is moving too fast, or there is a mechanical or electrical issue associated with the printer itself.
	Blobs and zits	This occurs due to the retraction and coasting of the extruder or error in the start point setting.
	Incoherence	This can be caused by several issues, which include filament getting stuck or tangled, clogged extruder, very low layer height, incorrect extrusion width, poor quality filament, and mechanical extruder issues.
	Stringing or oozing	This situation arises due to one of the following; retraction distance, retraction speed, temperature too high, long movements over open spaces, or inappropriate movement speed.

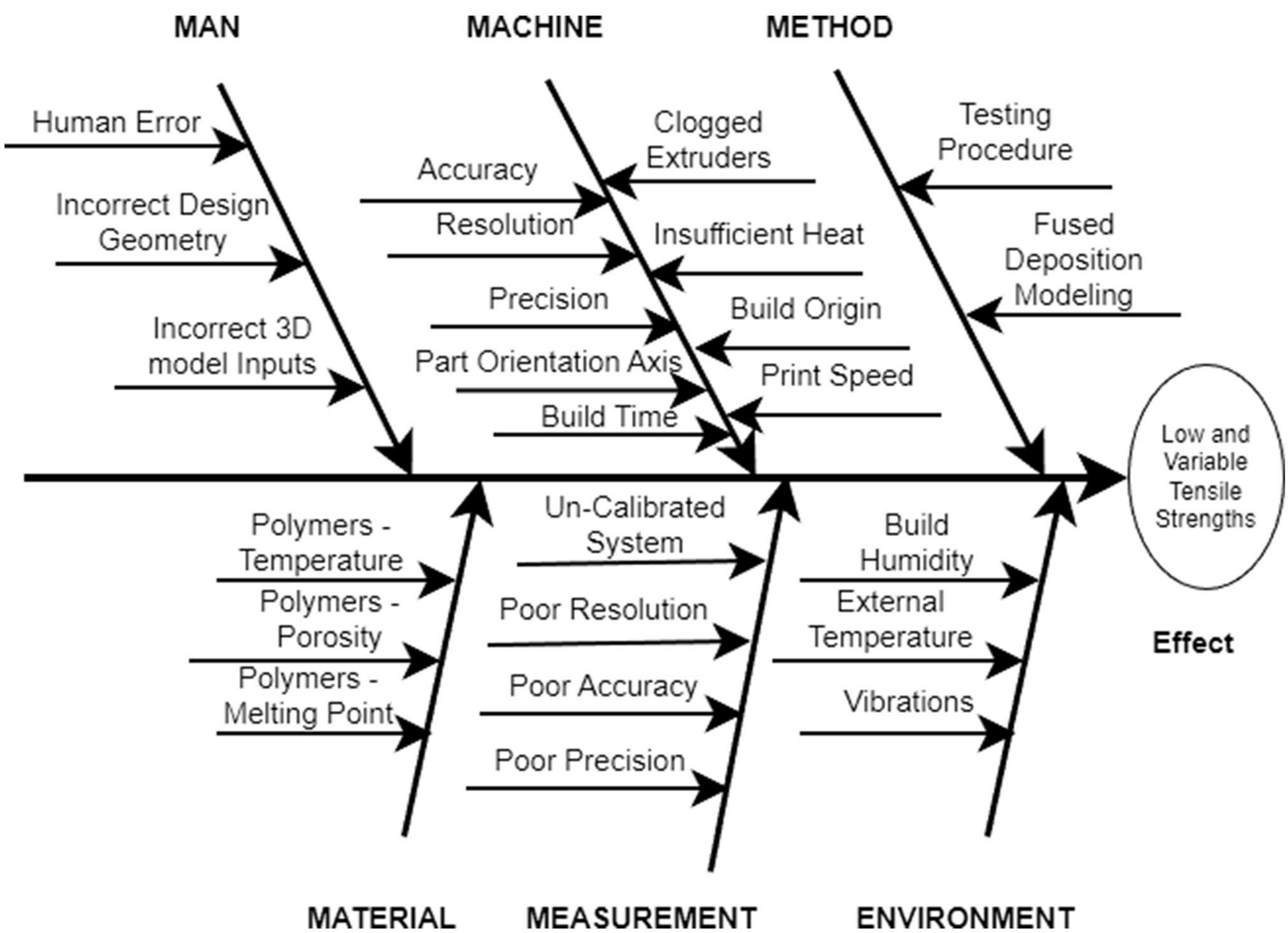


Fig. 5 Fishbone diagram of 3D printing process errors [34]

Table 5 The cause of failure types [35]

Type	User error	Machine error	Designer error
Unused filament	×	×	
Platform heating	×	×	
Part shape	×		×
Layer shift		×	×
Supporting material removing	×		×
Printer stops	×	×	×
Calibration	×	×	
Skip layers		×	
Non-physical defect			×

reorganised according to their causes, locations of occurrences, and corresponding mitigation methods of those defects:

- *Abnormality*: The term expresses the defects that are temporarily not categorised or identified. The term also refers to minor errors that are difficult and unnecessary to investigate their exact causes under the circumstances.
- *Inaccurate dimension*: A generic term that describes the type of phenomenon in which the actual 3DP product dimensions do not match the design, which may further cause problems when using the 3DP product. This defect could result from incorrect settings of 3D printers, the coarse level of voxelisation during the slicing process, and poor designs that do not consider the 3DP product tolerance. Inaccurate dimensions could lead to difficulties during assembly. Henson et al. [36] provided a method to detect the inaccurate dimensions of 3DP products by comparing the captured images with the geometrical model developed by the point view algorithm. Specifically, the defect will be detected when the ratio of difference from comparison reaches the set threshold. Holzmond and Li [37] used a similar comparison method that uses digital image correlation (DIC) to detect the relative displacement within a short time. This method is based on the same

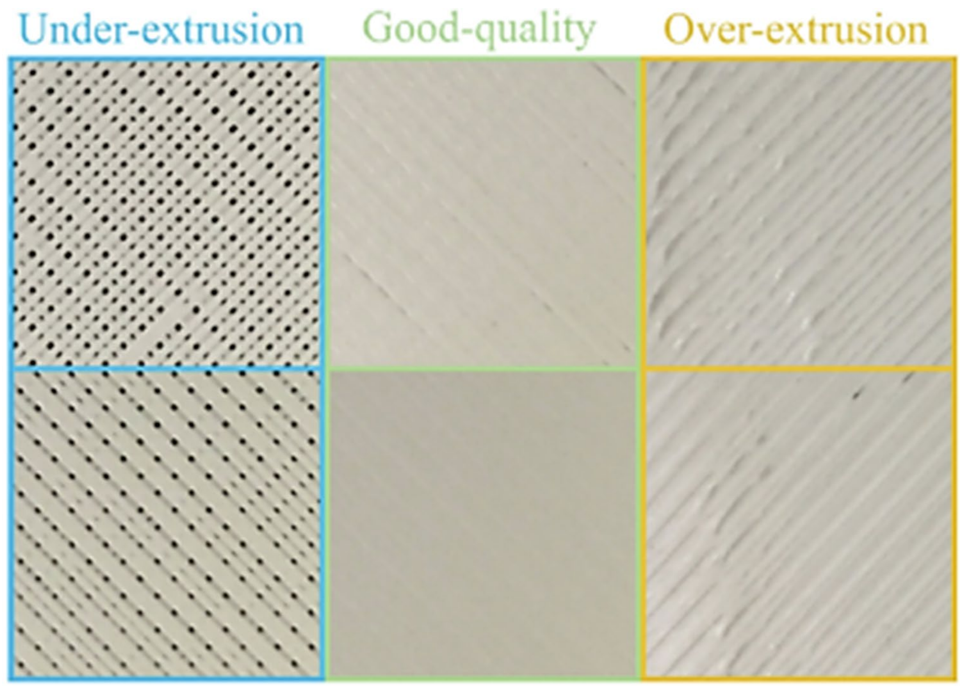


Fig. 6 Effects of extrusion settings on printing quality [38]

logic as the method mentioned in the study [36] to monitor the inaccurate dimensions of 3DP products.

