ANOMAL DETECTION FOR IN-SITU QUALITY CONTROL OF DIRECTED ENERGY DEPOSITION (DED) ADDITIVE MANUFACTURING

E. Dehghan-Niri*, S. C. Hespeler*, M. Juhasz†, H. S. Halliday‡, and M. Lang

* Intelligent Structures and Nondestructive Evaluation, New Mexico State University, Las Cruces, NM 88012
† Lawrence Livermore National Laboratory, Livermore, CA 94550
‡ Center for Advanced Manufacturing, Navajo Technical University, Crownpoint, New Mexico 87313
 FormAlloy, 2830 Via Orange Way, Suite H, Spring Valley, CA 91978
*Email: niri@nmsu.edu
nde@asu.edu

Abstract

One common cause for the rejection of parts produced during metal Additive Manufacturing (AM) is the presence of unacceptable defects within the part. While powerful, post-processing nondestructive techniques can be unapproachable due to time constraints or simply impractical for certain inspection and quality control applications of the AM, especially with parts of high complexity. The AM process requires a layer-by-layer execution to build parts, allowing for a unique opportunity to collect data and monitor the process in real/semi-time. The incipient phase of AM monitoring and control typically consists of developing an automated unsupervised statistical anomaly detection algorithm that is capable of detecting irregularities through parameter measurement and sensing features. In this paper, we develop a simple and effective method for detecting anomalies through use of statistical distances from data collected during the laser-based Directed Energy Deposition (DED) AM process.

Introduction

Conventional manufacturing techniques have long been used to produce parts for a variety of applications however, the present-day push to produce parts with complex shapes in a competitive and time-sensitive market has led to great interest in metal AM. The AM process has completely revolutionized the field of manufacturing because of its ability to streamline Computer Aided Designs (CAD) to produce parts that reach

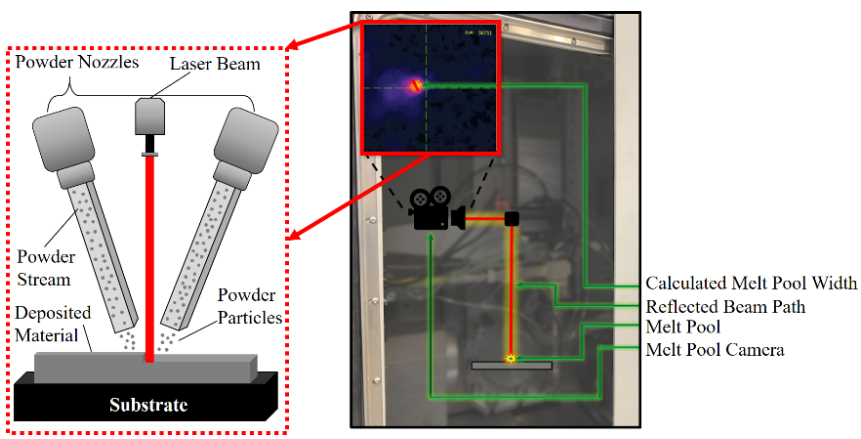


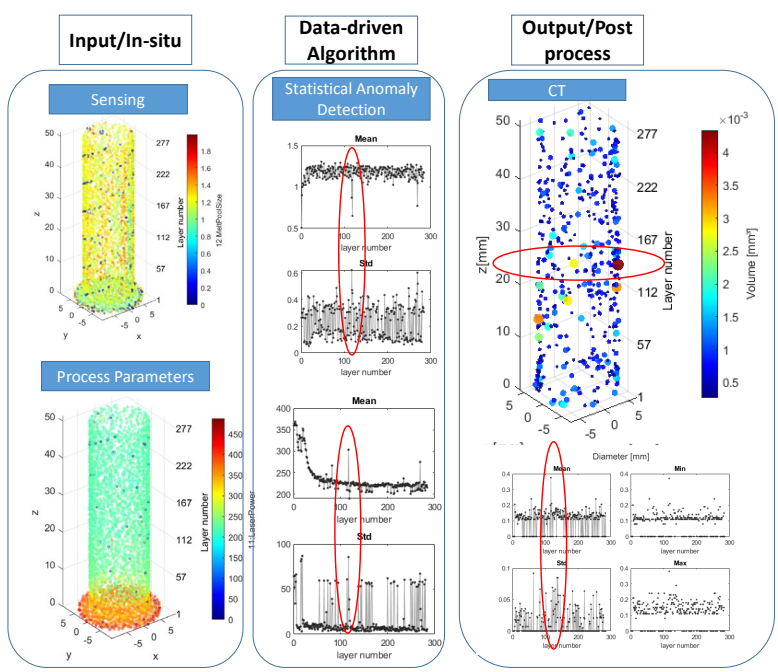
Figure 1. Schematic of FormAlloy L2 metal AM system with MPS Camera

