# Defect Optimation Methods in 3d Printing Process

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**Abstract.** 3D printing technology has revolutionized manufacturing with its ability to produce complex components, yet defects such as pores, cracks, deformation, and surface irregularities hinder its widespread adoption. Therefore, in recent years, many defect detection and optimization methods have been designed by researchers related to the above problems. This paper reviews defect optimization methods in 3D printing, focusing on three key approaches: computer vision-based detection, real-time sensor monitoring, and process parameter optimization. Computer vision techniques, leveraging high-resolution imaging and deep learning, enable real-time defect identification and correction during the printing process. Sensor-based systems, including optical and acoustic sensors, provide dynamic feedback to adjust printing parameters. Process optimization balances thermodynamic and mechanical properties to minimize defects. Despite advancements, challenges remain, including complex defect mechanisms, material heterogeneity, and hardware limitations. Future directions emphasize technological integration, material innovation, precise process control, and interdisciplinary collaboration. Improvements to these issues will enhance 3D printing quality and expand its industrial application.

**Keywords:** Additive Manufacturing, Defect Optimation, Machine Learning

## 1 Introduction

3D printing technology, also known as additive manufacturing technology, is based on 3D Computer Aided Design (CAD) model data. After the design of a 3D object is completed, the object is layered, and solid parts are obtained by printing materials layer by layer. Through the continuous development and optimization of related technical means, this technology has evolved into a digital production technology with great transformative potential, effectively breaking through the limitations of traditional manufacturing processes in terms of collection complexity and material utilization rate. According to American Society of Testing Materials (ASTM) standards, 3D printing technology is classified into seven major categories, among which the material extrusion method, also known as fused filament manufacturing, being the most popular [1,2]. In recent years, the application spectrum of 3D printing technology has become increasingly extensive, spanning both the mass consumer market and professional industrial fields. It has demonstrated its unique value in areas


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such as daily necessities, customized medical devices, and aerospace manufacturing [1].

However, the quality control issue of solid parts obtained by using 3D printing technology has always been a key problem restricting the further industrialization of this technology. Due to the technical characteristics of layer-by-layer printing, various printing defects such as pores, incomplete fusion, distortion and deformation, and material overflow are highly likely to occur during the 3D printing process. These defects will significantly reduce the mechanical properties and dimensional accuracy of solid parts. Printing defects in special fields may even cause irreparable catastrophic failures. Therefore, scholars in various fields have also proposed a variety of defect optimization methods in response to the above challenges.

Since review articles in the field of 3D printing defect optimization methods are relatively scarce, this paper aims to summarize the relevant optimization methods, summarize their existing challenges and possible future development directions.

# 2 Types and mechanisms of defects in 3D printing

## 2.1 Classification of 3D printing defects

Due to the fact that 3D printing technology adopts a coupling method of multiple process parameters to superimpose the processing characteristics of materials layer by layer, it shows significant advantages in manufacturing complex components. However, several types of defect problems may also arise during the process. Research shows that during the 3D printing process, different defect forms will occur depending on the type of 3D printing technology, including macroscopic defects such as dimensional deviation and surface roughness, as well as microscopic deviations such as pores, cracks, and residual stress [3]. According to the morphological characteristics and influence degree of defects, they can be further classified into four major categories: pore-type defects, crack-type defects, deformation-type defects and surface defects. These flaws will directly affect the manufactured parts' mechanical qualities, surface finish, dimensional correctness, and other characteristics. Therefore, exploring the optimization methods of defects is of great value for improving the printing process level [4].

## 2.2 Generation mechanism

**Pore-type defects**. Pore-type defects are one of the most common defect types in metal 3D printing technology. The research suggests that pore-type defects can be further classified into two categories: unfused pores and pores [3]. Unfused pores refer to the areas where the metal powder particles are not completely melted during the 3D printing process using metal materials due to insufficient laser energy or overly fast scanning speed, resulting in unfused zones between the layers or channels of the printed material. For pores, it refers to the situation where the gases entrapped in the molten pool fail to escape completely during the rapid solidification process, thus forming spherical or nearly spherical pores.