- *Over-/under-extrusion*: The term refers to the undesired filament extrusion results due to improper settings, inadequate quality control, or design error. Figure 6 compares the over-extrusion, under-extrusion, and good-quality surface of the 3DP product [38]. The over-extrusion could cause the extruded filament to be thicker than expected, leading to the filament exceeding the expected volume, which further leads to the total dimension of the printed product being bigger than expected. The over-extrusion could also cause the unsmooth surface of the finished product as the oversized extruded filaments tend to press at each other. However, the under-extrusion may

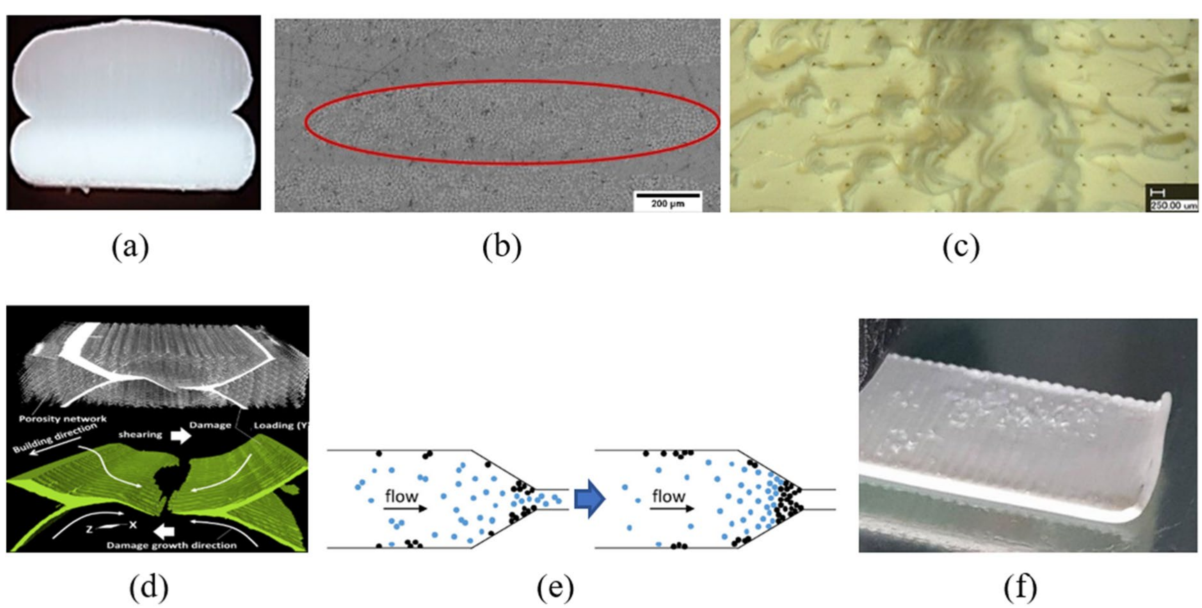


Fig. 7 **a** Bonding condition study between layers [39], **b** biodegradation—impregnation [40], **c** biodegradation—yellowing [21], **d** breakage study [41], **e** model of clogging formation [42], **f** edge warpage of ABS prototypes due to low chamber temperature [43]

result in decreased structural strength, more voids, and an unsmooth surface of the printed product.

Figure 7 shows the defects observed by multiple researchers, which are illustrated [21, 39–43].

- *Bonding condition*: It describes the adhesion strength between each extruded filament. The uneven cooling rate of extruded filament caused by low nozzle temperature could lead to weak bonding conditions that impair the printed product integrity.
- *Biodegradation*: Biodegradability is a property of biomaterials that are widely used in AM due to their recyclability. Impregnation reduces material service life and strength as a result of excessive biodegradability [40], which could also affect product appearance in the form of yellowing [21].
- *Breakage*: It refers to the rupture of the interior structure of 3D printing products when exposed to external forces. Guessasma et al. [41] investigated one type of breakage that occurs during the extrusion process, which could be caused by exterior disturbances, poor filament quality, and improper storage conditions. Breakage defects are easier to detect compared to other defects as the breakage occurs instantaneously. However, it could not be calibrated without manual interference. Pappas et al. [44] observed the fracture surface of carbon fibre–reinforced composite (CFRC) samples from both macro and micro perspectives. Moreover, they conducted parametric studies with the change of material deposition rate, print speed, and nozzle tilt angle, which leads to different void rates, to investigate the cause of breakage of 3DP parts. As a result, they find that the higher rates of voids in CFRC would cause the breakage of CFRC fibre.
- *Clogging*: It refers to the phenomenon that the melted filament cannot flow through the nozzle. The premature solidification of the filament may trigger clogging before it fully extrudes from the nozzle. The nozzle clogging has a significantly increased possibility of occurring below 180 °C [45]. One cause of clogging is the increasing friction between filament particles and the wetted surface, which drags back the particles and makes the filament remain on the wetted surface. Clogging is also attributed to machine errors like impurities of materials and unreasonable printing parameter settings [46]. To identify the reason for clogging, Beran et al. [42] conducted a study of nozzle flow test with self-developed testing devices using analytical modelling. The study concluded that there is an increasing chance of clogging when the ratio of nozzle diameter (D) and filler diameter (d) during the extrusion process achieves the limit of $D/d \leq 6.2$. Their study also found that the clogging could not be mitigated by increasing extrusion force or varying the melted filament viscosity.
- *Warpage*: It is also titled as distortion, wrapping, curl [2], or contraction. The warpage occurs when the bonding force between the first layer of printing parts and the printer heating bed is due to excessively low temperatures. In particular, the weakened bonding force in the printing parts renders them susceptible to the body contraction force due to the temperature difference across printing layers. Schmutzler et al. [47] explained the warpage as "Time delayed shrinkage of the separate part layers leads to different elongations". Armillotta et al. [48] established an analytical model to investigate wrapping by doing controlled experiments with variable parameters. Saluja et al. [49] researched the formation of warpages by investigating the printed filaments layer by layer. Kuo et al. [43] studied different causes of warpage by evaluating different environmental conditions.

The following microscopic defects were categorised based on [50] and are presented in Fig. 9:

- *Blob*: This defect describes the phenomenon of drop-like extrusion in the printed parts due to the retraction from a nozzle. The retraction refers to filament flow pulled back from the nozzle, caused by the difference between air pressure and temperature inside and outside the nozzle. Incorrect initial settings on 3D printers can also cause blobbing [33].
- *Void*: It is also named pore/hole. It could occur at multiple locations at different scales. Some voids exist inside the unprinted filament and cannot be easily observed [51], while some voids in Fig. 8 are apparent enough to be observed by the naked eye [52]. Those voids are generated from filament overlapping. The overlapping is caused by diffusion, which could result in a rough product surface. And the existence of certain voids could help compensate for this effect (Fig. 8(b)). However, void size determines the extent of breakage hazards between/across layers caused by external force/thermal contraction.
- *Crack/fracture*: It is a similar phenomenon to the void defect as shown in Fig. 8. Cracks could be caused by interlayer/intralayer weak bonding and exceedingly tensions, which could rapidly initiate crack propagation and irreversibly damage the printing parts. The propagation and deterioration of cracks may also cause fractures, and an exigent defect may lead to the malfunction of the printed object.

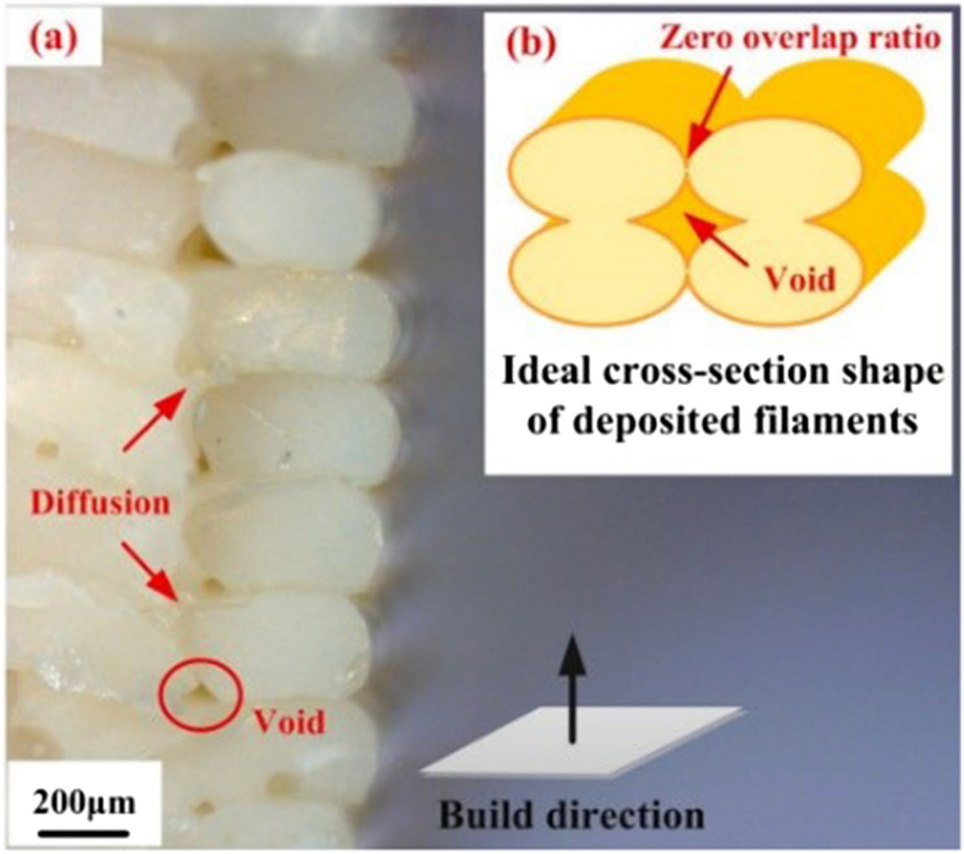


Fig. 8 (**a**) Void and diffusion observed in cross-section, (**b**) ideal model of the cross-section shape of deposited filaments [52]

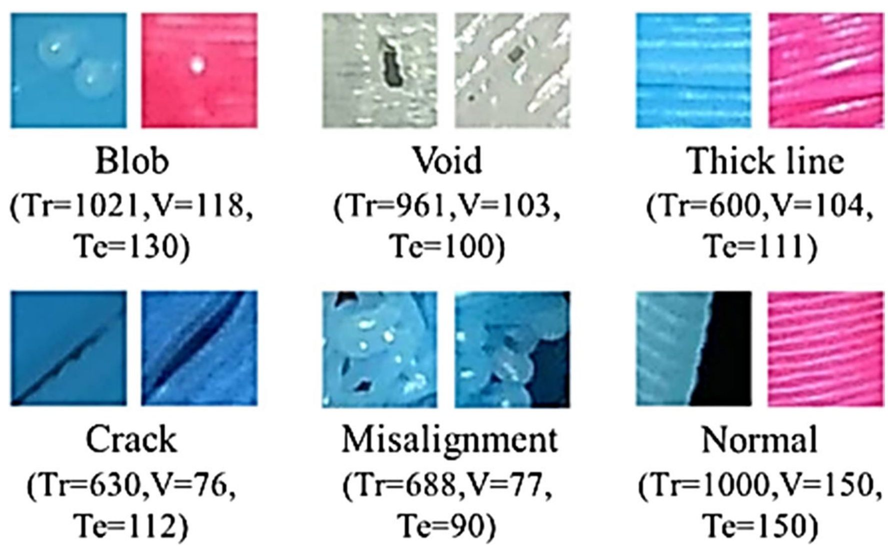


Fig. 9 Multiple defects in or on layers, with parameters of labelled CNN sets: Tr (training), V (validation), and Te (test), respectively [50]

- *Thick line*: It is a sudden increase in extrusion volume during the extrusion process. It usually causes the extruded filament to have a slightly larger diameter.
- *Layer misalignment*: Layer misalignment refers to the tiny interlayer displacement. This defect is also described in the study [33], as shown in Table 4. The sudden/temporal phenomenon of over-extrusion causes the unevenness of each printed layer, leading to layer misalignment with a potential hazard of malfunctioning the printed product (Fig. 9).