the market in reduced time, reduced waste when preparing parts, ability to utilize multiple materials during production and print harsh complexity demands.

Figure 1 highlights the DED process used to produce parts for this investigation. DED is a metal AM method that involves the use of thermal energy to melt material during deposition (Tofail, 2018). During the DED process, metal powder (or wire) is fed from the feedstock until it reaches contact with the laser of the electron beam and is melted. Then it is deposited on top of a substrate, this process repeats until the final layer of the part is printed (Zhang, 2018). The DED technique is widely used among researchers and industry professionals because it produces high-quality parts with a high degree of controllable grain structure (Tofail, 2018). In this investigation, we use a Laser-based Directed Energy Deposition (LB-DED) technique (Shown in Figure 1) with a powder flow method for the production of metal parts. There has been a tremendous amount of research completed to identifying and classifying defects in metal AM parts (Roh, 2021) however, many of these techniques are computationally time-consuming or require ex-situ methods to identify the defects. This investigation serves to present the idea of utilizing an unsupervised statistical monitoring technique with real printing features as an initial phase of Quality Control (QC).

Methodology

Two hollow cylinder samples were produced, made of Inconel 625 and were fabricated by FormAlloy using a FormAlloy L2 metal AM system, shown in Figure 1 (FormAlloy 3D Metal Printing Machines and Technolo, 2022). The L2 system works in a similar fashion to how most metal AM processes function. First, the powder nozzles permit the powder stream to continuously flow, supplying powder particles to the laser beam. Next, the stream and particles come into contact with the laser beam which melts the particles and deposits the new material onto the substrate. The entire method ensues under the supervision of the Melt Pool Size (MPS) camera. The L2 system uses a laser as the main proponent of the heat source in contact with metal powder from the feedstock. This system comes fully equipped with a continuous wave (CW) fiber laser utilizing a focused spot diameter of 1.2 mm and maximum output power of 2 kW. The in-situ sensing component is an MPS camera that was set in the path of the laser. As the melt pool moves, the camera measures the width of the pool during the entire printing process. The



uniqueness of the L2 system is that it provides users with real-time measurement of the melt pool dynamics. In total, two samples were produced, one low-quality (sample 1) and one high-quality (sample 2).

Figure 2 highlights the layout of this investigation, which began with a visual analysis of the printed parameters collected in real-time. Next, a feature selection is used to truncate the original dataset and an unsupervised statistical method is utilized for outlier detection of the selected printing features. Finally, ex-situ processing takes place to identify and measure defects within the parts. Acceptable and unacceptable layers were identified through a user adjustable technique. Literature in the research community defines feature selection as the act of reducing a subset dataset from an original complete feature dataset through the use of a feature selection technique (Cai, 2018). Modern forms of data are measured and recorded at extremely high rates however, not all data is deemed informative. When data is highly dimensional or dynamical (or both), it benefits the experimenter to reduce the useable dataset, especially when the correlation among features is highly. When feature selection is executed, many times the overall computational time during the experiment is reduced and model performance can sometimes be increased. The Random Forest algorithm is widely accepted by literature for a feature selection technique due to its interpretability and ability to provide the user with *important* values (Petkovic, 2018). The RF technique works to reduce variance through the bagging (bootstrap aggregation) technique. It comprises a mean of noisy and unbiased models (Hastie, 2009). The main aspect of RF is the tree-growing process where arbitrarily selected input variables are bootstraped on the data. The purpose of this is to de-correlate the trees without swelling the variance (An introduction to feature selection, 2013). RF chooses m number of variables by randomly pulling from p features so that $m = \sqrt{p}$. The main process is driven by the classification predictor, mathematically represented as (Hastie, 2009):

Figure 2. Design Diagram

$$\hat{C}_{rf}^{B}(x) = majoirty\ vote\{(\hat{C}_B(x))\}_1^B \tag{1}$$

Where B is the total number of trees that we are predicting on a new point x. Figure 3 highlights the result of the two samples produced during printing and the corresponding printer features collected in-situ during the printing process.