**Crack-type defects**. According to the different formation mechanisms of crack-type defects, they can be classified into hot cracks and cold cracks. Hot cracking refers to the tensile stress generated by the contraction of the residual liquid phase between dendrites at the end of solidification due to the constraint of the surrounding solid phase. When this tensile stress exceeds the high-temperature strength of the material, hot cracking is formed. Cold cracks are mainly caused by residual stress and often occur in high-hardness materials. This is because during the 3D printing process, rapid cooling can cause the superposition of organizational stress and thermal stress. When the local stress exceeds the material's fracture strength, cold cracks are formed.

**Deformation-type defects**. Deformation-related absences generated during the 3D printing process can mainly be divided into warping deformation and failure of the supporting structure. Warpage deformation refers to the warpage deformation of the part edges caused by the internal stress resulting from the shrinkage difference due to the uneven cooling of the material during the polymer printing process. The failure of the support structure refers to the fact that during the 3D printing process using metal materials, the large cantilever structure originally requires support to prevent deformation. However, when the support design is unreasonable or the process parameters do not match, it may lead to support fracture or part sagging.

**Surface defect**. Surface defects are common problems in the 3D printing process, directly affecting the assembly accuracy, fatigue performance and post-processing cost of the formed parts. It mainly includes three types: the first one is the spheroidization effect, that is, when the metal powder melts, due to poor wettability, the molten pool shrinks into spherical droplets, resulting in a significant increase in surface roughness and unfused defects. The second is the step effect, which is caused by the discrete characteristics of layered printing, making the curved surface present a stepped morphology. This affects the appearance and leads to stress concentration and an increase in post-processing costs. The third issue is surface powder adhesion. Because of the powder's properties or the molten pool's instability, unmelted powder adheres to the surface of the parts, which interferes with dimensional measurement and may cause contamination or wear problems due to powder shedding.

## 3 Classification of defect optimization

### 3.1 Defect optimization based on computer vision

Through real-time image gathering and analysis, computer vision-based defect optimization enables automated tracking and closed-loop management of the 3D printing process. Its core processes include image acquisition, defect detection and decision feedback [5-8]. The 3D printing defect optimization method based on computer vision has a wide range of application fields. The following four fields are representative to a certain extent.

**Molten pool monitoring and defect prediction**. Monitoring and defect prediction of 3D printing molten pools based on computer vision technology refers to collecting data such as the temperature and morphology of the molten pool through sensors to construct a labelled training set. After extracting the features of the molten pool, supervised algorithms are adopted to establish the mapping relationship between the features and the defect categories. The trained model can predict the printing status in real time, identify defects such as pores and non-fusion, and achieve closed-loop control of the process.

Gobert, Christian, et al. focused on the metal powder bed melting additive manufacturing process [9]. A high-resolution digital single-lens reflex camera was used to capture multiple images during each layer's construction process. By utilizing a linear support vector machine for identifying binary information and retrieving multi-dimensional visual characteristics, the regions in the images were classified as defect or normal construction regions. Image-based defect detection was achieved by converting the coordinates in the Computed Tomography (CT) data to the layer-by-layer image domains, which can be seen in Fig 1(a) and Fig 1(b). The results show that this method achieves a defect detection accuracy rate of more than 80% in the cross-validation experiment.

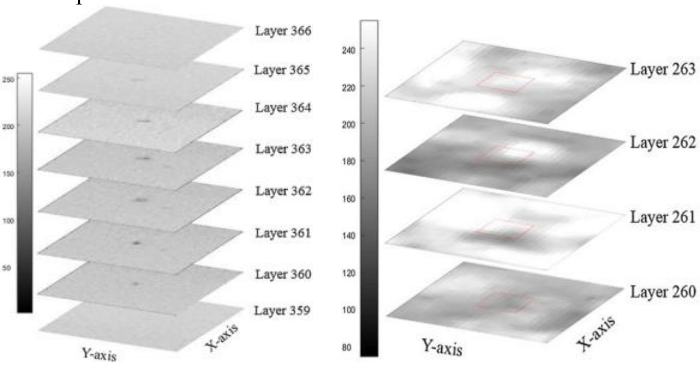


**Fig. 1.** Cross-domain visualization of a pore cluster defect in metallic powder bed fusion additive manufacturing [9]. (a) CT image layers 359 to 366 containing an anomaly pore cluster detected comprising of 36 CT voxels from layers 360 to 364 in the CT scan domain, (b) Anomaly pore cluster from (a) in the in-situ sensor domain of flash module 6, with the representative size of the feature extraction filter marked in red.