The defects mentioned above are primarily classified based on the exterior features rather than the mechanisms based on which they occur. However, different defects could also be caused by the same source in different processing environments. Understanding the relationships between these defects is crucial for developing defect detection and identification methodology.

4.2 Analytical tools—algorithms and software

Although existing technologies can reduce defect generation, the excessive costs and technical difficulties of applying such technologies to FDM are the bottlenecks to improving FDM production quality. Monitoring defects is the first step to mitigating defects which requires the understanding of conditions and factors of defects occurrence. With the advancement of computational power and the development of artificial intelligence (AI), AI could now be used in AM industries for defect detection and identification at the commercial scale.

The following reviews show how AI helps improve AM printed product quality in defect detection during AM processes. Qi et al. [53] reviewed the neural network algorithms applied to detect defects and failures and addressed the challenges of applying such algorithms. Meng et al. [54] summarised the function of multiple ML models in AM technologies in Fig. 10. Supervised learning could realise defect detection. Razvi et al. [55] reviewed the application of ML in metal and alloy-specialised AM processes, especially in laser powder bed fusion (LPBF).

Integrating various AI algorithms could help realise smart and efficient defect detection and identification, as each algorithm has its specialised type of data processing. Deep learning (DL), as an essential branch of ML, uses algorithms such as artificial neural networks (ANNs) to learn and gain experience without the guidance of human force. One distinct advantage of DL for defect identification is that the algorithm can self-correct by learning from a calibrated historical database. The characteristic of self-correction of DL also enables it to help regulate the 3DP process parameters to mitigate the generation of defects. Convolutional neural network (CNN) is a typical DL algorithm that features self-adaptive and self-correction ability. As [50] previously demonstrated in Fig. 9, they applied the CNN algorithm for defect/failure detection, which requires the image data input, which CNN can further recognise. ML is an ideal tool for numerical defect model analysis in AM technologies. The CNN can also be applied to predict the defect propagation of composite with material distribution modelling [56].

4.3 Influences of key parameters of FDM on defects and failures

Parametric studies could help investigate how the factors involved could affect the results of the studies and seek an optimised combination of those factors. The quality of FDM printed products could be quantified by the mechanical properties such as tensile strength, Young's modulus, and hardness. Also, defect severity could be quantified according to the related properties or the statistical data of the defect's phenomena. Both results for quality evaluation and the factor parameters involved in the parametric studies should be measurable and controllable. These parameters could be categorised by the place where they occur and their adjustability, which is shown in Fig. 11.

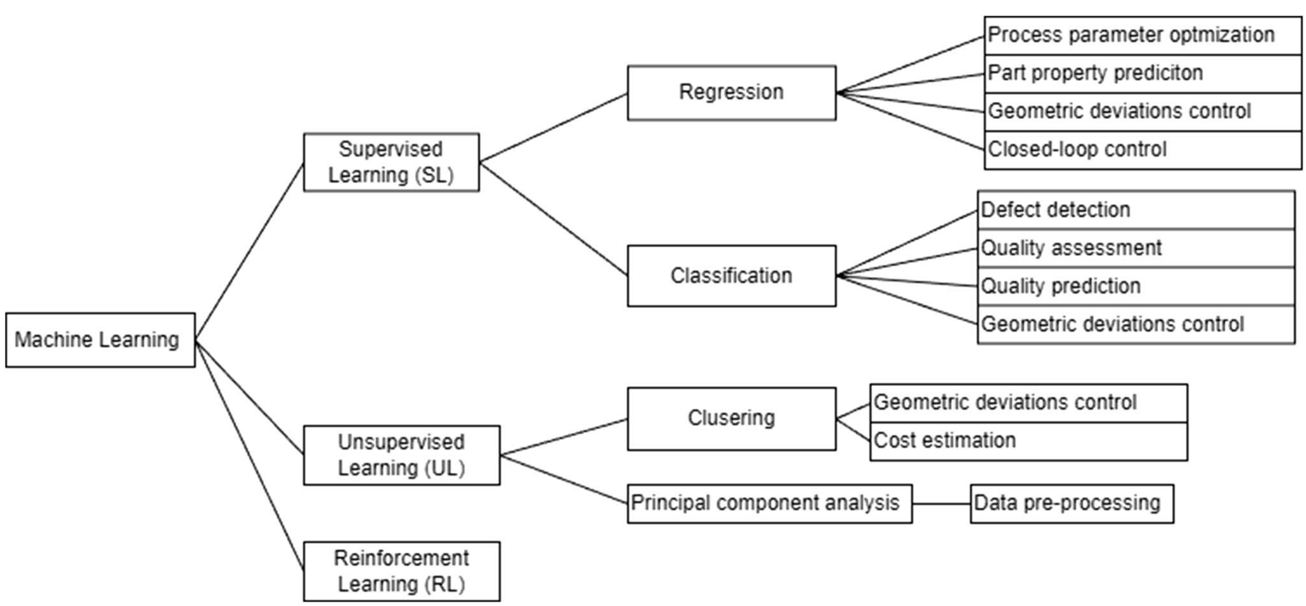


Fig. 10 Taxonomy of ML applicable scenarios in the AM field [54]

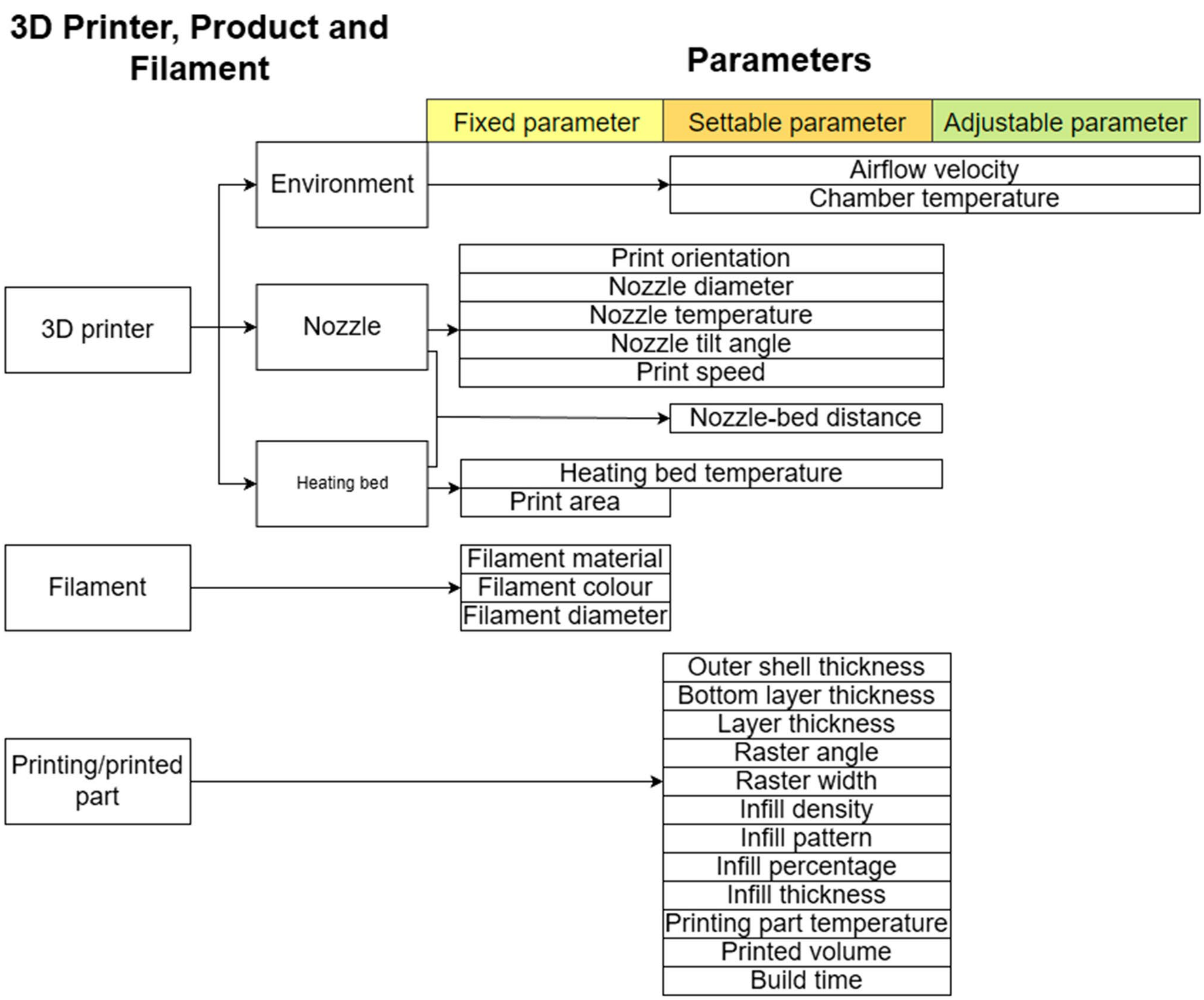


Fig. 11 Structure of the parametric study

To be much more specific, three types of parameters regarding the adjustability are as follows:

- *Fixed parameter*: These parameters are from inherent properties of the printing machine, such as the specifications or the filament material.
- *Settable parameter*: The settable parameter stands for the parameters set in the printing machine or the slicing software before the printing process.
- *Adjustable parameter*: The parameters could be adjusted during the printing process. The function of adjustment depends on the feature machine. For example, the chamber temperature is adjustable only if it is an enclosed chamber FDM printer.