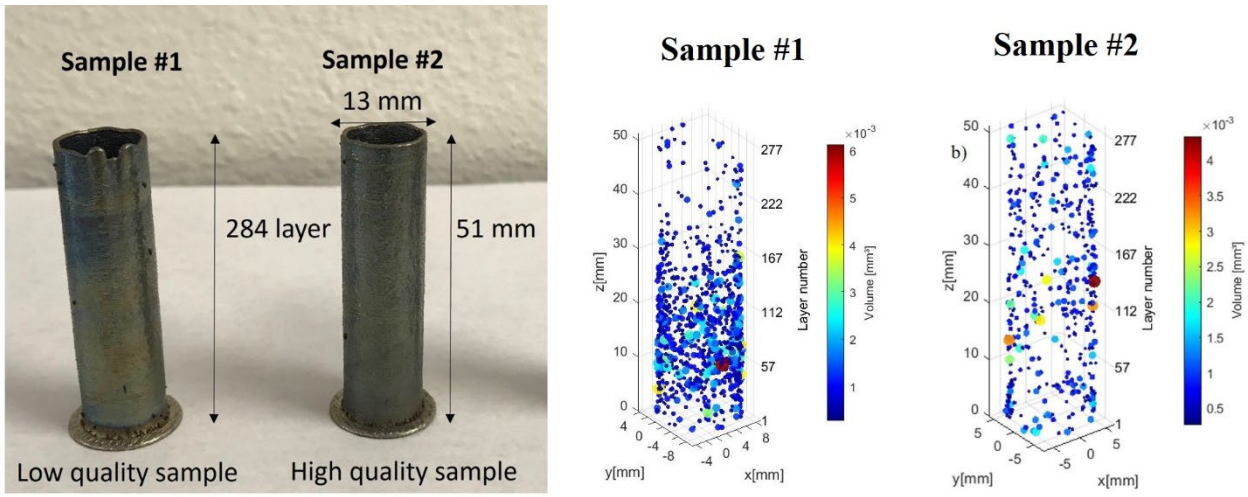


Figure 3. Sample 1 and 2 (left) and Inter-layer low-density identification (right)

To determine if the condition of a part has deviated significantly from its normal state, we highlight the use of a statistical method for identifying outliers. For this multivariate dataset, we define p number of features and n number of observations. Figure is a visual explanation of how the technique identifies outliers. The Mahalanobis squared distance has been utilized to detect multivariate outliers for structural health applications and used in this investigation. It a non-negative scalar defined as (Farhidzadeh, 2014):

$$D^2 = (x - \mu)^T \cdot C^{-1} \cdot (x - \mu) \tag{2}$$

Where, x is a vector measurement that corresponds to a possible outlier, μ and C correspond to the mean vector and covariance matrix, respectively.

