Activity Recognition With Machine Learning in Manual Grinding

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Capturing data about manual processes and manual machining steps is important in manufacturing for better traceability, optimization, and better planning. Current manufacturing research focuses on sensor-based recognition of manual activities across multiple tools or power tools, but little on recognition within a versatile power tool type. Due to the strong influence of operator skill on process performance and consistency as well as many disturbance variables, activity recognition is a challenge in manual grinding. It is unclear how accurately manual activities can be recognized within one handheld grinder type across diverse trials. Therefore, this article investigates how manual activities can be recognized in diverse trials within an angle grinder type in a leave-one-trial-out cross-validation in comparison to classical cross-validation to identify the effect of diverse trials with four different classifies. An experimental study was conducted to collect measurement data with data loggers attached to two angle grinders, four manual activities with different abrasive tools, and three operators. Results show very good accuracies (97.68%) with cross-validation and worse accuracies (70.48%) with leave-one-trial-out cross-validation for the ensemble learning classifier. This means that recognition of the four chosen manual activities within an angle grinder is feasible but depends on how much the trial deviates from the reference training data. For further research on activity recognition in manual manufacturing, we propose the explicit consideration and evaluation of disturbance variables and diversity in data collection for the training of machine learning models. [DOI: 10.1115/1.4054905]

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1 Introduction

In the area of manufacturing, data collection on processes and machining steps is very important for better traceability [1]. For this purpose, systems are equipped with a growing number of sensors. These sensors are connected via communication technologies, which are described as the Internet of things (IoT). This enables Industry 4.0, where it is essential to collect a wide range of information to monitor, intervene in, and optimize production. In manual manufacturing, it is important to capture manual production steps that are performed by humans [2,3]. These can be part of assembly processes, screwdriving operations, or machining steps such as manual grinding. The recognition of manual production steps can be classified as human activity recognition (HAR). For HAR, this work focuses on the approaches that use wearable sensors opposed to external sensors.

The use of sensors and the evaluation of sensor data is the subject of numerous research projects for assembly processes: The recognition of individual steps of assembling a front lamp into a car body was studied using wearable and environmental sensors [4–6]. The recognition of activities in terms of tools used was studied using IMUs on both wrists of a worker in an assembly process of a piece of furniture [7,8]. A combination of an inertial measurement unit (IMU) and surface electromyography was used to recognize assembly tasks and used tools [9]. The recognition of used tools was also performed using sensor gloves [10] or a smartwatch [11]. For the production step of manual grinding in the manufacturing industry, the recognition of different activities was investigated in conjunction with a specific handheld grinding machine (palm grip orbital sander, right angle sander, trimming shear, jitterbug sander, polisher, stone grinder, and rotating carbon blade cutter) [12].

The previous work on HAR in manufacturing has focused on recognizing activities with different handheld tools and power tools such as different grinders, screwdrivers, hammers, or wrenches. With versatile power tools, such as a handheld grinding machine, different activities can be performed within the same power tool. Therefore, the general problem is to recognize manual activities on a finer level within a power tool.

Manual grinding activities used in manufacturing, e.g., cleaning up weld seams or abrasive finishing on complex surfaces is part of the production of molds and dies in the foundry industry [13,14] and the repair of turbine vanes in the aerospace industry [15]. Due to the strong influence of operator skill on process performance and consistency [16], HAR is a challenge in manual grinding. A case study of HAR was carried out on a small data set with one operator and data collected with laboratory measurement technology with a sampling frequency of 25 kHz, including a contactless distance sensor to measure the displacements of shaft, speed sensor, and current sensor from one angle grinder [17]. An accuracy of 99% for the activity recognition could be achieved for the small data set with laboratory measurement. In another case study, the activities “grinding” and “not-in-process” were distinguished with an accuracy of 93%, and the activities “machining of steel” and “machining of aluminum” were distinguished with an accuracy of 90% using an accelerometer, gyroscope, microphone, and current sensor [18]. In a preliminary study by the authors, the detection of the grinding, cutting, and roughing applications was investigated in a small data set based on a current sensor, voltage sensor, an IMU, and one operator with an accuracy of 80% [19]. In the three studies on HAR in manual grinding, the measurement data were randomly divided into training and validation or test data or with classical cross-validation (CV). Since individual trials in manual grinding can deviate greatly due to the lack of process consistency [20] and disturbance variables such as deviating battery level or grinding disc wear, there remains the problem that it is unclear how accurately manual activities can be recognized within one handheld grinder type across more diverse trials.

