Online Error Detection in Additive Manufacturing: A Review

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***Abstract*—Additive manufacturing (AM) is increasingly used in production as possibilities like no geometrical constraints, fabrication of complex assemblies in a single piece and fast iteration delivers a huge additional benefit. However, the printing process is still prone to errors, even though the technology is several decades old. Depending on the object and the used material a complex set of parameters have to be chosen to produce a durable object that fulfills the requirements. The errors can occur at any time during the print process so the current state has to be checked regularly. This is currently done manually as only a few printers use sensors for error detection. But most of them only check for hardware faults like axis misalignment or blocked filament flow control.**

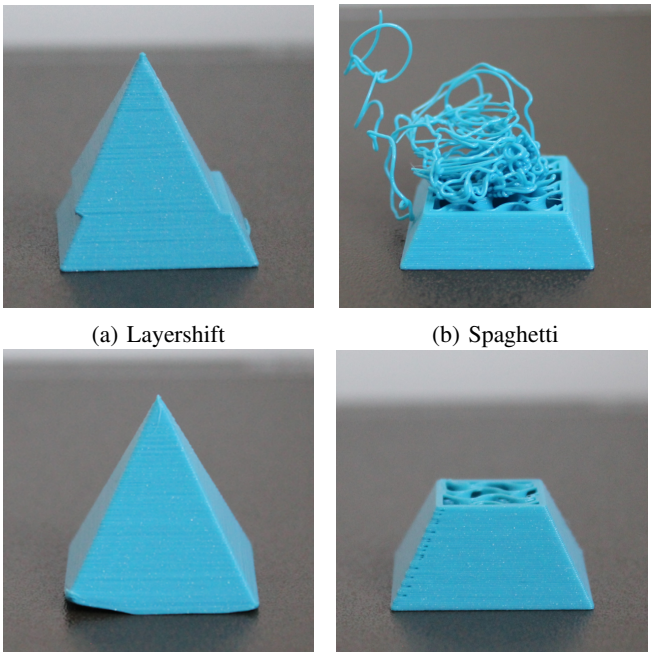
Meanwhile, a lot of research has been done to improve the material, the printer's hardware as well as to detect errors during the printing process. The goal of this publication is to summarize the current state of the art in terms of the error detection aspect. Therefore, we studied multiple techniques to detect errors like using different sensors concepts, classical sensor data processing, and neural networks. Several promising approaches exist, but so far, only a few are currently used in some commercially available printer. As the research continues, further approaches will be developed and might also be considered in production.

***Keywords*-Additive Manufacturing, Error Detection, In-Situ, In Process, Online, Quality Inspection, Quality Assurance, Fused Filament Fabrication, Powder Bed Fusion**

I. Introduction

Although the basic technology is several decades old, there are still challenges that need to be solved for the productive use of additive manufacturing (AM) in industry [1]–[3]. One of these is the susceptibility to errors in the process itself. Up to now, the components have had to be extensively monitored in the process, otherwise the final result could not meet the required standards. The earlier a failed print is detected and stopped, the more material and time are saved. At the same time, the new print can start earlier, and possibly the corresponding parameters can be adjusted. In the industry, in particular, machine utilization is an important criterion for determining whether and how quickly a machine will pay off for itself.

Up to now, monitoring the current printing process is either not possible due to the process or is carried out manually in a time-consuming manner. However, there are already some approaches and processes to improve the error detection as far as possible. For this purpose, the respective processes (Fused Filament Fabrication (FFF, FDM), Powder Bed Fusion (PBF), Stereolithography (SLA), ...) use appropriate and suitable sensors to deal with the conditions of the process. For example, 2D, 3D, and also thermal imaging cameras are used to assess the current printing process. Error detection in additive manufacturing is not easy as the printed object can have a large variety of shapes.



(a) Layershift (b) Spaghetti

(c) Warping (d) Clogged Nozzle

Figure 1: Possible errors, that might occur during FFF printing when one of the many parameters is not correct. This is only a small subset of possible errors. Merely for FFF printing the amount of errors exceeds 25 [4]. Many more error categories occur in other additive manufacturing techniques.