Kwon, Ohyung et al. studied the image classification model of the molten pool in the metal additive manufacturing process using selective laser melting [10]. Based on the deep neural network, the images of the molten pool were classified to identify the image features under different laser powers. This network can handle molten pool images of various shapes through training, and the classification failure rate is less than 1.1%. The experimental results show that with the increase of laser power, the width of the molten pool increases, the pores decrease, and the density of the parts increases. Researchers optimized the classification performance by adjusting the number of hidden layers and nodes of the neural network.

**Interlayer and surface defect detection**. For the defect detection of interlayer and surface in 3D printing, it is to obtain the interlayer morphology or 3D point cloud data of the surface of the printed part through optical or laser scanning or industrial CT, mark the defect types, and after extracting the geometric features, use the supervised algorithm to train the classification or regression model to establish the mapping relationship between the features and the defects. The trained model can detect poor interlayer adhesion or surface abnormalities online, achieving real-time quality assessment and process adjustment.

Jin, Zeqing et al. targeted interlayer defects in fused Deposition modeling technology [11]. Researchers have developed a real-time monitoring system. The model ultimately obtained an accuracy rate of 91.0% on the test dataset and 97.8% on its validation dataset. By installing a Universal Serial Bus (USB) camera beside the printing nozzle, images during the printing process are collected, and a convolutional neural network is used to classify the images. In addition, researchers have established a new method based on strain measurement to predict the occurrence of warpage. By setting strain gauges on the print bed, the strain changes generated during the printing process can be monitored in real time, thereby predicting the warpage trend in advance.

Cui, Wenyuan, et al. proposed a surface defect detection method for metal additive manufacturing parts based on convolutional neural networks [12]. Researchers used laser metal deposition technology to manufacture parts and obtained cross-sectional images of the parts through an optical microscope. Then, data augmentation techniques were adopted to improve the performance of the Convolutional Neural Networks (CNN) model. In addition, L2 regularization and Dropout techniques were also applied to avoid overfitting situations. The finally constructed CNN model is capable of identifying four quality states on the surface of parts: good, crack, porosity and non-fusion. This model had an accuracy percentage of 92.1% on the test set, and the recognition time of a single image was only 8.01 milliseconds.

An online quality inspection system based on Bayesian classifier was studied for layer-by-layer quality monitoring in the metal powder bed melting additive manufacturing process [13]. The experimenter developed an imaging system that can capture the images of each layer in real time during the construction process. By adjusting process parameters such as laser power and scanning speed, a layer image database containing different quality levels was constructed. Based on these images, the researchers extracted features related to quality and trained them using a Bayesian classifier. Ultimately, the system was able to identify the defective areas with 89% sensitivity and 82% specificity.

**Post-processing quality assessment**. The principle of 3D printing post-processing quality assessment based on supervised learning: Obtain the surface or internal data of the post-processed parts through optical scanning, CT or 3D imaging, and mark the quality grade or defect type. After extracting geometric or texture features, the supervised algorithm is used to train the model and establish the correlation between features and quality indicators. The trained model can automatically classify or regression evaluate the post-processing effect, achieving efficient quality inspection.

Gobert, Christian, et al. proposed a machine learning-based X-ray computed tomography image segmentation method for the porosity analysis of metal additive manufacturing parts [14]. Researchers combined threshold segmentation with Nobuyuki Otsu method and CNN to develop a tool called Automated Computed Tomography Segmenter (ACTS) for automatically segmenting pores in X-ray computed tomography (XCT) images. The benchmark of machine learning performance was established through the segmentation of the same control sample by multiple XCT experts. The research finds that the performance of ACTS in pore segmentation is comparable to or better than that of experts, showing a higher ability of automated pore segmentation.