Results and Discussion

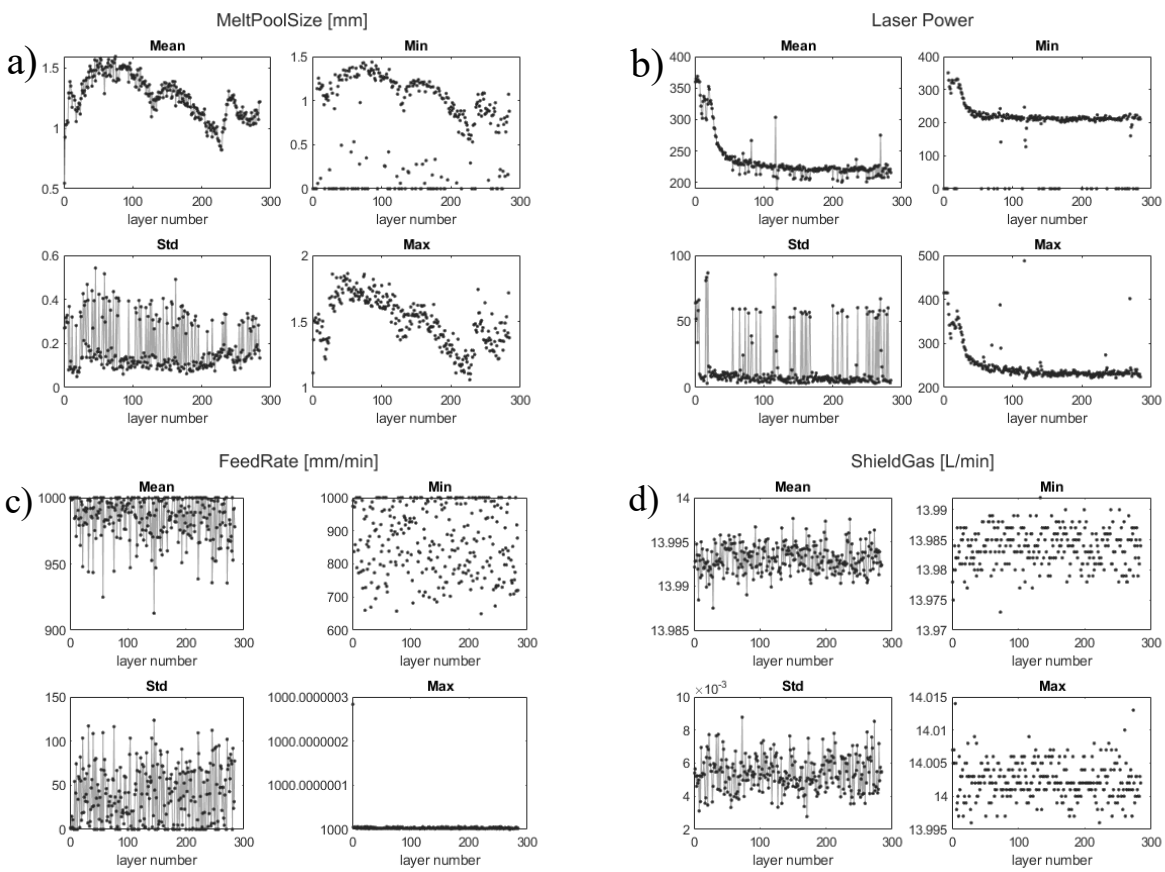
Before advanced detection techniques are used, simple unsupervised methods may present a possible solution to quick and reliable outlier detection. Based on a feature selection using RF (importance values shown in Table 1), five features are focused on for further statistical analysis. This step is crucial to limiting the useful information collected during the AM build process. Figure 4 presents the mean, maximum, minimum, and standard deviation trends of the printing parameters. It serves the purpose of an initial visual stage of identifying any peculiarities during the metal AM build. Several outliers can be seen in the Laser Power feature, Figure 4b. Some minor outliers can be visualized from the MPS feature in Figure 4a. The other features do not demonstrate any clear trends for a user to visually identify.

Table 1. Feature selection results

Feature	Importance Value

Laser Power	0.191
Melt Pool Size	0.181
Shield Gas	0.113
Powder Carrier Gas	0.121
Feed Rate	0.033

Figure 5 highlights the Mahalanobis Distance results of both samples. In Figure 5a, the low-quality sample shows three distinct levels of measurements. This is not the case in Figure 5b, the high-quality sample showing only two levels of distance values. The low-quality sample shows a high frequency of squared Mahalanobis Distance values between 3.5-7, where the high-quality sample showcases the highest frequency of Mahalanobis Distance values between 4.5-4.8. It is clear from the calculations of the squared Mahalanobis Distance that a distinguished separation of multivariate measurements takes place among high/low-quality samples.



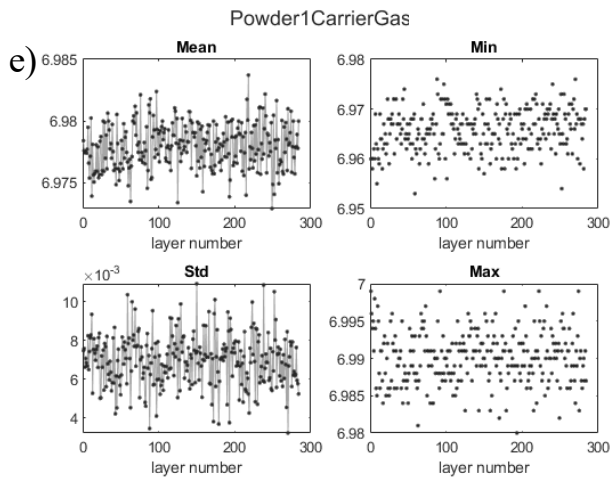


Figure 4. Visual statistical analysis of a) MPS, b) laser power, c) feed rate, d) sheild gas, and e) powder carrier gas