It is noticed that multiple parameters may have slight variations in the experimental process under the influence of surroundings, even if they were fixed or have been set. The comparison of effective parameters with their set value helps find out the quality of the machine, or the material, as the fewer the differences, the better the quality of the printed results. In particular, the nozzle diameter is one of the inherent properties of a nozzle. However, the study of [57] claimed that the increase in nozzle temperature might minorly decrease the actual nozzle diameter due to the thermal expansion on the nozzle. Mwema et al. and Manoj et al. [58, 59] also conducted similar parameter categorising works.

Table 6 demonstrates the list of those parametric studies conducted by other researchers [21, 34, 39, 41, 43, 44, 51, 52, 57, 60–88]. All collected parameters and their influences on material properties, defect severity, and effective factors are demonstrated in the table.

Table 6 Parametric studies about the FDM process and products [21, 34, 39, 41, 43, 44, 51, 52, 57, 60–88]

Material properties, defects severity and effective factors		Variance parameter	References
Mechanical/rheological/thermal properties	Compressive strength	Layer height, raster angle, infill density, weight (material consumption)	[60]
		Layer thickness, raster angle, infill density, nozzle temperature, build time	[61]
		Sample size, load of compression, raster angle	[41]
	Compression/flexural/tensile strength	Nozzle-bed distance	[62]
	Extruded filament temperature	Nozzle diameter, nozzle-bed distance, print speed	[63]
	Flexural/shear/tensile strength	Raster angle, print speed, infill density	[64]
	Tensile strength	Filament material	[65]
		Filament material, filament colour	[66]
		Infill Density, infill thickness, nozzle temperature, print speed	[34]
		Infill density, printing orientation, raster angle, layer thickness	[67]
		Infill density	[68]
		Infill density, outline layers	[69]
		Infill density, layer thickness	[70]
		Infill pattern, infill percentage	[51]
		Layer thickness, raster angle	[71]
		Layer thickness, raster angle, raster width	[72]
		Nozzle tilt angle, print speed	[44]
		Raster angle, nozzle temperature	[73]
		Infill pattern, infill percentage, layer thickness, nozzle temperature	[74]
		Nozzle diameter, raster angle	[39]
		Layer thickness, printing orientation, print speed	[75]
		Raster angle, thermal ageing	[89]
	Tensile strength, filament bonding degree	Infill rate, print speed, layer thickness, print speed	[76]
	Tensile strength, printed volume	Infill density, filament material, nozzle temperature, heating bed temperature, print speed, layer thickness	[77]
	Tensile strength, extruded filament temperature	Airflow velocity, raster angle	[78]
	Tensile strength, viscosity	3D Printer machine type, recycled materials	[21]
	Tensile strength, warpage extent	Nozzle temperature, raster angle, print speed,	[79]
	Tensile/flexural strength, hardness	Print speed, infill density, layer thickness	[80]
Product quality	Dimensional accuracy	Infill percentage, layer thickness, print speed, print temperature, raster angle	[81]
		Layer thickness, print orientation, raster angle, raster width, raster air gap	[82]
		Infill density, raster angle	[83]
	Separation angle	Layer thickness, raster angle	[84]
	Surface quality	Raster angle, layer thickness	[85]
		Layer thickness, infill density, support style	[86]
	Warpage extent	Chamber temperature, heating bed temperature, nozzle temperature, print speed	[43]
	Voids and bonding conditions	Heating bed temperature, print speed	[52]
Material/machine inherent property	Filament pigment	Print speed	[87]
	Filament viscosity	Heating bed temperature, printed part temperature	[88]
	Effective nozzle diameter	Filament material, nozzle temperature	[57]

The features of data in parametric studies affect the way that how data is analysed. Some results of parametric studies with a single changed parameter could show clear relations. According to [63], the airflow negatively impacts the extruder temperature, while increasing the infill density helped improve the tensile strength of printed parts.

Comparatively speaking, multi-factor parametric studies focus more on the influences of several factors on outcomes, and they are more practical than single-variation parametric studies. However, finding out the mutual effects among factors becomes more complex, and there might be potential relations among them. Nguyen et al. [67] conducted parametric studies on multiple parameters and sought their influences on tensile strength. Partially investigated parameters, such as the infill density, could reflect a clear positive correlation. However, more factors like nozzle temperature and raster angle did not illustrate a clear correlation with the result of the study.

Analytical modelling is dedicated to calculating and validating statistical research findings, while algorithms have also emerged as an effective approach for processing large datasets involving multiple factors. One way to build up the analytical models is to try different modelling types and find the best fit for the tested data. Dev and Srivastava [60] established an analytical model to predict the compressive strength of printed parts based on the experimental results of parametric studies regarding layer height, orientation angle, and infill density. Eswaran et al. [83] applied the regression analysis to find the relationship between circularity error on the surface of a 3D printed specimen and the configuration data of the printing machine. Similar work has also been done by Dey et al. and Elkaseer et al. [61, 81].

Taguchi method is one systematic way to evaluate the quality of product design. It could seek the optimised results from multiple key parameters and the range of each of them. Taguchi method could be utilised to investigate the results from the parametric studies of surface roughness. The effect of each parameter on the result has been quantified in several aspects. Another way of establishing analytical modelling is based on theoretical equations of the corresponding fields. Prajapati et al. [63] established analytical modelling for developing heat transfer of filament in a standoff region during the printing process and compared the results from the model to those from the experiments. Tofangchi et al. [39] established mathematical modelling to calculate adhesion energy in ultrasonic vibration and found a suitable vibration frequency to enhance printed parts' adhesion force.

The strengths are the significant mechanical properties that can be used to evaluate the quality of printed parts. The strengths, including tensile, flexure, and compression, are regularly investigated. Other mechanical properties such as ductility, hardness, and yield strength are also worth studying. However, the mechanical properties would have distinctive features in various stages, making it more complicated to predict the properties with analytical modelling. It is ordinary for complex data to exhibit a lack of evident relationships, necessitating supplementary aid from analytical tools to address the issue. Environmental factors also impact printed products. Khosravani et al. [89] studied the effect of thermal ageing by designing defective specimens with different raster angles to simulate crack defects. Young's modulus was reduced by up to 66% with the effect of cracks and thermal ageing. Ductility is impacted significantly by the increased raster angle of the crack and further expands with thermal ageing. The ageing also aggravates the surface roughness.

Machine learning could help find the relation that is hard to observe and help predict the result with variation changes. Artificial neural networks (ANN) can help find the optimal filament materials and machine configurations with given inputs in the parametric studies, such as the dimension and maximum tensile strength of the prototype [90].

Even though parametric studies do not explicitly contribute to mitigating FDM defects, those methods provide insight into how we can use them in FDM defect mitigation. Some defects could be evaluated by the methods mentioned above if the defect situations are quantifiable. Kuo et al. [43] conducted parametric studies regarding what factors caused the warpage defect according to the warpage extent, which is the angle between the edge of the printed prototype and the horizontal printing bed.

5 Review of defect detection technologies

The reviewed methodologies are summarised as a general pattern that most studies have followed. The pattern consists of several sections as follows:

The research target in this chapter is to summarise and categorise the articles aiming to eliminate defect problems with MCM. The methodologies that cover multiple angles and distinct stages are focused on in this study as those methodologies could deal with more challenging and complex scenarios of defect studying.

Figure 12 shows the connections between those research scopes.

- *Data collection*: This section exhibits the data collected from devices and discusses the alternative methods for data collection.
- *Data processing*: These are tools used for classifying obtained data by data denoising and feature extraction. It includes AI algorithms such as Machine Learning or the non-AI algorithms used for image or signal data processing.
- *Defects identification*: The collected data will be processed to identify the detected defects. The identified defect data helps to select a corresponding mitigation method based on the type of defects.

