

AI-Supported Process Monitoring in Machining

In-Process Quality Assurance of Inhomogeneous Materials Using Feature-Based Machine Learning Methods

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In this study, AI-supported anomaly detection methods in the milling of inhomogeneous sample materials are investigated. To simplify data generation, targeted boreholes were introduced into homogeneous material samples. Process data were collected by means of acceleration measurements on both the workpiece and tool sides and force measurements on the tool side. Implementing targeted feature extraction and applying feature-based machine learning algorithms achieved precise material classification and reliable differentiation between drilled and undrilled samples for process monitoring.

Introduction

In recent years, there has been a notable increase in demand for lightweight and durable materials in several industrial sectors, including e-mobility and aerospace [1-3]. Cast materials, particularly aluminum, are frequently employed in the manufacture of components due to their advantageous strength-to-weight ratio, rendering them optimal for incorporation in electric vehicles and planes [4]. However, casting defects, such as porosity and shrinkage cavities, can significantly compromise these components' structural integrity [5, 6]. In the e-mobility context, defective parts in battery

housings, motor housings, or other critical components could result in product recalls.

To address these challenges, there has been a growing interest in leveraging advanced technologies such as machine learning (ML) to improve quality assurance during the manufacturing process.

Gao *et al.* summarize the use of artificial intelligence in manufacturing and provide a perspective of future directions [7]. Multiple studies have already explored the use of machine learning for defect detection in casting materials [8-13]. Many scientific papers have shown the usage of ML and image recognition, especially with X-rays. Bosse *et al.* en-

hanced the porosity detection in aluminum die-casting using X-ray radiography and Convolutional Neural Networks (CNN), achieving high accuracy with a false-positive rate below 1 percent [8]. Nouri *et al.* proposed Decision Trees (DT) with model order reduction and optimal transport with shape morphing to optimize shrinkage porosity, showing promising results in aluminum casting [9]. Parlak *et al.* applied even deep learning, specifically YOLOv5, for detecting defects in X-ray images of aluminum parts, achieving 95.9 percent accuracy [12]. Fang *et al.* used deep learning models to improve defect detection via infrared thermography, enhancing segmentation accuracy for non-destructive evaluation [14]. Chen *et al.* developed machine learning models to predict surface defects in steel and cast-iron foundries, with Extreme Randomized Trees (ET) performing best in reducing defects [15]. For acceleration data and force measurements, in [16], it is shown that the detection of voids is possible using autoencoders. Ramme *et al.* [17] have even presented that the generation of build-up edges in chip-forming processes can be detected based on acoustic emission signals.

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Building on the advancements outlined in previous studies, this paper focuses on the application of machine learning to detect porosity defects in different materials. While existing research has demonstrated the efficacy of deep learning models and other machine learning algorithms in identifying casting defects, this paper extends the analysis by applying feature-based algorithms to detect anomalies during milling. Integrating these approaches into quality assurance workflows aims to explore new paths for improving defect detection and reducing material and energy waste in high-performance manufacturing environments.

Experimental Setup and Methods

In this chapter, the idea and the resulting methodology of analog testing, the machine setup, and the experiment execution are presented. Furthermore, data acquisition and the subsequent data processing up to machine learning are introduced.

Method for Analogy Testing

Training machine learning algorithms typically require extensive datasets derived from relevant processes. However, analyzing cast components is costly and time-consuming, thus posing challenges in data collection. To address this, an analogy-based approach is used here to represent inhomogeneities in material specimens. Traditional methods, such as X-ray scanning, can map void locations accurately but are costly, while optical systems are simpler but limited to two cutting planes, risking undetected voids. Using these two planes provides only a rough estimation of void positions, leaving uncertainty about whether the voids form a continuous cavity or are separate. Additionally, smaller voids might exist within the machined layer but remain undetected by microscopy, potentially impacting data integrity for machine learning applications.