A deep learning-based ultrasonic non-destructive testing method was proposed for evaluating the porosity of additive manufacturing parts [15]. Firstly, the researchers obtained high-resolution C-scan images of the additive manufacturing samples through scanning acoustic microscopy. Then, the pore types were further analyzed using an optical microscope, providing a training basis for the deep learning model. Researchers also extract features through ultrasonic signal processing, similar to the feature extraction process in computer vision. Ultimately, the deep learning model based on these features was able to accurately evaluate the porosity, verifying the effectiveness of this method in the quality assessment of Additive Manufacturing (AM) parts.

**Discussion**. Computer vision technology has significant technical advantages in defect detection and optimization of 3D printing. Through high-resolution imaging and deep learning algorithms, real-time monitoring and classification of defects during the printing process can be achieved. For example, classifying the molten pool image by using the CNN can identify the printed layers of different qualities according to the laser power, thereby optimizing the printing parameters and bettering the quality of the parts. The defect optimization of 3D printing based on computer vision technology improves the accuracy and efficiency of defect detection, and at the same time it reduces the spend and mistakes of manual detection, providing strong support for the industrial application of 3D printing.

Although 3D printing defect detection and optimization based on computer vision technology have significant advantages, there are several interconnected aspects that make 3D printing defect identification extraordinarily difficult. First of all, intricate fault morphologies—like co-occurring or irregularly shaped flaws—frequently elude detection by standard image processing, necessitating the use of more advanced Artificial Intelligence (AI) algorithms for precise identification. Furthermore, these challenges are made worse by material heterogeneity, which produces hidden flaws such internal bubbles and cracks that visually mix with typical structures and are therefore almost undetectable using conventional computer vision algorithms. Moreover, environmental factors and hardware constraints naturally limit the efficacy of detecting systems, as poor imaging conditions commonly result in decreased image quality and, in turn, decreased detection accuracy. When taken as a whole, these elements emphasise the necessity of comprehensive developments that include sophisticated algorithms, material-specific detection techniques, and improved system resilience in order to accomplish strong defect control.

### 3.2 Real-time monitoring optimization based on sensors

The sensor-based 3D printing defect monitoring system collects physical signals during the printing process in real time through multimodal sensors, and combines data analysis to achieve defect early warning and dynamic optimization. Its core processes include: signal acquisition, defect diagnosis and closed-loop control.

**Optical sensor**. The defects in the 3D printing process were optimized by using the optical sensor technology of optical coherence tomography associated with 3D extrusion bioprinters [16]. In terms of defect detection, it analyzes and quantifies the wire diameter and layer thickness based on imaging data. Meanwhile, for the defects generated by different paths, researchers have also pre-constructed feedback mechanisms. For example, for the defects of straight paths, starting and ending points, and corners, parameters such as pressure, speed, and node positions are adjusted respectively through pre-experiments. This technology can effectively reduce the errors of filament diameter and layer thickness, improve the printing fidelity and optimize the printing effect.

By using optical sensors to obtain images from above the printing layer, they are decomposed into small image blocks [17]. For these image blocks, bag-of-words combined with three machine learning architectures, namely support vector machine, convolutional neural network and convolutional autoencoder, are adopted for classification to identify defects. The experimental results show that the classifier based on CNN and trained from scratch for the test cases performs the best and can detect defects such as abnormal adhesion between adjacent filaments, thereby providing a basis for optimizing the 3D printing process.

**Acoustic sensor**. Kononenko, Denys Y., et al. proposed a 3D printing in-situ crack detection method based on acoustic emission signals and machine learning [18]. Laser powder bed melting technology was used in the study. By monitoring Acoustic Emission (AE) signals during the printing process and for a period of time after completion, possible crack events were captured. The experimenters installed the high-temperature AE sensor on the substrate beneath the printed samples. By conducting threshold detection and feature extraction on the AE signals, the signals were classified into two categories: "cracks" and "noise". Meanwhile, multiple machine learning models were used to classify the AE events. Finally, a classification accuracy rate as high as 99% was achieved in the principal component space of the spectrum.