The MCM systems consist of the hardware (devices) and software (algorithms and applications). The devices

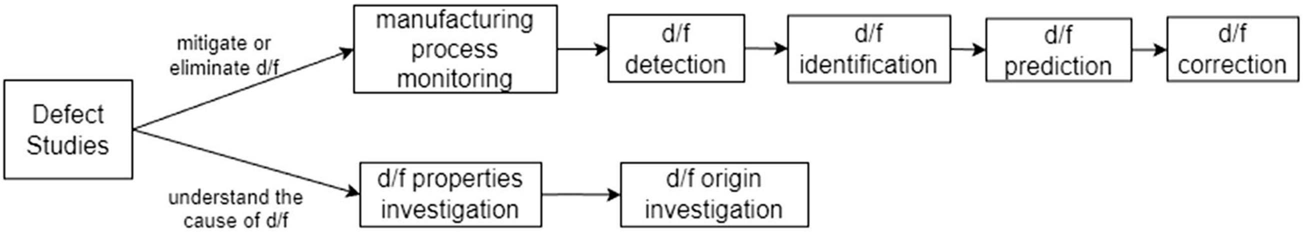


Fig. 12 Schematic of defect detection methodology

capture the required data, and the software helps analyse and convert the data. Most commercial monitoring devices come with corresponding software. However, to further analyse the defects, the acquired data will be used by other software or algorithms. Hence, the design and establishment of the MCM framework are particularly important. The characteristics of different MCM equipment determine that they have corresponding advantages in detecting certain defects. Therefore, in the process of establishing the MCM framework, the comprehension of MCM equipment can also help with better defect analysis [38, 91–93]. Also, the MCM application in traditional manufacturing can also be referred to as the establishment of 3DP MCM, as there are similarities in methodologies [94].

This chapter provides a general classification and detailed discussion on the use of collected MCM equipment. The following tables demonstrate the defect methods by diverse types of data acquisition equipment of MCM, including charge-coupled device (CCD) cameras in Table 7 [28, 32, 33, 36, 38, 41, 44, 49, 50, 95–103], optical microscopes in Table 8 [21, 39, 40, 44, 52, 70–72, 78, 104–107], scanning electron microscope (SEM) in Table 9

Table 7 Defect study methods by using CCD Cameras [28, 32, 33, 36, 38, 41, 44, 49, 50, 95–103]

Research scope	Algorithm function	Object of function	Data processing tool	Detected defects	Reference
Mechanical properties investigation	N.A.	N.A.	N.A.	Fracture	[44]
d/f origin investigation	N.A.	N.A.	N.A.	Breakage	[41]
In-situ d/f detection	Feature extraction	Dimension deviation	Image processing	Dimensional accuracy	[95]
				Crack	[96]
		Model of object	Image processing	Porosity	[33]
				Dimensional accuracy	
				Colours abnormality	
	Classification	Type of defects	DL	Blob	[50]
				Void	
				Thick line	
				Crack	
				Misalignment	
		Quality of model	UL	w/ or w/o defects	[101]
In-situ d/f prediction	Classification	Dimension deviation	SL	Dimensional accuracy	[97]
In-situ real-time d/f detection	Data integration	Model of object	Image processing	Dimensional accuracy	[98, 99]
	Noise mitigation	Noise of data	Image processing	Over-/under-extrusion	[32]
	Feature extraction	Model of object	Image processing	Over-/under-extrusion	
		Abnormalities	Image processing	Over-/under-extrusion	
		Dimension deviation	Image processing	Dimensional accuracy	[100]
		Model of object	Image processing	Dimensional accuracy	[36, 103]
		Abnormalities	DL	Stringing	[102]
	Classification	Type of defects	DL	Warpage	[49]
		Abnormalities	DL	Dimensional accuracy	[28]
		Model of object	Image processing	Dimensional accuracy	[98]
In-situ real-time d/f correction	Classification	Quality	DL	Over-/under-extrusion	[38]

Table 8 Defects observed using optical microscopes [21, 39, 40, 44, 52, 70–72, 78, 104–107]

Research scope	Defects and scope of monitored object	Calliper scale (Mm)	Reference
Mechanical properties investigation	Fracture	0.2, 0.1-0.7	[71, 72]
	Biodegradation	0.25	[21]
	Porosity		
	Biodegradation	0.2	[40]
	Surface abnormality	0.02	[104]
	Bonding condition	0.1	[39]
	Void	0.03/0.1	[44]
	Breakage		
d/f origin investigation	Fracture	0.02, 0.5	[70, 78, 105]
	Void	0.1	[106]
	Dimensional accuracy	0.2	[52]
In-situ process monitoring	Bonding condition	N.A.	[107]

[27, 40, 45, 51, 65, 67, 71, 75, 104, 105, 108, 109], and cameras with embedded image processors in Table 10 [37, 41, 46, 63, 70, 78, 87, 107, 108, 110–115].

Optical devices were used for data acquisition in FDM defect detection. CCD camera is the most popular optical device due to its low cost and capability of capturing

Table 9 Defect types observed using SEM [27, 40, 45, 51, 65, 67, 71, 75, 104, 105, 108, 109]

Research scope	Defects and scope of monitored object	Calliper scale (Mm)	Reference
d/f origin investigation	Fracture	0.01/0.1/0.5	[105]
	Curing	0.001	[108]
Mechanical properties investigation	Bonding condition	1	[45]
	Filament abnormality	1	[27]
	Crack	0.5	[71]
	Fracture	0.5	[75]
	Surface abnormality	0.1	[104]
	Biodegradation	0.1/0.3/0.5/1	[65]
	Void	0.2, 0.01, 0.02/0.5, 2	[40, 51, 67, 109]

Table 10 Defect detection methods by using devices embedded with image processing [37, 41, 46, 63, 70, 78, 87, 107, 108, 110–115]

Research scope	Data collection	Algorithm object	AI algorithm	Detected defects	Reference
Mechanical properties investigation	IR camera	N.A.	N.A.	Warpage	[110]
	IR camera	N.A.	N.A.	Temperature abnormality	[78, 108, 111]
d/f origin investigation	IR camera	N.A.	N.A.	Temperature abnormality	[63]
	Micro-Ct X-ray	Feature extraction	N.A.	Breakage	[41]
	DIC measurement system	Feature extraction	N.A.	Fracture	[70]
In-situ process monitoring	IR camera	N.A.	N.A.	Temperature abnormality	[112, 113]
			N.A.	Clogging	[46]
In-situ real-time d/f monitoring	IR camera	N.A.	N.A.	Temperature abnormality	[107]
	Micro-Ct X-ray	N.A.	N.A.	Projection of extrude filament	[87]
In-situ real-time d/f detection	IR camera	Classification	SL	Over-/under-extrusion	[114]
				Warpage	
				Void	[115]
	DIC measurement system	Noise mitigation Feature extraction	N.A.	Dimensional accuracy	[37]

high-resolution images that reveal defects with good clarity. These features make the CCD camera a suitable device for low-cost applications where only superficial defects are required to be detected; thus, the connected detection system can send the alarm. CCD cameras are also compatible with AI algorithms such as DL, which can help with image processing to detect better and identify defects. Jin et al. [38] used the CNN algorithms to identify the status of extrusion (under/normal/over). They found that 98% of the study cases successfully predicted the extrusion status by calibrating errors and adjusting the extrusion volume of filament from the nozzle [38]. Chen et al. [116] developed a real-time defect detection system on surface defect detection with different deep learning algorithms. The missing rate of defect detection is less than 10% at the running speed of 7 mm/s. Y. Wang et al. [50] detected multiple intralayer defects in the same printed object by applying DL algorithms o characterise those defects with different feature values. Apart from AI, other algorithms could also help extract the features of defects but are less adaptive in dynamic processing environments than AI. Lin et al. [32] utilised an algorithm-based technique to detect the over-/under-extrusion defect by comparing the CAD model with the RANSAC (random sample consensus) algorithm processed point cloud that is obtained by a laser scanner. The defects on the edges of printed parts were also detected by Canny edge detector, during which course the sliding window algorithm was used to de-noise the irrelated data to reduce the computation time.

Optical microscopes (Table 8) and SEM (Table 9) are specialised to observe tinier parts and details that the naked eye cannot see. SEM is a specific type of microscope that can observe objects with more details at the microscopic level than other optical microscopes. The size range of objects to be observed could be as small as 1 μm [108]. The image-generating time of microscopes is usually much longer than other optical devices due to the mechanism it generates an image. This is why microscopes can hardly be used for real-time and in-situ defect detection and identification, despite their advantages in d/f investigation.

The image acquisition equipment with built-in data processors (Table 10) brings excellent conveniences to defect detection and identification when used in their specialised fields. The infrared (IR) camera is a device that can display the thermal information of the monitored objects, which can detect thermal abnormalities and temperature distributions. Like CCD cameras, IR camera is also capable of displaying real-time images. Thus, it is suitable for in-situ and real-time monitoring. Monitoring with an IR camera can also be enhanced by AI algorithms. Hu et al. [114] utilised an IR camera to detect the defects on 3DP parts and identify those defects by applying the support vector machine (SVM) algorithm to classify the types of defects. DIC technique could locate the defects by measuring the deformation of recorded objects micro-CT could help observe the interior microstructure to understand the cause of defects better.

Aside from image acquisition devices, signal sensors (Table 11) are commonly used tools to extract data from a measured object [2, 56, 57, 87, 91–93, 104, 117–125]. There are sensors like acoustic emission (AE) sensors, piezoelectric vibration sensors [93], and accelerometers [57] that can monitor mechanical properties like vibration and displacement. Vibration characteristics include but are not limited to amplitude, frequency, and acceleration. The strain gauge directly measures the strain of the object to which it attaches. The torque-force sensor can measure the force and torque, which is restrained to the specific application locations, as the proper instalment of the torque-force sensor requires a particular interface with the machine. Some sensors, such as the triangulation sensor [126] and incremental optical encoder [119], rely on varying optical signals. The FBG sensor measures the varying Bragg wavelength, allowing it to measure multiple mechanical properties such as stress, strain, temperature, pressure, and relative displacement. The current sensor reflects the varying electric current within electronic devices and has a versatility advantage in many applications. Unlike the other sensors, applying the current sensors requires close observation of an anomaly in the current change to identify the defects with the help of dedicated algorithms or software.