In this paper, the different processes are divided according to the printing technology. The need for special and individualized parts in low quantities in industry encourages the use of new production processes like additive manufacturing. Even 40 years after the first patents, lots of open challenges still exist and have to be solved before these techniques can be used in production at large scale. The objectives are tackled in different ways for example with

classical computer vision or machine learning. Nowadays, there are many different processes, but we have focused on these two: Fused filament fabrication (Section II) and powder bed fusion (Section III). However, key elements of the possible approaches of the respective technology can be transferred to similar technologies with relatively small effort. Fig. 2 presents an overview of the most common additive manufacturing techniques including the category they belong to.

The parts manufactured with additive manufacturing machines according to the current state of the art often show inconsistent quality resulting in unpredictable mechanical properties [6], [7]. In addition lot sizes in AM are often small and thus human, environmental and material factors can also have a negative effect on the process reliability [8]. As functional end products, however, additively manufactured parts must meet strict functional and geometric specifications. This results in increased requirements for quality assurance control [9].

Since individual parts are often produced in AM, non-destructive measuring methods such as tactile and optical measurement or computer tomography [10] are particularly suitable for quality assurance. These methods can be applied at different stages of the manufacturing process. In preparation [11]–[14], during the construction process or during post-processing [15]. Thus, quality deviations can be detected in an early stage and it is possible to counteract by stopping or adjusting the production parameters. Furthermore, this enables a documentation of the parts throughout the whole process [16]. In this phase, various process variables can be monitored with the help of one-, two- and three-dimensional sensors, e.g. color, 3d or infrared cameras.

The structure of this paper is as follows. In Section II, we present approaches based on FFF manufacturing, whereas Section III, we focus on approaches based on PBF manufacturing. In Section IV, we describe already implemented and existing approaches for online error detection in AM. Finally, we provide conclusions and perspectives in Section V.

II. In-Process Monitoring in Fused Filament Fabrication

Monitoring in FFF printing can be performed in many different ways addressing the numerous categories of potential errors. Furthermore, it is possible to trigger the errors on purpose by choosing the wrong parameters or mechanical manipulation during the printing itself.

Liu *et al.* presented an approach in which an acoustic emission sensor attached to the extruder monitors the machine state of an FFF printer [17]. Using a clustering approach, they are able to detect different machine states, such as loading and unloading, as well as interrupted filament supply. Using a similar test setup, Wu *et al.* were

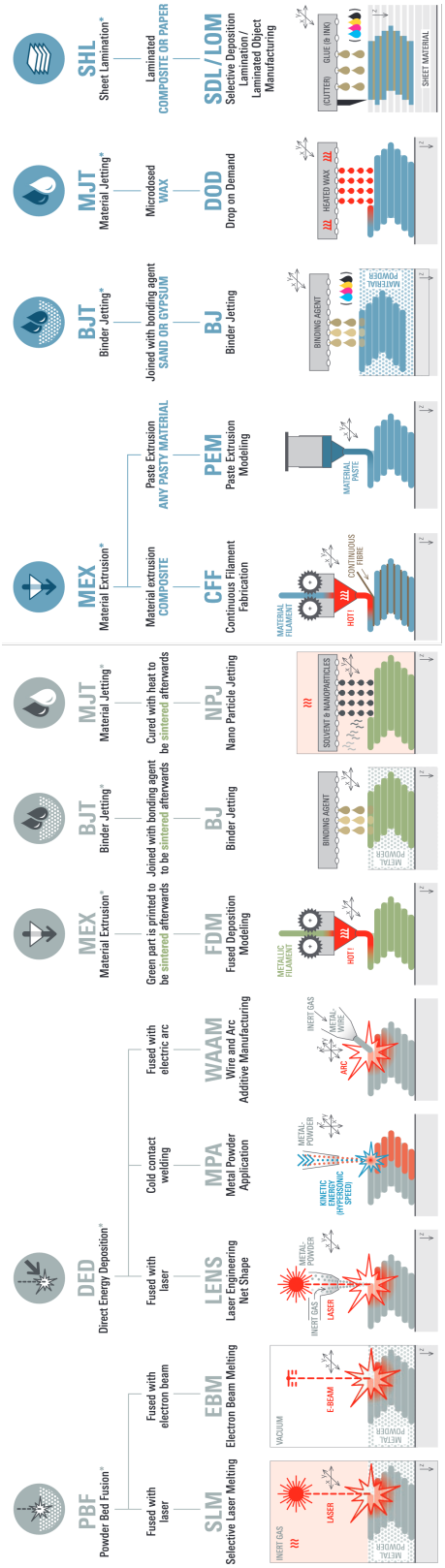


Figure 2: An overview of currently existing additive manufacturing technologies in different categories. In this paper we are going to focus on MEX/FFF/FDM and PBF as they are the most common methods currently [5].