**Multisensor fusion**. By using multiple sensors and combining with machine learning, the detection and optimization of defects in the 3D printing process are achieved [19]. In terms of detection, multiple sensor data were collected through the powder bed fusion additive manufacturing (PBFAM) test platform. Meanwhile, high-resolution CT scanning was used to obtain the true location of the defects. After data registration and rasterization processing, real labels are extracted from CT scans to provide data support for machine learning. Data fusion and classification are carried out using neural networks, a classification model is constructed, and the model performance is evaluated through four-fold cross-validation. The experimental findings demonstrate that this model's detection accuracy can reach 98.5%. In terms of optimization, the information content of each sensor mode and its subsets was evaluated through sensitivity studies. It was found that the information content of the interlayer electro-optical (EO) mode was high, the correlation was good after the fusion of the scanning vector modes, while there was redundancy in the multispectral and acoustic data.

**New sensor technology**. Wolff, Sarah J., et al. investigated the formation mechanism of pores during the laser powder blown directed energy deposition additive manufacturing process by using synchrotron radiation high-speed X-ray imaging technology [20]. According to the study, the powder feeding procedure has an immediate impact on the emergence of pores. Thus, strategies to reduce pores have been proposed, such as improving the quality of the powder, adjusting the kinetic energy of the powder to better match the surface energy of the molten pool, and ensuring that the powder distribution area is smaller than the surface area of the molten pool. These strategies help optimize the 3D printing process, reduce the formation of pores, and thereby improve the quality and performance of the printed parts.

Yazhou et al. Utilized an electron bombardment ion source time-of-flight mass spectrometer (EI-TOF) to track in real time the changes of the gas environment above the molten pool during the laser Directed energy deposition (LDED) process, thereby optimizing the oxidation defects and spatter problems [21]. The core function of EI-TOF is to detect the concentration changes of $O_2$, $N_2$ and $H_2O$ near the molten pool with high-frequency sampling once per second, and reveal the dynamics of the oxidation reaction through high-precision gas analysis. It also collaborates with high-speed cameras to form a multimodal data chain of "gas - splashes - defects", providing a basis for intelligent regulation and control. The EI-TOF data was used to guide the adjustment of laser power. Experiments proved that when the laser power was 600 W, the molten pool was more stable, the oxygen content of the deposited layer decreased, and the density was increased to 95.4%.

**Discussion**. In the 3D printing process, sensor-based real-time monitoring technology brings significant advantages to defect optimization. Through real-time monitoring, defects such as pores, cracks, and uneven material deposition can be detected immediately during the printing process. This enhances the accuracy and efficiency of defect detection and reduces production costs and material waste. By promptly identifying and correcting defects, the quality and performance of printed parts can be significantly improved, thereby promoting the wide application of 3D printing technology in high-precision fields such as aerospace, medical care, and automobiles.

Although sensor-based real-time monitoring technology in the AM process has significant advantages in defect optimization, the accuracy, response time, and adaptability of the existing sensor technology are restricted, especially when dealing with complicated materials or different printing settings, which might result in inaccurate detection results. Large datasets are generated by real-time monitoring, but current algorithms find it difficult to effectively process and analyze them. Large-scale adoption is further hampered by the high cost of precision sensors and sophisticated data systems, while increased process complexity could lower production efficiency. Additionally, because some defects are difficult to rectify and corrective actions run the danger of creating new problems, defect repair and feedback control are still immature. In conclusion, the real-time monitoring technology based on sensors in 3D printing still needs further improvement and optimization in terms of sensor performance, data processing, cost control, and feedback repair mechanisms in defect optimization, in order to enhance its performance in all aspects.

### 3.3 Defect suppression through process parameter optimization

In the 3D printing process, process parameter optimization refers to suppressing the generation or deterioration of defects by precisely regulating key variables such as temperature, speed, and extrusion volume. The core principle is to balance the thermodynamic behaviour and mechanical properties of the material. Through experimental tests, numerical simulations or real-time sensor feedback, the system dynamically adjusts these parameters, thereby achieving controllability in key links such as material curing, shrinkage and adhesion, and ultimately achieving the goal of reducing defects and improving printing accuracy [22].