To precisely identify the same defects, the following research took different approaches using different equipment or methodologies to examine the same defect from different perspectives. Holzmond and Li [37] applied the DIC technology to monitor the relative displacement and used the microscope to observe the optical pattern in polylactic acid (PLA) and ColorFabb Woodfill Fine filament. Hart and Wetzel [105] applied an optical microscope to locate the defects of 3D printed parts and investigated the nature of those defects via SEM micrographs. Garg and Bhattacharya [71] also applied the CCD camera and SEM to detect the defects. Miao et al. [91] used temperature data from the thermistor and the IR sensor to detect the warpage. The warpage detection was validated using SVM of the SL model and ANN of the DL model to verify the thermistor obtained data by using linear regression of the SL model to verify the grayscale image obtained from the IR sensor.

Figure 13 shows the investigated defects and corresponding data acquisition devices. Inaccurate dimensions and abnormalities are the focus of many studies since they are easier to be detected and identified. The categorised d/f, such as warpage, over-/under-extrusion, void, and fracture, are also extensively investigated due to the high occurrence rate, ease of observation, and hazard of product quality. Tensile strength tests aim to investigate the material's microstructure

Table 11 Defect detection methods by using sensors [2, 56, 57, 87, 91–93, 104, 117–125]

Research scope	Data collection	Object of function	Data processing tool	Detected defects	Reference
Mechanical properties investigation	RFID reader	N.A.	N.A.	Temperature abnormality	[104]
d/f prediction	N.A.	Prediction	DL	Crack	[56]
In-situ process monitoring	Accelerometer	N.A.	N.A.	Clogging	[57]
In-situ process monitoring	Photoacoustic imaging	Feature extraction	Image processing	Surface abnormality	[117]
In-situ d/f monitoring	Ae sensor	N.A.	N.A.	Filament abnormality	[118]
In-situ d/f detection	Ae sensor	Classification	SL	Looseness	[2]
				Curl	
	Thermistor, IR sensor	Classification	SL	Warpage	[91]
	Optical incremental encoder	N.A.	N.A.	Filament abnormality	[119]
In-situ d/f prediction	Strain gauge	Classification	DL	Surface abnormality	[120]
	Thermistor, IR sensor	Classification	SL	Warpage	[91]
In-situ real-time d/f monitoring	Micro-CT X-ray	N.A.	N.A.	Projection Of extrude filament	[87]
	Thermal couple	N.A.	N.A.	Temperature abnormality	
	Current sensor	N.A.	N.A.	Warpage	[121]
				Clogging	
				Printing condition	
In-situ real-time d/f detection	Accelerometer	Classification	SL	Vibration abnormalities	[122]
	AE sensor	Classification	UL	Surface defects	[123]
				Clogging	[92]
			SL	Vibration abnormalities	[122]
		Feature extraction	Signal processing	Warpage	[124]
	Current sensor	N.A.	N.A.	Warpage	[121]
				Clogging	
				Printing condition	
	Piezoelectric vibration sensors	Classification	SL	Warpage	[93]
				Leakage	
				Clogging	
	Torque-force sensor	N.A.	N.A.	Force abnormalities	[125]

mechanical property and study the breakage mechanism and the fractures that occurred during the test. However, it is unusual to see fractures during the in-situ 3DP monitoring process.

The data acquisition devices are selected based on the feature of interested data. Optical devices feature the advantage of flexibility in that they can observe objects at different scales by adjusting lens focus. A wide range of optical devices can also be selected for different applications. For example, a CCD camera is suitable for macro scale monitoring, while SEM suits for micro scale observation.

Sensors are attached close to the concerned location with precautions according to non-destructive testing (NDT) method principles. The extruder is typically the ideal location for sensors to monitor the vibrations during the FDM process. Alternatively, sensors can be mounted to the heating bed to contact the extruder and printing part. The torque-force sensor requires a specific interface for installation, which is unsuitable for all machines. Temperature sensing devices such as IR cameras and thermistors are applied to the 3D printer components that are heat sensitive such as the nozzle, which changes its performance with temperature [111]. The filament is primarily monitored as its quality can heavily impact the printing results. The filament quality can be reflected by the uniformity of its diameter, which can be measured by incremental optical encoder based on luminance signal [119]. Although the data can be accurately collected, without the help of specialised algorithms, the collected data cannot be directly used to identify defects and failures. The complexity involved in the 3DP process is another challenge that hinders the realisation of d/f detection and identification [50].

Figure 14 depicts the function of algorithms and corresponding used devices and their frequency in reviewed works of literature. Figure 15 shows the function of algorithms and corresponding types of algorithms and their frequency in the reviewed literature.

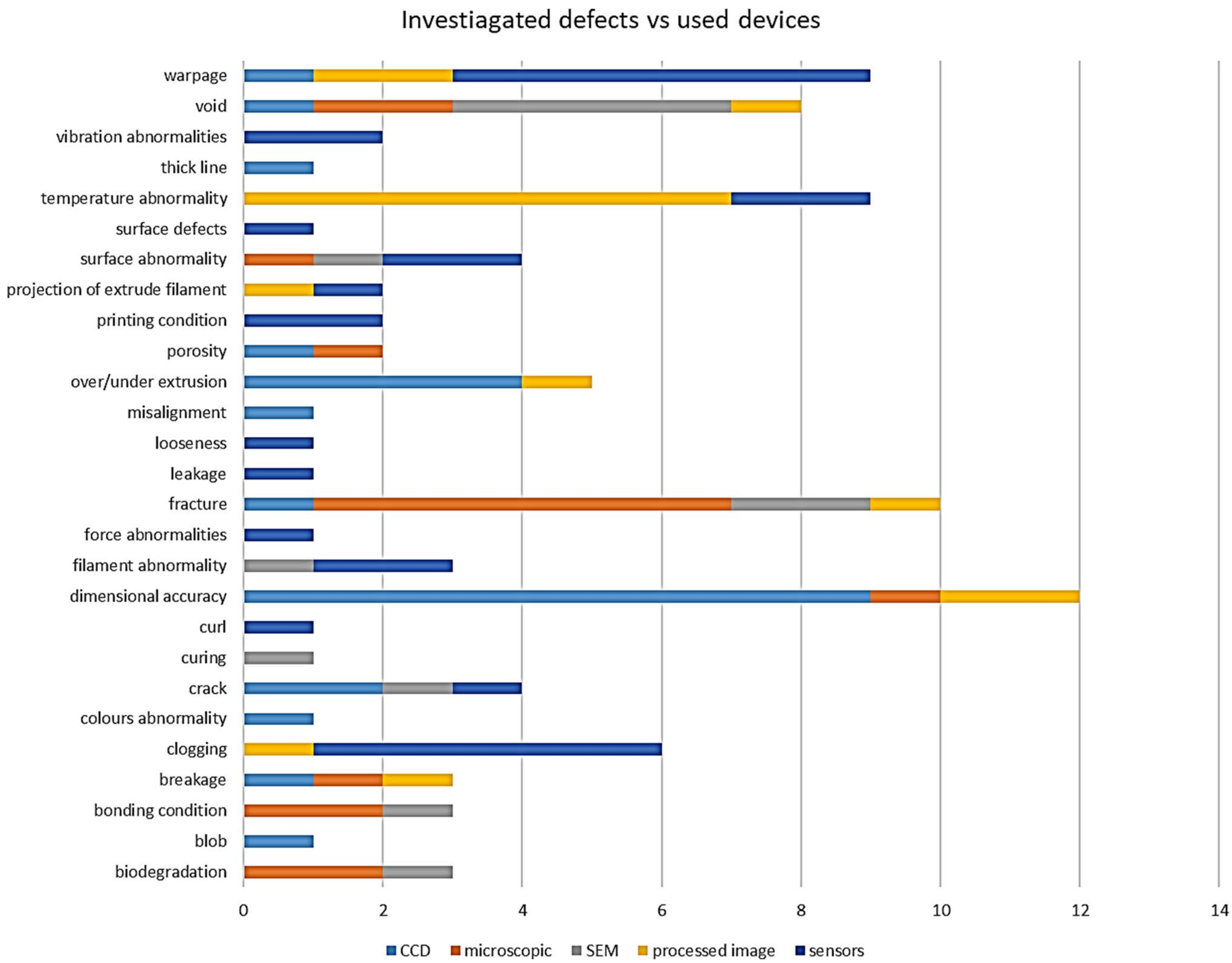
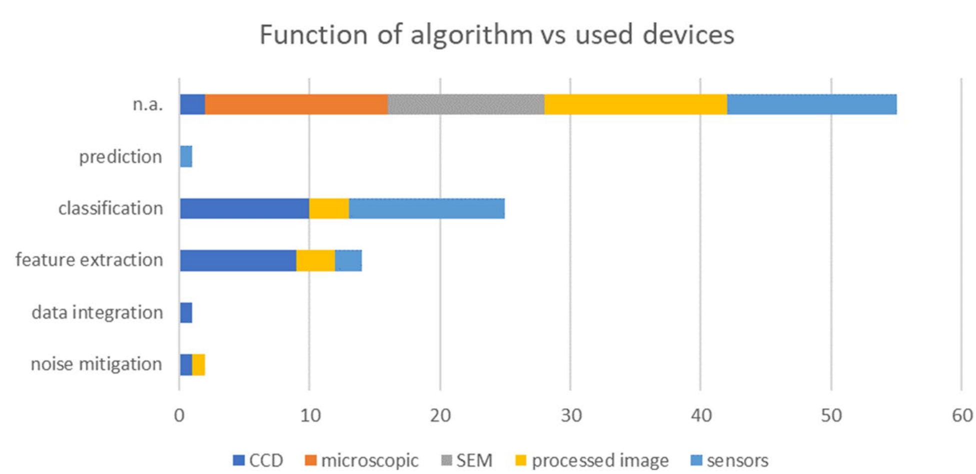