X-Ray Computed Tomography (CT) was performed on both samples to provide porosity information. The distribution of porosity diameter and the number of porosity per layer are shown in Figures 6 and 7. A deeper inter-layer analysis is shown for samples 1 and 2 in Figures 6 and 7, respectively. Squared Mahalanobis Distance values are able to identify a high frequency of porosities that cause defects. For sample 1 (Figure 6b), a high frequency of 'unacceptable' layers based on an adjustable ex-situ threshold is highlighted in the blue shaded region and corresponds to the Mahalanobis Distance values calculated in Figure 6a. The high-quality sample (sample B), shown in Figure 7, highlights the unsupervised statistical anomaly method to detect maximum porosity values (Figure 7a). Visual clarity is present between maximum porosities early in the build (outlined with purple) and later in the build (outlined in red).

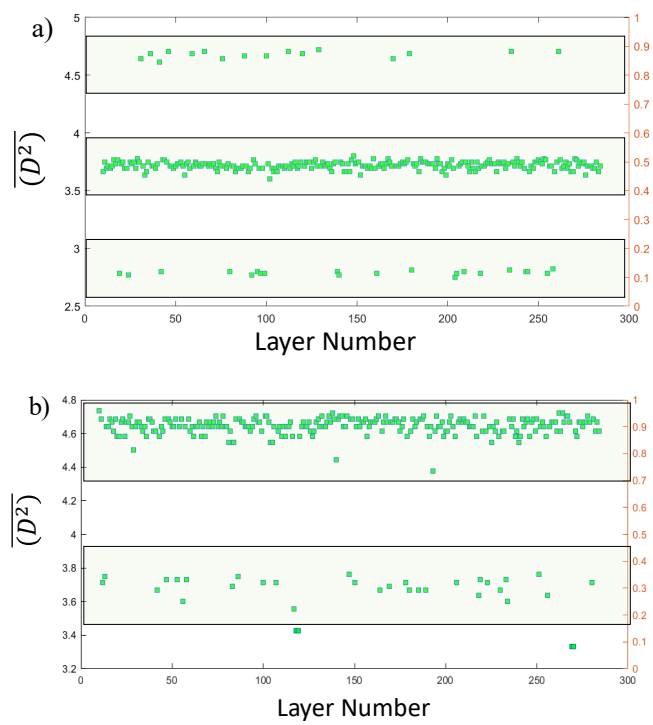


Figure 5. Mahalanobis Distance results of a) low-quality (sample 1) and b) high-quality (sample 2)