The here selected approach reverses this issue: rather than first analyzing positions and then linking them to data, material inhomogeneity is generated based on predefined data. A MATLAB script creates randomized borehole positions (drill pat-

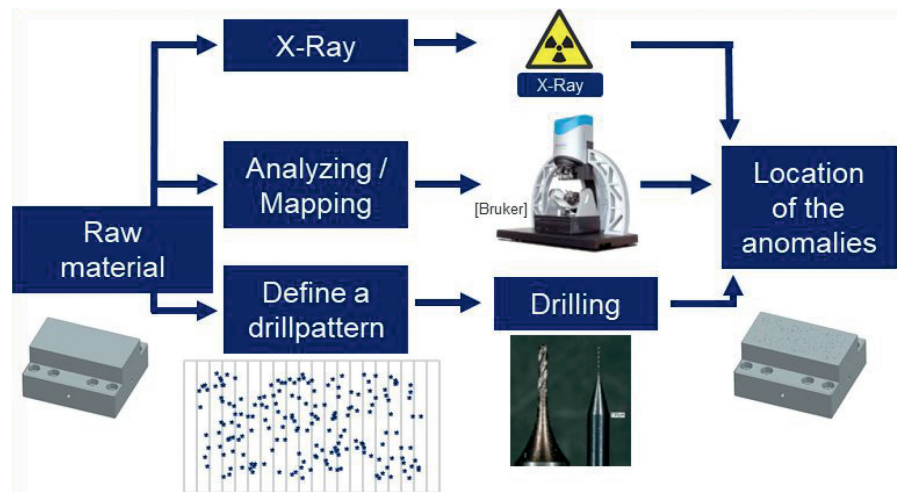


Figure 1. Methodological approach for generating labeled data for void detection

tern), translated into NC code for machining. To mimic inhomogeneity in aluminum casting, 0.3–0.5 mm boreholes are drilled, while homogeneous samples are left unmodified for comparison. This method allows machining and measurement to be carried out in the same configuration, enabling a direct correlation between borehole positions and measurement data, as illustrated in Figure 1. Using this information, labeled data for machine learning training is easily acquired.

Data Acquisition, Measurement Setup and Experimental Procedure

The test specimen is connected to different sensors to obtain various measurements on the workpiece side. Figure 2 shows the sample body mounted to the force measurement platform (Kistler 9129AA), providing the process forces FSpec. An acceleration sensor, gathering vibration signals ACCSpec, is attached to the specimen with wax. The data about acceleration and force are recorded utilizing Type 9230 and 9223 measurement cards (by company National Instruments) at a sampling rate of 10 kHz. Data acquisition is initiated by the machine's NC code (DMG Lasertec 65 3D hybrid), enabling all systems to capture data within the same time window.

Furthermore, the trigger enables the precise calculation of the milling cutter's position at any given time. On the tool side, a sensory Intendo² tool clamping system (by company SCHUNK) is used to obtain vibration signals ACCTool. This

hydro-deformable chuck is equipped with an acceleration sensor to record raw data at a frequency of 15 kHz.

Grooves are milled along the specimen using a 5 mm, four-tooth Ratio Cutter RF 100 Sharp (by company GÜHRING). To minimize influences of tool wear effects, separate tools for homogeneous and inhomogeneous specimens are used. The grooving process involves a 5 mm width of cut (ae) and 0.5 mm depth of cut (ap) at a cutting speed of 180 m/min and 0.0264 mm feed per tooth. This results in a measurement time of 3.29 s and 329000 samples in acceleration and force data for each milling path.

Twenty grooves are milled, and data is recorded for each mounted specimen, including homogeneous and inhomogeneous samples and incorporating the materials EN10083-1 (C45), EN AC-42100, as well as EN-GJS-400-15 and EN-GJS-500-7 cast iron. A randomized experimental plan is used to account for material types and porosity levels (0.5% and 1%). For each specimen, 100 paths were utilized to validate the algorithm, while at least 200 undrilled homogenous probes were being milled. Machining parameters remain consistent with those for C45 material. A thin oil layer was applied to the sample to prevent tool clogging and breakage during aluminum machining.