Fig. 13 Investigated defects with used devices

Fig. 14 The function of algorithms and corresponding used devices



All studies utilised microscopes, and SEM did not use algorithms for data processing as these devices cannot easily interface with data processing software. Also, some image processing devices are embedded with feature extraction functions equivalent to data processing algorithms. Although frequently used in reviewed studies, data arranging

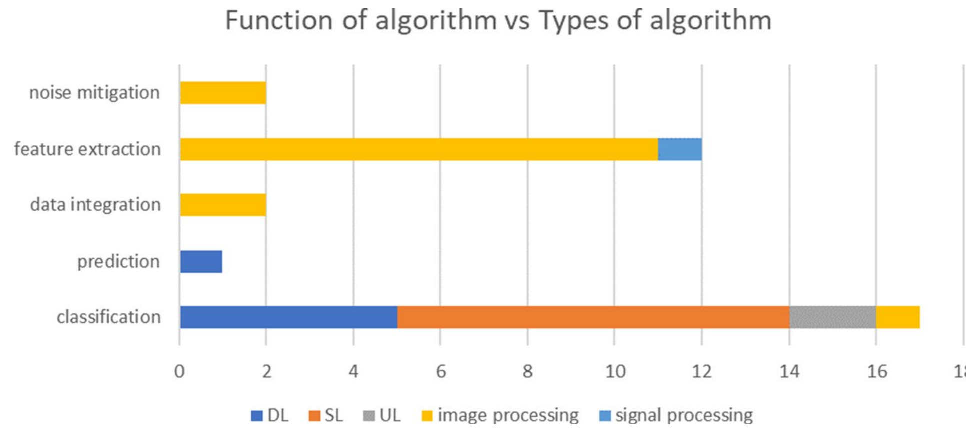


Fig. 15 Function and corresponding types of algorithms

and denoising have not been extensively discussed due to their matured application.

The prediction is an expected outcome of the established d/f detection and identification system. Accurate prediction of defects and failures is based on understanding the mechanism of defects and failures and the appropriate implementation of relevant technologies.

Regarding AI algorithms, unsupervised learning (UL) is commonly used for abnormality detection and defect categorisation. It can also be used as a training database to further supervised learning (SL) and deep learning (DL).

SL was often used for in-situ defect classification compared to UL and DL [32, 127], as UL requires no preliminary training data to detect and locate d/f. Furthermore, researchers could identify and label the detected d/f from UL for future reference. The application of SL for real-time d/f monitoring systems is limited by the pre-training requirement of SL when it operates without existing pre-trained data [92]. Their study used multiple SL algorithm models in conjunction with AE sensors. SL requires more computational power to achieve the desired result accuracy than other algorithms.

In a dynamic and complex environment where multiple variables coexist, it is often challenging to identify the most appropriate method without resorting to trial and error for each one. Khanzadeh et al. [115] tested multiple SL algorithms to predict the surface porosity of printed objects by analysing obtained thermal images. The study achieved the highest accuracy of 98.44% in predicting the correct type of defects. However, this method was designed for AM technologies such as PBF and EBM. The attempt to adapt the procedure that [115] presented to FDM is worth discussing.

Aside from AI, other technologies can also contribute to d/f detection and identification. Some image processing techniques, such as grey scaling [128] and image entropy [96], can de-noise raw images. Image processing technology helps extract features from images, which could visualise the image data for better understanding than numerical data. The image processing technologies in Fig. 16 distinguish relative distance in the picture according to colours [70, 71, 95, 99]. Nuchitprasitchai et al. [98, 99] worked continuously to seek improvements in using cameras by increasing the number of cameras to cover more aspects of the monitored object and reconstructing the image from 2D to 3D (Fig. 16d).

There are still obstacles involved in multiple aspects of data collection and technology application to fully achieve the auto-correction function. Jin et al. [38] developed a real-time correction function that achieved a near-ideal performance, although with certain limitations:

- Only certain types of defects (over-/under-extrusion)
- Only capable of simple parameter calibration
- Excessive algorithm processing duration for defect correction

6 Challenges and future research development

There are three critical aspects of data utilisation, including data acquisition and processing, real-time and in-situ capability, and data transmission efficiency. To determine the appropriate algorithm for a given dataset, it is essential to consider the characteristics of the data and explore the available algorithms for processing.

6.1 Data acquisition and processing

The accuracy of data obtained from sensors is one of the key factors affecting data reliability. To obtain accurate data, the selection of sensors should be based on the principles of NDT. The installation of the sensor should be easy, and the sensor should not affect the operation of the monitored machine.

As the direct input of d/f detection and identification, the data acquisition method must be strictly controlled to ensure

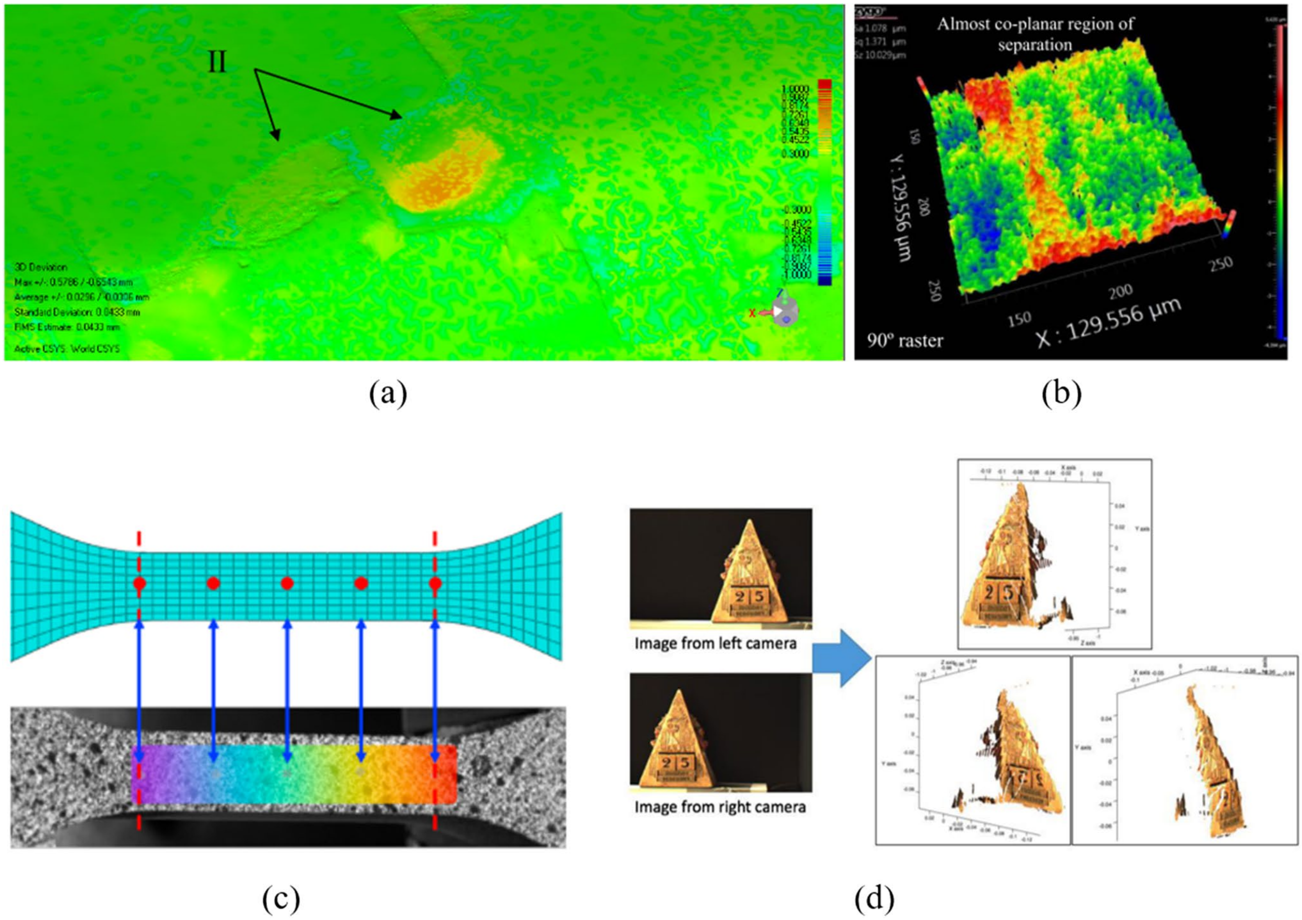


Fig. 16 **a** Scanned 3D Deviation image for analysis [95]. **b** Fractographic images of the fracture surface and layer thickness [71]. **c** DIC matching with FE model during tensile testing [70]. **d** reconstructing images from 2D to 3D [99]

reliability. To obtain high-quality data, the operators who instal and utilise the data should have specific knowledge and experience in data acquisition and processing. Users could hardly acquire data correctly without relevant data acquisition knowledge [129].