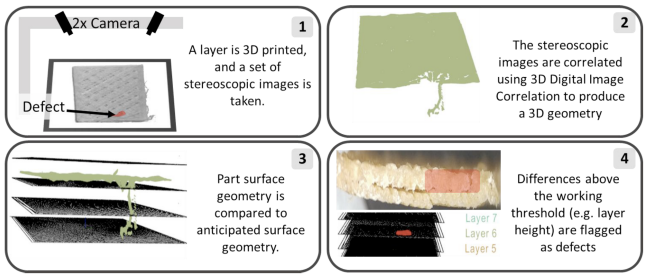


Figure 3: Graphical abstract of the work of Holzmond *et al.* A two-camera setup was installed within a FFF printer to certify the print while the part was built. With 3D digital image correlation (3D-DIC) and a comparison with the computer model they were able to detect errors while printing [22].

able to distinguish clogged nozzles from unclogged ones using support vector machines (SVM) [18]. In both approaches, the distinction is based on specific features in the frequency range of the measurement. To detect defects in the printed component, Becker *et al.* analyzed the Mel frequency cepstrum coefficient of audio measurements near the extruder [19]. The converted representation of the frequency spectrum could be distinguished into error-free and error-prone prints by using neural networks. Tlegenov *et al.* attached an accelerometer to the extruder and were able to detect a clogged nozzle [20]. Since the extruders of an FFF printer are usually moving, the first step was to design a printer with a fixed extruder and a movable platform. Depending on the material and the temperature, the usual vibrations were determined and an average value was calculated. A correlation between acceleration amplitude and the clogged nozzle was documented by means of deliberate error simulation. Thus, a strong increase in the vibration measured at the extruder can be assumed to be due to a blocked nozzle. In a further study, Tlegenov *et al.* were able to establish a direct correlation between the electrical current at the extruder motor and a blocked die [21]. If the die begins to clog, the effective diameter of the die decreases, which increases the backpressure. To keep the extrusion speed constant, the current at the stepper motor must also be increased. This increase is monitored by a current meter.

Since in an additive manufacturing system there is usually more than one source of error, it is obvious to combine the available sensors in one sensor system. For this purpose, Rao *et al.* and Moretti *et al.* have equipped a printer with several specific sensors [23], [24]. In both approaches, errors are identified by a deviation from the determined normal state. Rao *et al.* combined thermocouples for measuring the extruder and bed temperature with acceleration sensors for measuring the extruder and bed vibrations. In addition to a borescope to record the entire printing process, they extended the system for temperature measurement at the melting point with an infrared thermometer. Using a combination of Dirichlet process mixing models and evidence theory, process errors could be identified with a high (F1-Score = 86%) probability. The approach of Moretti *et al.* combines position and filament measuring devices with thermocouples and a camera. It is shown that more than one individual sensor is often required to detect a fault. For example, a superficial defect can be detected by combining position measurement with feed rate.

The approaches of Rao *et al.* and Moretti *et al.* show the great advantage of visual monitoring. Some error categories cannot be assigned to one-dimensional sensor data. For example, the detachment of the print object from the building platform cannot be detected by the nozzle temperature or the feed rate. In the same way, *Warping* depends not only on the bed temperature but also on the temperature of the adjacent layers and can therefore not be measured by the internal sensors alone.

In principle, optical control methods are based on one or more cameras for monitoring the print object from one or more angles. However, there are also approaches like the one of Greeff *et al.* where the filament feed is monitored by a camera to determine the feed speed and condition of the filament [25].