**Representative research**. Dilip et al. took the selective laser melting process of Ti-6Al-4V alloy as the research object, and the process was optimized by changing process parameters such as laser power and scanning speed, thereby suppressing the defects in the 3D printing process [23]. Researchers studied the relationship between the geometry of a single molten pool and the porosity of bulk parts, the window for optimizing process parameters was determined, thereby effectively suppressing defects during the 3D printing process.

Chia, Hou Yi, et al. first determined the key process parameters, and then constructed the optimization framework through means such as experiments and simulations [24]. When designing experiments, full-factor design, Taguchi method and other sampling and analysis methods were used to reduce the number of experiments. In the modeling stage, mechanical models were adopted to deeply understand the physical mechanism, and surrogate models were combined to reduce the computational cost. In terms of optimization algorithms, multi-objective optimization algorithms reduce the parameter space when the input-output relationship is known. Finally, the appropriate process window was determined, multi-objective conflicts were balanced and print quality was enhanced.

Shirmohammadi et al. focused on the effect of optimizing process parameters in 3D printing on suppressing surface roughness [25]. Through the Central Composite Design, five parameters, namely nozzle temperature, layer thickness, printing speed, nozzle diameter and material density, were selected to design 43 groups of experiments. Rectangular samples were printed with a 3D printer and the surface roughness was measured. The secondary model was constructed using the Response surface method. It was found that an increase in layer thickness, roughness would grow as a result of nozzle temperature and diameter, while an increase in printing speed and density within a certain range would lead to a decrease in roughness. To better the settings, a hybrid approach that combines the particle swarm optimization technique with the multi-layer perceptron neural network is utilized. Experimental verification shows that the prediction error of the hybrid algorithm is 4.88% and the RSM is 8.75%, both of which can effectively optimize and predict the surface roughness.

**Discussion**. Suppressing 3D printing defects based on process parameters has its unique advantages and performs outstandingly in terms of cost, universality and deepening of process understanding.

In terms of cost, there was no need to purchase complex equipment, avoiding equipment-related costs, and it could also reduce material waste and time costs in production. In terms of universality and adaptability, different 3D printing technologies can suppress defects by adjusting process parameters. This method can also deeply understand the essence of the process, grasp the causes of defects by studying the relationship between parameters and defects, and provide theoretical support for technological development. In terms of data acquisition and model establishment, it is relatively simple and improves research efficiency.

However, the technology of suppressing 3D printing defects based on process parameters still has many limitations. Firstly, it has a high degree of dependence on experiments and consumes a lot of time and resources. Secondly, in terms of universality, the process parameters of different materials and equipment vary greatly, lacking universality. The determined optimized parameters are difficult to be directly applied to new situations. The relationship between process parameters and defects is extremely complex, with numerous mutual influencing factors, making it difficult to grasp comprehensively and accurately, which increases the difficulty of optimization. Moreover, the current research on process parameters is mostly based on experience and trial and error, lacking systematic theoretical guidance, making it difficult to achieve precise control and optimization of process parameters.

# 4 Current challenges and future trend

## 4.1 Current challenges

3D printing faces multiple challenges in defect detection and optimization, involving areas such as defect formation mechanisms, detection technologies, optimization methods, and the relationship between process, structure, and performance. These challenges restrict the further development and wide application of 3D printing technology [26,27].

**Complexity**. Multiple interrelated factors contribute to the complexity of defect formation in 3D printing. For example, in metal printing, hot cracks are dependent on liquid films, thermal stress, and alloying elements, whereas in bulk metallic glass, compositional changes, structural relaxation, and exposure to high temperatures cause crystallisation defects. Defect diagnosis and process optimisation are made more difficult by this complex mechanism. Furthermore, control is made more difficult by the nonlinear link between process parameters, microstructure, and performance; whereas molten pool dynamics, grain growth, and defect formation are all sensitive to parameter changes, material-specific responses make generalisations challenging. These interdependencies are difficult for traditional experiments and models to fully capture, which makes it difficult to create accurate defect detection and optimisation techniques.