6.2 Real-time and in-situ capability of data transmission

The data must be transmitted in-situ and in real-time to achieve fully automated d/f monitoring. Although some monitoring methods can achieve real-time d/f detection and identification, the printing process still needs to be paused for a short duration during data acquisition. The schematic in Fig. 17 [33, 98] shows that the 3D printer was paused for 10s, and the extruder resets to the starting position during the image-capturing process. The study carried out by Bowoto et al. [33] used a similar monitoring procedure with a longer pause time (20 s). The cooling effects due to the pausing may affect the quality of the finished product. Additionally, the current printing mechanism that requires the extruder to always be above the printing part during the printing process makes it difficult to capture clear and unblocked images of printing parts in real time.

6.3 The efficiency of data transmission

Another factor that affects data reliability is data transmission efficiency. Data timeliness is crucial to the correct functioning of a real-time monitoring system. Excessive hardware or software processing time of data is one of the most common causes of data expiration. For example, SEM is not an excellent choice for real-time monitoring as it requires hours and even days to obtain the desired image. Nonetheless, SEM is suitable for investigating the nature of defects and failures since it can observe d/f at a microscopic level. Processing time is one of the essential factors that limit the operation of 3D printers. The prolonged processing time due to poor data transmission makes it challenging to realise the real-time monitoring of every layer during the printing process, as the printing speed is faster than the data processing time [98].

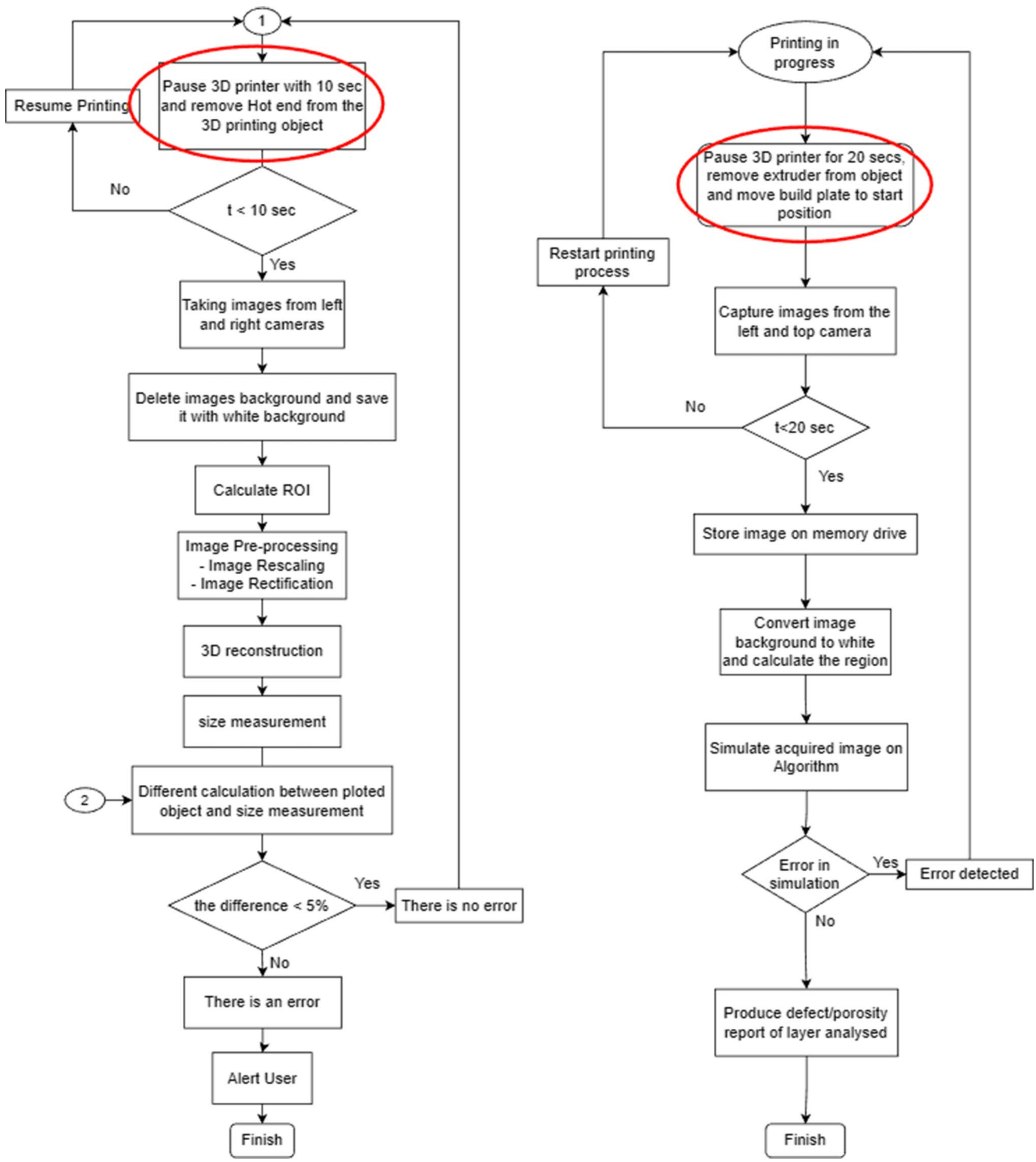


Fig. 17 Pause action in schematics of model detection procedure marked with a red circle (**a**) [98] and (**b**) [33]

6.4 Algorithm selection and application

The correct algorithm application with monitoring devices is the key to successfully implementing the d/f detection and identification system. There are many already developed algorithms available. However, it is essential to consider their dependency on pre-training, their specific suitable application, and data processing efficiency. UL was the most suitable algorithm for in-situ d/f detection due to its advantage of preliminarily detecting abnormalities and extracting their feature from input parameters without being trained with existing data. However, UL cannot identify the d/f that it detected directly, and SL is heavily dependent on pre-training but can be used to build a training database for other algorithms as it is able to identify and label different d/fs.

On the other hand, the DL algorithm that features the self-adapting ability is recognised as the optimal algorithm for most applications due to its superior performance and quick processing time. Many other technologies, besides AI, can facilitate the d/f detection and identification process, such as the grayscale technique. These technologies each come with their advantages and disadvantages. However, they cannot self-adapt and self-learn like AI-based algorithms, which is almost imperative for a fully automated monitoring system.

The MCM implementation of other types of 3D printing could be referenced in FDM. For example, the discussion about applying digital twin to metallic printed parts [10] could also refer to plastic printed parts manufactured by FDM. The major consideration in the reference process is the changes in the monitored object.

7 Concluding remarks

This article reviews the latest advancements in detecting and identifying defects and failures that occur during the 3DP/FDM processes, including lower latency monitoring, wider d/f identification coverage, and higher d/f detection efficiency driven by advanced algorithms, higher monitoring resolution, and AI-empowered d/f prediction. A generalisation of the reviewed study methodologies is provided. The methodologies in the reviewed studies are categorised according to the type of devices used, the defects investigated, the pros and cons, and the analytical tools involved. Based on the research findings, the following conclusions are drawn:

- Understanding defects benefits the study of MCM implementations on FDM. The methodology differences depend on the types of investigated defects, applied devices, algorithm, and expected output. For example, CCD cameras can detect most visible defects. Vibration sensors can detect defects caused by nozzles.
- Defect/failure detection and identification are critical for improving the quality of the FDM printed products, which can help expose the defect and reduce the hazard [32, 95, 99, 100]. The ambiguous nomenclatures, such as the types of defects referred to in different names in literature, are unified for clarification.
- Causes and severities of defects can be analysed with parametric studies. Optimisation of the settings can help prevent and mitigate the occurrence and severity of defects.
- It is beneficial to collect and analyse defect/failure data in real-time and in-situ using appropriate means [102, 120, 124, 129]. Some devices, such as SEMs, can help investigate the cause of defects, but they are not suitable for monitoring as they cannot provide real-time and in-situ data.
- The generalised method of defect/failure data analysis used in literature can be identified with four interlinked steps: (a) set research target, (b) select data collection methods and collect valuable data, (c) analyse data via data processing tools, and (d) obtain and evaluate the results from the analysis. This method needs to be further developed to be more interactive and agile.
- AI algorithms play a significant role in data analysis, as they can extract the data pattern quickly and precisely. It can further predict the defects based on collected data, which can potentially prevent or correct the d/f in the process.
- The prolonged processing time is a challenge to successfully applying real-time detection and identification methods, which is the foundation of a comprehensive FDM manufacturing defect detection, prediction, and correction system [33, 98]. Reducing processing time requires more in-depth research work to be conducted and focus on the realisation of consistent and accurate real-time and in-situ monitoring.

To detect and identify d/fs effectively, a monitoring system that can receive real-time and in-situ data and process them immediately should be developed. Such a system should also help with defect prediction and mitigation procedures when necessary. An ideal monitoring system should be able to detect and identify diverse types of defects and require multiple devices and algorithms. AM technologies, including FDM, are in principle compatible with a digital twin, which provides the benefits of online working and remote control. Future research should focus on developing a multiple-defect MCM system with a specialised digital twin that facilitates AM to realise its full potential.

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Declarations

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