Baumann *et al.* developed a monitoring system for an FFF printer that uses a camera to locate the center of the printed object and detects a release of the print by comparing the position over time [26]. In addition, a canny filter is used to determine the upper edge of the printed object and the distance to the marked extruder is measured. If the measured distance exceeds a certain limit value, an interrupted extrusion is identified. In contrast, Becker *et al.* selected a Sobel filter for edge detection [27]. In the presented approach, the positions of the pixels occupied and not occupied by the Sobel filter are detected. Thus, the error class *stopped extrusion* can be identified as soon as the number of pixels between the upper edge of the print object and the printing nozzle exceeds a threshold value. For *Warping* and dimensional deviations, the number of pixels from the image of the printed object is compared to a rendered image of the target state. Certain percentage deviations are detected as errors. With the presented approach, the majority of errors can be detected, but the rate of images falsely identified as defective is very high.

In the published approach of Nuchitprasitchai *et al.,* the FFF process is paused at several significant points and a 3D model of the current production status is reconstructed with the help of two cameras [28]. This reconstructed object is now compared with the STL file of the object to be manufactured via a perspective image. If the images differ by more than 5%, the print is classified as faulty. In the previous approach, only finalized prints were analyzed and therefore the in-situ capability was not confirmed. Furthermore, it is problematic that printed objects are compared with STL objects, which have a much better surface quality even if the print is flawless. Using the approach of three-dimensional

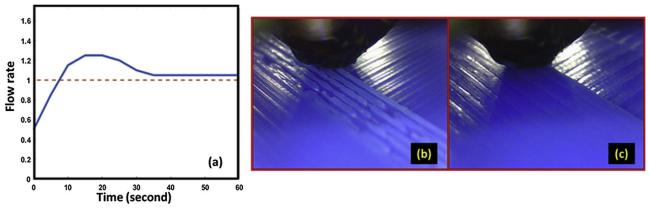


Figure 4: In their approach, Liu *et al.* mounted two digital microscopes to the extruder and adapted the flow rate of the filament when an error was detected. These pictures show the flow rate during the process (a), the image from the microscopes before (b), and after (c) the controller adaptation. This adaptation was learned by a k-NN and exceeded alternatives like LDA, SVM and NBC [29].

digital image correlation presented by Holzmond *et al.,* a spatial reconstruction from two image perspectives was also generated (see Fig. 4) [22]. In contrast to Nuchitprasitchai *et al.,* the CAD model was not used for the comparison, but rather the machine path (G-Code) of the print object. By reconstructing the G-Code as a point cloud, the surfaces can be created more realistically through the print artifacts. Similar to the approaches described above, a print is classified as faulty when its deviation exceeds a specific tolerance limit. With the system presented, local defects such as filament droplets or insufficient material flow can be identified. The approach published by Moretti *et al.,* in which an image taken during the construction process is compared with a digital twin of the print object goes in a similar direction [9]. Since the resolution of conventional cameras is often too low, an electron microscope is used here. Due to the small image area of the microscope, a specific path is determined for each layer, on which the microscope traces the contours of the print object. The comparison via the digital twin proves to be comparatively resource-saving and efficient for the high-resolution images.

The presented methods are based on numerical and analytical models. For large amounts of data and especially for image data, such approaches require an enormous amount of computing power. For example, with the approach of Moretti *et al.,* it is not possible to react in time to the detected error, because the calculation time exceeds the printing time of one shift [9]. In order to continuously process this high-dimensional and high-frequency data, advanced calculation and analysis tools are required [30]. Here, the development in the field of machine learning offers great potential. With machine learning, implicit (previously unknown) knowledge can be discovered, relationships in large production data sets can be identified, and thus unprecedented amounts of data can be transformed into usable and insightful information [31], [32]. The models are not a long list of physics-based equations, but automatically learn the relationship between input features and output targets based on previous data [33].

Machine learning applications of binary and multiclass classification are particularly relevant in-process monitoring. Delli *et al.* used support vector machines to identify the FFF printing process as either error-free or error-prone at specific points in time [34]. This is done by pausing printing and moving the extruder to the side to get a bird's eye view. This image is now classified by the trained support vector machine. To classify the non-linear classification problem with a support vector machine, the kernel trick is used. To detect particularly delicate deviations in the FFF printing process, [35] uses 3D point clouds that are converted into 2D images. Through the conversion, each image contains the average Z-value as a pixel value. The method of random forest is used for the classification, which is structured in cascades. Each cascade level contains a number of decision trees whose outputs are combined to a common output over the maximum average value. So-called deep forests are an alternative to the deep neural networks often mentioned in connection with image classification and may even exceed them, as in [35].