Machine Learning

For quality monitoring, a two-stage procedure with anomaly detection and material classification is employed. This ap-

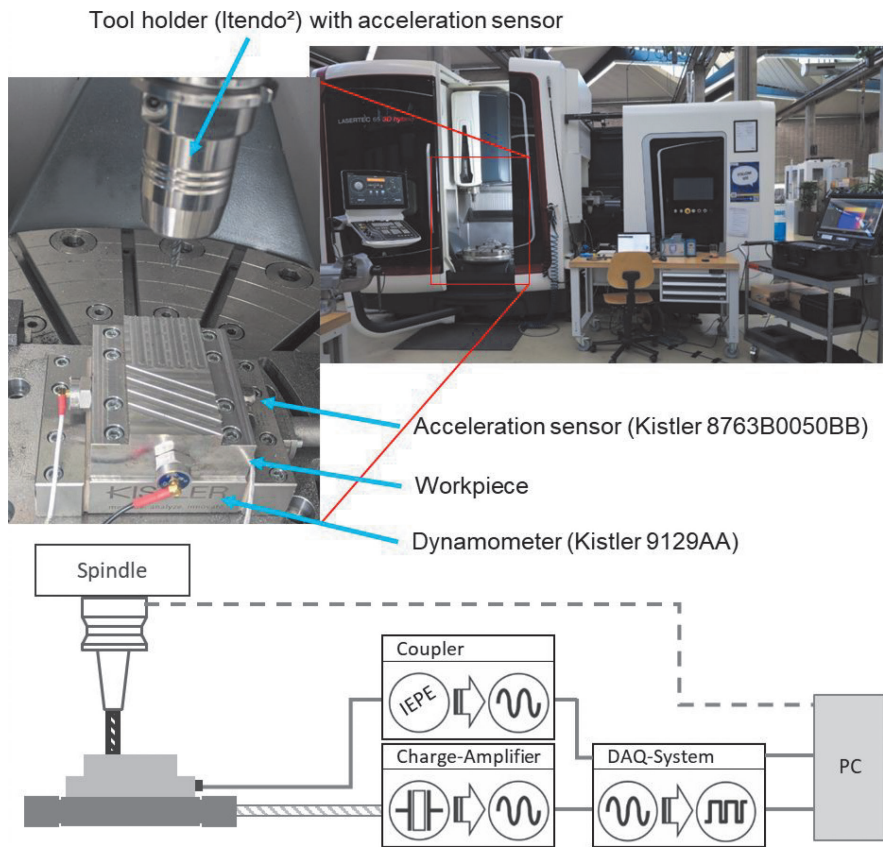


Figure 2. Experimental setup and measurement technology

proach enables simultaneous operation, enhancing the monitoring process's efficiency and effectiveness.

As demonstrated in [16], neural networks such as an autoencoder can detect anomalies. In contrast, this study utilizes feature-based machine learning algorithms such as Support Vector Machines (SVM), Naive Bayes (NB), k-Nearest Neighbours (KNN), Adaboost (ADA), Isolation Forest (IF), Decision Tree (DT), Extra Trees (ET), Linear Discriminant Analysis (LDA), Ridge (RID), Light Gradient-Boosting Machine (LGBM) and Random Forest (RF) for the anomaly detection. Feature-based machine learning algorithms are supervised learning techniques that rely on predefined features from the data to make predictions or decisions.

The acquired data undergoes initial processing for training purposes, which involves removing the periods of idleness and tool entry/exit regions. Subsequently, the data is normalized, and a mean-shifting transformation is applied to align the mean with a Y-axis intercept of zero.

Each milling path is sliced into small datasets of 200 points. With the knowledge of the borehole positions, the data is being labelled. To accommodate material variations and the influences of wear or other anomalies, these factors are intentionally varied. Algorithm training is implemented using randomly assembled data from experiments conducted on different test days and under varying wear conditions. Randomized milling paths are also generated and examined for the tested specimens. In each instance, 100 paths are utilized to validate the algorithm.

The Spyder integrated development environment (IDE) was utilized to imple-

ment the algorithms and handle the data, with Python as the programming language. The Scikit-learn library and LightGBM toolbox were employed for machine learning tasks, enabling the application of the previously named supervised learning methods.

Results

In the following, the two-stage approach will be discussed. First, the results of material recognition will be presented, followed by the analysis of porosity detection.