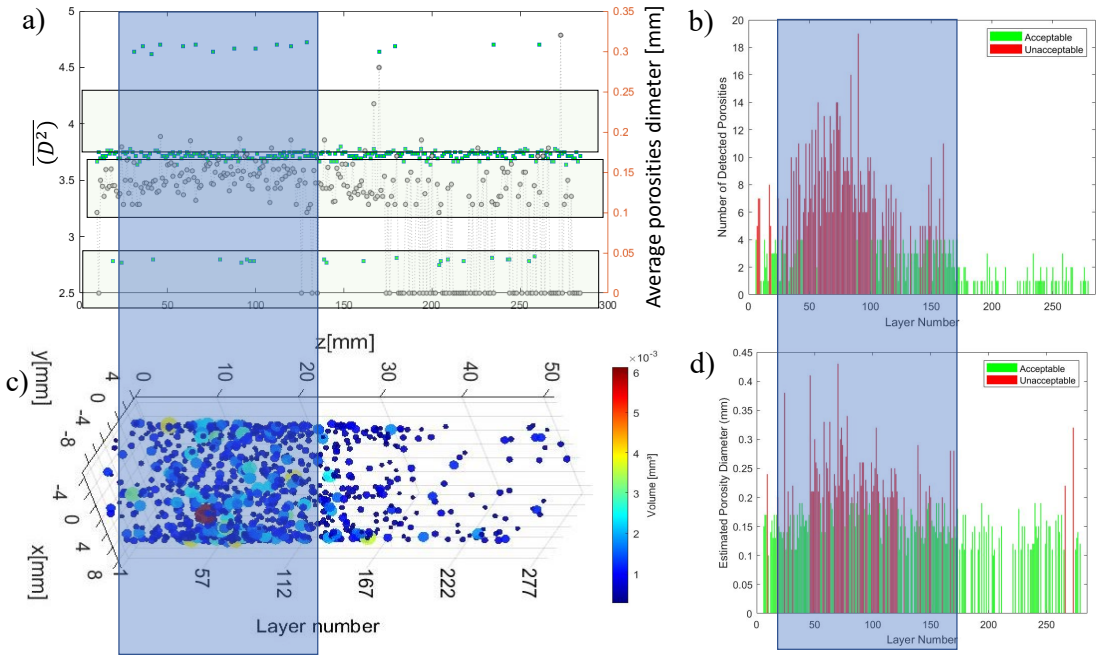


Figure 6. Evaluation of sample 1 a) Mahalanobis Distance measure, b) number of detected porosities, c) inter-layer porosity size measure, and d) estimated size of porosity (mm)

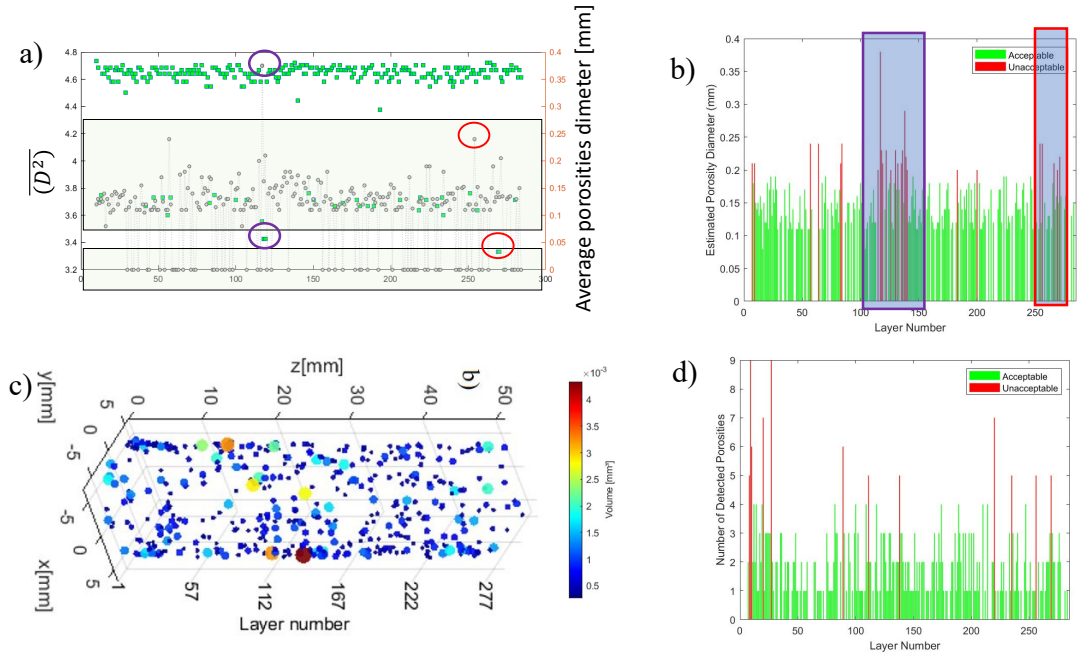


Figure 7. Evaluation of sample 2 a) Mahalanobis Distance measure, b) number of detected porosities, c) inter-layer porosity size measure, and d) estimated size of porosity (mm)

Conclusion

Demand for anomaly detection within the metal additive manufacturing field is increasing due to the desire to reduce manufacturing costs and produce highly-complex designed parts. The unique layer-by-layer process of AM provides an exceptional opportunity to monitor and control the quality of parts. This study demonstrates the usefulness and effectiveness that a simple unsupervised anomaly detection method can have on early defect detection and prevention. Included in the study is a feature selection technique and visual analysis that aid in this incipient phase of the manufacturing process. If on-boarded to an AM system, this technique could give a user confidence while monitoring the build process and potentially prevent defects without the need for advanced defect classification methods.

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