In contrast, Zhang *et al.* use a convolutional neural network (CNN) for FFF anomaly detection [36]. In their study, they investigate the characteristics of the deep learning application and the relationship between different parameters and their influence on the number of correct classifications. With an accuracy of 70%, it could be shown that the algorithm correctly classifies the majority of images. To build a monitoring system at FFF especially for the error class *Warping*, Saluja *et al.* also used a CNN [37]. To ensure the best possible monitoring of the error type *Warping*, the algorithm focusses only on the relevant part at the lower corners of the print object where the error is expected. In their study, they checked the influence of different optimizers, activation functions, and dropout. With the approach presented, they achieve an accuracy of 97% and validate the results using different geometries. In addition to the so far presented so-called binary or anomaly detection, different multiclass classifications in-process monitoring were investigated. For example, Liu *et al.* proposes an approach for process monitoring of FFF printers, in which the first step is to extract textural information from camera images using a gray value matrix [29]. For this purpose, two digital microscopes are attached directly to the extruder (see Fig. 4). Statistical feature vectors can be determined from the textural interpretation. Based on these features contrast, correlation, energy, and homogeneity, the images are assigned to the three possible classes by means of k-NN. The presented approach with k-NN exceeds alternatives like latent dirichlet allocation (LDA), support vector machines, and naive bayes classifier (NBC) in the prediction probability. In a further publication, Liu *et al.* listed a classification in two stages [38]. The first stage distinguishes between faulty and error-free prints. The faulty ones are assigned to the respective error class in a second stage. Thus, capacities in the multiclass classification can be

saved. Wang *et al.,* for example, use a CNN with two so-called residual blocks to classify six superficially occurring defect classes [39]. In order to be able to detect defects on the entire print object, a rotating camera setup is chosen that can monitor the print build-up from any angle. In order to cover the largest possible surface area, an optimal position plan of the camera is generated depending on the geometry of the object to be produced. The images are not classified as a whole but divided into individual segments of the relevant area. The relevant area is selected via a mask, which is generated from a rendered image of the CAD object from the same perspective. The approach is promising with an accuracy of 91% and surpasses known meshes such as ResNet50 [40] or Inception [41] in a conducted comparison. Banadaki *et al.* use CNN to classify the production parameters print speed and filament temperature of the printing process based on images captured in the process [42]. Thus, the parameters determined via the algorithm can be used to directly determine which parameters are incorrectly set in the preparation. The entire print object is monitored from a fixed perspective. In their approach, they use the pre-trained model Inception-3 [43] to identify 21 classes that result from combinations of temperature and speed. Using a camera attached to the extruder, Jin *et al.* developed a system to distinguish the error categories *under- and over-extrusion* from error-free print webs [44]. They expanded the system to include automated adjustment of the material flow rate in response to the detected defect class. They used the pre-trained model ResNet50 to train the classifier. To get the required output size of three, they modified the final Layer. The system has a very high accuracy of 98% and can correct the detected errors. Jin *et al.* and Banadaki *et al.* used for the transfer learning the models ResNet50 and Inception-3 for the image classification [42], [44]. As Wang *et al.* found out, these enormously deep models (Inception-3 42 Layer, ResNet50 50 Layer) are very generalized with 1000 classes to be recognized [39]. Transfer learning works well when the tasks to be performed are very similar. Whether the task of distinguishing between 1000 classes and the task of detecting errors on the print object is sufficiently similar also depends on the nature and number of the respective available training data [45].

III. In-Process Monitoring in Powder Bed Fusion

In contrast to FFF, powder bed fusion (PBF) technology is playing an important role in industrial use cases. Especially the possibility to manufacture objects from metal powders enables light-weight but durable objects. But still, errors during the manufacturing process are a problem. To control the quality of a part after it has been printed, it is usually x-rayed. This leads to huge effort especially with small-scale series where every part has to be checked afterward. Several approaches have been researched to do quality assurance during the manufacturing process for example by adding a sensor in the machine.