Material Classification

The results in Table 1 indicate that using an SVM allows for successful material identification during machining, accurately distinguishing among the four classes EN10083-1, EN AC-42100, EN-GJS-400-15, and EN-GJS-500-7. The system achieves an accuracy of 86 percent and an F1 score of 0.857 [18]. Analysis of the confusion matrix shows that most errors occur when predicting steel and cast iron materials. Specifically, EN10083-1 is misclassified as EN-GJS-500-7 in 15.32 percent of cases, while EN-GJS-500-7 is misclassified as EN10083-1 in 10.81 percent of cases. This is likely due to the similar mechanical properties of EN10083-1 and EN-GJS-500-7, such as hardness and tensile strength, despite the more homogeneous microstructure of EN10083-1. These similarities in the machining data create challenges for SVM in distinguishing between these two classes, leading to higher misclassification rates compared to more distinct material pairs, like EN10083-1 and EN AC-42100. Overall, while SVM effectively classifies materials, the shared properties between certain materials contribute to misclassification, suggesting that refining feature selection or including additional distinguishing features could help reduce these errors.

SVM	EN10083-1	EN-GJS-400-15	EN-GJS-500-7	EN AC-42100
EN10083-1	80,64	13,63	10,81	0
EN-GJS-400-15	4,03	81,82	6,77	0
EN-GJS-500-7	15,32	3,02	82,43	0
EN AC-42100	0	1,51	0	100

Table 1. Confusion matrix for material classification using a SVM algorithm

To evaluate the various algorithms analyzed in this study, Table 2 lists accuracy and F1-scores. Results indicate performance variation across the algorithms within a constant dataset. ET and RF achieved high F1-scores above 0.98, while NB and IF performed poorly with F1-scores of 0.64 and 0.078, respectively. The strong performance of ET and RF suggests these algorithms excel at identifying relevant patterns and handling high-dimensional data. In contrast, with their specific assumptions, NB and IF may be less suited to this classification task.

Significant variations also occur between datasets, such as acceleration versus force. For example, Adaboost's F1 score drops from 0.771 with acceleration data to 0.444 with force data, whereas the KNN score improves from 0.815 to 0.941. However, compared to the triaxial accelerometer, the influence of data from the ACCTool is not as pronounced. For instance, the ADA algorithm achieves an F1 score of 0.77 with the triaxial sensor, whereas it reaches 0.7 with the one-axis sensor of the ACCTool. Similarly, in the case of force measurements, the ACCTool sensor slightly outperforms, with the ET algorithm achieving an F1 score of 0.934-0.01 points higher than with the triaxial sensor. These findings emphasize the importance of dataset selection in influencing algorithm performance, suggesting further investigation is needed to optimize feature selection and model outcomes.

Name	F _{Spec}		ACC _{Spec}		ACC _{Tool}	
	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy
ADA	0,444	0,5329	0,7712	0,7517	0,7072	0,6854
DT	0,9718	0,9689	0,903	0,8912	0,8875	0,8648
ET	0,9868	0,9862	0,9329	0,9252	0,9348	0,9274
IF	0,0778	0,173	0,1025	0,2415	0,0994	0,2187
KNN	0,9406	0,9377	0,8153	0,7993	0,7927	0,7668
LDA	0,9528	0,9481	0,7219	0,6871	0,7284	0,6923
LGBM	0,9723	0,9723	0,9452	0,9386	0,9346	0,9278
NB	0,6473	0,6436	0,3742	0,4388	0,3184	0,4179
RF	0,9972	0,9965	0,9209	0,9116	0,9201	0,9109
RID	0,9253	0,9204	0,7225	0,6905	0,7340	0,7001
SVM	0,9542	0,9481	0,8048	0,7755	0,7988	0,76645

Table 2. Comparison of F1 scores and accuracy for material classification across various ML algorithms for acceleration and force datasets

Void Detection

In a second approach, this paper aims to detect intentionally introduced voids, classifying them into drilled or undrilled categories. The results of various algorithms are presented in Table 3. ET, RF, and SVM achieve excellent results in this context. All other algorithms also differentiate between normal and abnormal states, achieving F1 scores exceeding 0.98.

When considering the IF algorithm, the performance comparison shows a clear analogy to the material recognition task. The accuracy of the IF stands at 56 %, which is more than 40 percent lower than the worst-performing among the other algorithms.

The results highlight the effectiveness of different algorithms in detecting drilled voids. However, the performance of the IF indicates its limitations in this classification task, reinforcing the importance of selecting appropriate algorithms for specific types of data and classification challenges.