**Limitations**. The existing detection technologies have deficiencies in 3D printing. Some detection methods have limited accuracy and resolution, and cannot accurately detect minor defects. For example, ultrasonic testing has poor detection ability for minor defects, and the data interpretation is complex. The results of optical coherence tomography during detection are uncertain and inconsistent. Some detection techniques have limited application scopes and cannot be detected in real time. For example, X-ray computed tomography is often used for post-print characterization. Some technologies are greatly disturbed by the printing environment. During the laser powder bed fusion process, optical detection is easily affected by the optical scattering of the powder bed and the molten pool.

**Difficulties in balancing multiple objectives**. When optimizing 3D printing defects, it is difficult to take multiple goals into account. Adjusting the process parameters may cause new problems. When decreasing pores, altering the laser's strength and scanning speed could result in hot cracks. The post-treatment methods also have limitations. Although hot isostatic pressing can eliminate internal cracks, it may cause grain growth and reduce strength. For bulk metallic glass, it may also cause crystallization. Moreover, different optimization methods may conflict with each other, increasing the difficulty of comprehensive optimization [28].

### 4.2 Future trend

3D printing has broad prospects for development in defect optimization. Overall, 3D printing defect optimization will focus on areas such as technological integration and innovation, material performance improvement, precise process control, data management optimization, and cross-disciplinary collaborative development. These directions are the key to solving the current defect problems of 3D printing and important ways to promote the wide application of this technology in more fields.

**Technological Integration and Innovation**. In the future, the defect optimization of 3D printing will focus on the integration of multiple technologies and be further fused with data from other sensors to improve the detection accuracy. Qi, Xinbo, et al. proposed to combine machine learning with traditional detection techniques, and utilize the powerful pattern recognition ability of neural networks to analyze detection data such as ultrasound and infrared, so as to achieve precise detection and classification of defects [29]. Khan, Mohammad Farhan, et al. utilized the convolutional neural network to analyze the image data collected by the camera to detect defects in the 3D printing process [30].

**Material Performance Improvement and Innovation**. The development of new high-performance materials is an important direction for defect optimization in 3D printing. Jakus, Adam E pointed out that future material research and development will focus on improving the printability of materials, reducing the shrinkage rate, and enhancing the interlayer bonding force, thereby reducing the occurrence of defects from the source [31]. Developing metal alloys, high-performance polymers and other materials specifically for 3D printing improves the thermal physical properties of the materials and makes them more stable during the printing process. It will also pay attention to the biocompatibility and functionality of materials to meet the strict requirements of high-end fields.

**Precise Process Control and Optimization**. In terms of process control, in-depth research will be conducted on the relationship between process parameters and defects to achieve precise control. It is mentioned that through machine learning algorithms to analyze a large amount of process data, an accurate model between process parameters and defects is established to predict the defect conditions under different parameter combinations, thereby optimizing process parameters and reducing defects [32]. Hardware and software of the printing equipment will also be improved to enhance the printing accuracy and stability, ensuring uniform material deposition and reduce interlayer defects.

## 5 Conclusion

3D printing technology, as a digital production method with great transformative potential, has demonstrated unique value in many fields. However, the defect problems generated during the printing process have severely restricted its further development and wide application. Through in-depth research on various types of defects, it can be known that the generation mechanisms of porosity type, crack type, deformation type and surface defects are complex, involving multiple factors such as heat-force coupling, material-process mismatch, as well as equipment and environmental limitations. To solve these problems, a variety of defect optimization methods based on computer vision, real-time sensor monitoring and process parameter optimization have been developed at present. However, they still face challenges in complex defect identification, dealing with material heterogeneity, sensor performance and high dependence on experiments.

To achieve significant progress in 3D printing defect optimization, a comprehensive strategy integrating multiple approaches is crucial. Firstly, machine learning should be merged with traditional detection methods and combined with AI and Internet of Things (IoT) technologies to establish intelligent monitoring and control systems. Secondly, developing advanced materials with enhanced thermal properties, printability, and interlayer bonding will address critical performance requirements. Third, leveraging machine learning to analyze process-defect correlations and optimize equipment parameters will improve printing precision. Finally, implementing standardized data management and advanced analytics will enable dynamic quality control. By systematically advancing these areas, 3D printing can overcome current limitations, enhance production quality, and expand its industrial applications, ultimately driving innovation in manufacturing.

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