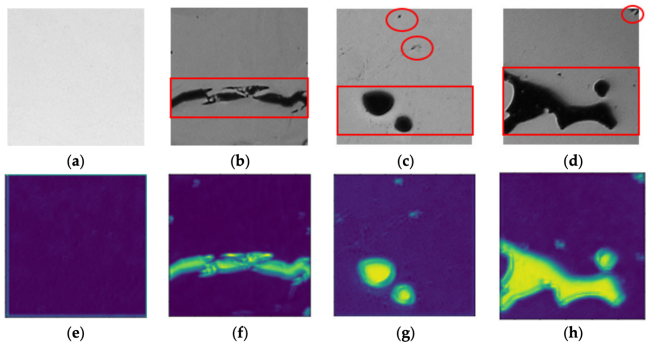


Figure 5: Four error classes (Good quality, crack, gas porosity, lack of fusion) have been identified by Cui *et al.* (a to d). In the attention maps (e to h) the image sections are bright where the CNN focuses most and also where the errors are detected [47].

Gobert *et al.* developed a system that detects errors in the PBF assembly process based on CT scans [16]. For this purpose, multidimensional visual features were extracted from the layered image stacks and evaluated using the binary classification technique of SVMs. By combining eight individual SVMs into one main SVM, the accuracy could be increased from 65% to 85%.

Neural networks tend to be the most frequently used algorithms for classification problems. For example, Petrich *et al.,* by using an NN instead of an SVM, were able to increase the accuracy of error classification in the powder bed fusion process to 90% [46].

Also in selective laser melting a multiclass classification can be done. In the work of Scime *et al.,* six occurring errors in the printing process of selective laser melting are classified [48]. The authors use the Bag-of-Keypoints (or BOW) approach. Instead of the SIFT algorithm often used in conjunction with BOW, a user-selected filter bank is used to generate as many feature vectors as possible from the individual pixels. In training, these features are now clustered with the k-Means algorithm and assigned to the defect classes. The images are then assigned by the algorithm patch-wise to the error class with the highest weight. Although the algorithm has problems distinguishing some classes from each other, it already achieves a total prediction accuracy above 80%. To avoid the human bias in feature generation and to improve the classification result, Scime *et al.* used a CNN in a continuation of the investigations [49]. They also superimposed the input images of the printing process with two-dimensional images of the CAD geometries in the correct position and orientation on the building platform. The CNN input also consists of three patches of different sizes that belong together. To save the training effort, the CNN used here is based on the already pre-trained AlexNet model using transfer learning. So only

the weights of the deep layers have to be learned. With the extended approach, significant improvements could be achieved. It also shows that the multi-layer input approach achieves significantly higher accuracy. The network thus benefits from the additional input features.

So that global, regional, and local features can be learned and thus recognized in equal measure, Scime *et al.* further modified the approach [50]. With parallel CNN global and local networks, local factors can be put into a global context. By no longer entering the input data patch by patch, but pixel by pixel, the presented approach can be transferred to other camera and manufacturing systems. Besides, the system can be extended more easily by adding another camera source or sensor data. Zhang *et al.* also used CNNs for the classification of occurring defect classes at the PBF [51]. In their study, they investigated the effects of input size, network architecture, and regularization. Using the presented approaches, overfitting could be reduced, training time shortened, and accuracy increased, as an image of the printing process is classified in blocks. By combining the entire blocks, an image was classified. The class with the highest percentage of identified blocks was selected. Thus a prediction probability of 100% could be achieved. Similar investigations were carried out by Cui *et al.* for LMD [47]. With a CNN four possible classes were classified (see Fig. 5). Besides network architecture and regularization, the influence of data augmentation was evaluated. To identify which pixels of the images attract the attention of the CNN model, so-called attention maps are used. The presented model reaches an accuracy of 93%.

Multiclass classifiers often have problems distinguishing between individual classes that are very similar. This is made more difficult by the long training duration and the often too small data sets. Instead of using even deeper nets, the combination of several classifiers to improve the results is also being investigated. For example, Scime *et al.* use parallel nets for global, regional, and local features in the already presented approach [50]. Since the constraints can be trained in parallel and the overall system is relatively flat due to the division into individual constraints, the system has significantly fewer parameters and allows for particularly fast classification speeds. Gobert *et al.* use an ensemble of eight SVMs [16]. The ensemble exceeds the performance of the individual classifiers.