Additionally, the sensor configuration subtly influenced detection accuracy, although the effect was not pronounced. Interestingly, the single-axis sensor in the ACCTool performed nearly on par with the triaxial ACCSpec sensor. This finding suggests that complex, high-dimensional sensor data may not always be necessary for effective ML-driven quality monitoring. However, it's possible that, in this specific case, the additional axes introduced noise, potentially acting as disturbance variables rather than enhancing the measurement. This possibility highlights the need for a more detailed analysis of the individual acceleration axes and their behavior. This could provide insights into optimizing sensor data configurations for improved accuracy in quality monitoring applications.

Summary and Outlook

This study highlights the successful application of ML in material identification during machining, with SVM, ET, and RF algorithms achieving impressive results. These algorithms effectively classified materials such as EN10083-1, EN AC-42100, EN-GJS-400-15, and EN-GJS-500-7,

Name	F _{Spec}		ACC _{Spec}		ACC _{Tool}	
	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy
ADA	0.9942	0.9925	0.9953	0.9942	0.9965	0.9954
DT	0.9914	0.9887	0.9859	0.9825	0.9833	0.9801
ET	1	1	1	1	1	1
IF	0.5965	0.5677	0.6986	0.6316	0.7087	0.6491
KNN	0.9882	0.985	0.9953	0.9942	0.9945	0.9939
LDA	1	1	0.9950	0.9938	0.9942	0.9931
NB	0.9826	0.9774	0.981	0.9766	0.8061	0.7018
RF	1	1	1	1	1	1
RID	0.9971	0.9962	0.9858	0.9825	0.9841	0.9815
SVM	0.9971	0.9962	1	1	1	1
LGBM	1	1	0.9907	0.9883	0.9899	0.9875

Table 3. Comparison of F1 scores and accuracy for void detection across various ML algorithms for acceleration and force datasets

reaching an overall accuracy of 86 percent and an F1 score of 0.857. Although challenges remained in distinguishing materials with similar mechanical properties, such as EN10083-1 and EN-GJS-500-7, the high performance of ET and RF, both achieving F1-scores above 0.98, emphasizes the strength of ML in material classification.

In a secondary approach, the study focused on detecting intentionally introduced voids in specimens, categorizing them into drilled and undrilled groups. ET, RF, and SVM performed exceptionally well in detecting voids like the material classification task. However, with an accuracy of only 56 percent, the IF algorithm fell short by over 40 percent compared to the other algorithms, underscoring its limitations in this context. This performance gap between IF and other models highlights the importance of selecting suitable algorithms for specific data types and classification challenges, especially in high-dimensional datasets.

These findings confirm that ML is viable and highly effective in various quality monitoring applications, including material classification and defect detection. The success of these algorithms in identifying material types and drilled voids demonstrates the potential of ML to enhance real-time process monitoring and quality assurance, making it a valuable addition to automated quality control systems in manufacturing.

Future work could focus on refining feature selection and incorporating additional distinguishing characteristics to improve classification accuracy, particularly for materials with overlapping properties. Additional studies might explore alternative datasets and data pre-processing techniques to enhance model performance further. Also, a reduction of needed features and the usage of the trained model on the milled aluminum cast material, GGG40 and GGG50, will be explored.

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Abstract

KI-gestützte Prozessüberwachung in der spanenden Fertigung – In-Prozess-Qualitätssicherung von inhomogenen Materialien mittels merkmalsbasierter Machine-Learning-Methoden. Diese Studie untersucht die KI-gestützte Anomaliedetektion beim Fräsen inhomogener Materialien. Zur vereinfachten Datengenerierung wurden in homogene Werkstoffproben gezielt Bohrungen eingebracht. Die Erfassung der Prozessdaten erfolgte durch werkstück- und werkzeugseitige Beschleuni-

gungsmessungen sowie durch werkzeugseitige Kraftmessungen. Durch gezielte Feature-Extraktion und den Einsatz feature-basierter Machine-Learning-Algorithmen konnte eine präzise Materialklassifizierung sowie eine zuverlässige Unterscheidung zwischen gebohrten und ungebohrten Proben zur Prozessüberwachung erreicht werden.

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Keywords

Process Monitoring, Machine Learning, Sensors, Machining, Signal Analysis

Schlüsselwörter

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