IV. Known Implementation of In-Process Error Detection

Next to the existing research approaches, error detection is already implemented in some printers or can be added via an external service. EOS for example offers a tool, called EOS Monitoring Suite [52] since 2017 to increase the reliability of powder bed printing processes. Therefore, multiple sensors are added and used to monitor the powder bed, the melting process, and the environment settings to be able to analyze the process in the best way. In total four systems are used: the first one, Exposure OT is based on an optical tomography for quality assurance of each layer. The second one, EOSTATE PowderBed, monitors the powder bed and each layer for irregularities to prevent errors based on missing or wrongly spread the powder. The third one, EOSTATE MeltPool analyzes the light emission captured from the melt pool during the manufacturing process. Last, but not least, EOSTATE Base monitors all production-relevant data. These are for example the surrounding environmental temperature and humidity, vibrations, etc. Trumpf also offers a similar solution call Monitoring TruPrint [53].

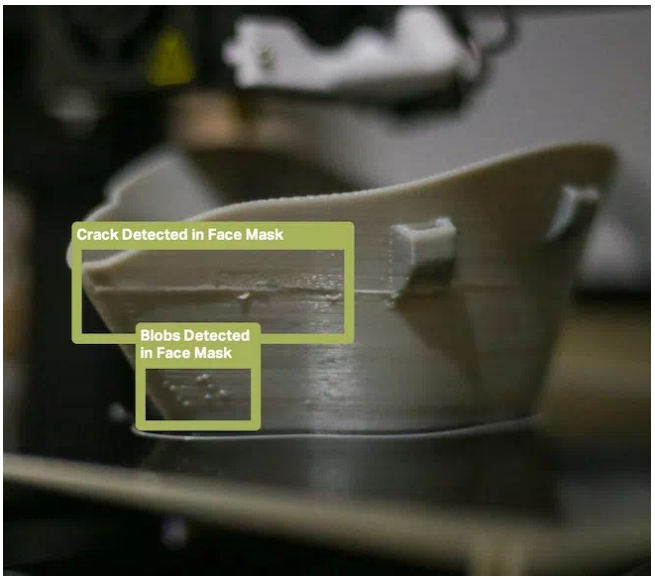


Figure 6: Example image from the Mattacloud error detection. Two errors have been detected by the software and are labeled within the image.

As the solution from EOS is just made for their products and the powder bed fusion process, it cannot be used in other machines. Approaches like The Spaghetti Detective [54], Mattacloud [55] or Addiguru [56] adds the functionality of real time monitoring independently of the brand. The integration into the machine and its sensors is done by the open-source software of OctoPrint [57], which connects to the machine and can be easily extended via plugins of all kind. The Spaghetti Detective uses the camera viewing the build plate to take a picture every ten seconds and processes them in their cloud. A trained deep learning network, YOLO [58], takes these images and checks for the spaghetti error within this picture. The result is shown via a web interface or, if an error occurred and the network detected spaghettis, the user is notified.

Also, Mattacloud is using the OctoPrint as a base system and the actual algorithms run again in the cloud. The user gets a notification and the detected errors are labeled within the image (see Fig. 6)

The Spaghetti Detective and Mattacloud are both focussing on the FFF process. In contrast, Addiguru focuses on the PBF process. A camera inside the machine is used to take pictures of the powder bed and after the laser has been active. These images are used to detect errors while the process is running. Furthermore, companies like SigmaLabs [59] or SLM Solutions [60] offer products to add error detection and monitoring for quality assurance to existing additive manufacturing machines.

V. Conclusion

So far lots of promising approaches regarding in-process real-time error detection have been researched and published. Reliable and fast error detection are crucial for the success of additive manufacturing in production, especially in some industrial sectors like aerospace. Different manufacturing techniques require different sensors and different technologies to analyze the actual state. Currently, multiple approaches lead to impressive results: Especially artificial neural networks perform with high reliability but the amount of initial data to train these is huge. The use of a well-performing network for a given perspective might not work for another setup and vice versa. Lots of aspects have to be considered and that might be one argument, why there is no final solution yet. Some companies like EOS or Trumpf already offer a solution for their products. But a public dataset with images of different errors in different additive manufacturing technologies would greatly facilitate neural network training in the research community and therefore accelerate the development of solutions for the online detection of errors.

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