Therefore, this article investigates how accurately manual activities can be detected in diverse trials within an angle grinder type with different abrasive tools in a leave-one-trial-out cross-validation

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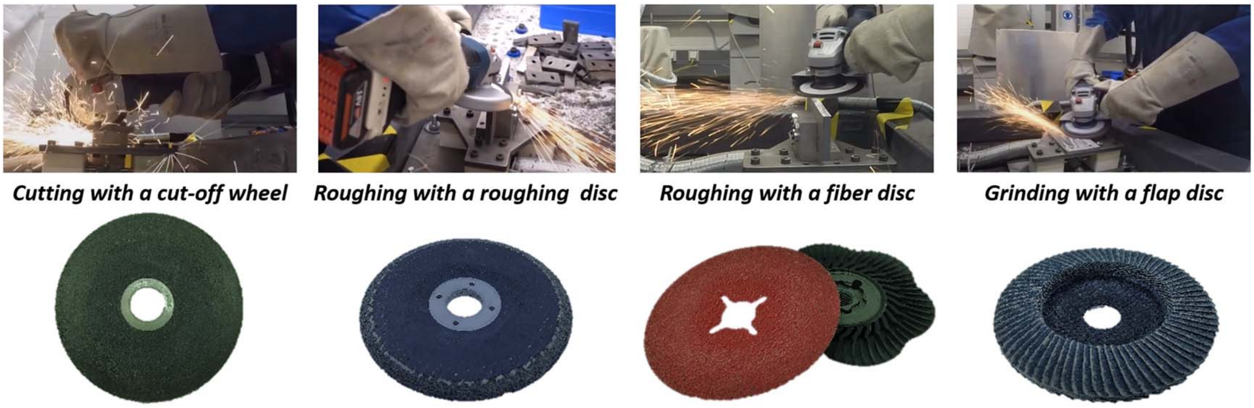

Fig. 1 Four manual activities and the corresponding abrasive tools were used in the study [21] (Creative Commons Attribution 4.0 (CC BY 4.0))

(LOTO CV) in comparison to classical CV, where the folds are randomly resampled. An experimental study was conducted to collect measurement data in diverse trials with different data loggers using two angle grinders, four manual activities, and three operators.

2 Materials and Methods

Section 2.1 describes the experimental study design and setup, the angle grinders used, the method of data collection, the methods of feature extraction and selection, and the classification framework.

2.1 Experimental Study for Data Collection. The experimental study consisted of four different manual activities with different abrasive tools: cutting with a cut-off wheel, roughing with a roughing disc, roughing with a fiber disc, and grinding with a flap disc. The activity "cutting with a cut-off wheel" consists of vertical cuts through a mounted workpiece. The activities "roughing with a roughing disc" and "roughing with a fiber disc" involve roughing the edges of the workpiece to represent the activity of workers roughing a weld in manufacturing. The activity "grinding with a flap disc" involves the continuous two-dimensional grinding of a surface. The activities and abrasive tools are shown in Fig. 1.

The data for the manual activities were measured in independent trials, in which the operator freely processes the workpiece with one of the four manual activities and its respective abrasive tool. When cutting with a cut-off wheel, the trial was terminated after four cuts, which corresponds to approximately 3 min. For grinding and roughing, the activity was terminated after 4–5 min of machining time. The workpieces were replaced after one or two trials depending on the material removal. The battery was changed during the trial to represent a realistic work process, which resulted in interruptions and different voltage levels during a trial. The abrasive tools were replaced after one or two trials depending on wear. Due to the long duration of the trials, the heat generated by the angle grinders led to a short shutdown in some trials or even a termination of a trial. These disturbance variables were accepted to allow realistic and diverse trials.

In addition to the four activities with different abrasive tools, we have added the class "not-in-process" because the real-world application of an angle grinder consists of several additional steps before, partly during, and after the actual activity. The actual activity such as "cutting with a cut-off wheel" includes only the time when the grinding disc is in contact with the workpiece. The class "not-in-process" includes all the time where the angle grinder gets moved around, runs at idle speed, and is switched on and off, but is not in contact with a workpiece. For two operators, the trials contain a combination of the actual manual activity class and, to a small extent, the "not-in-process" class. For these trials, the measurement was started before the activity and stopped after the activity. Since the trials of the two operators, as usual in a real-world application, only contain a small number of switch-on and switch-off operations and the duration of load-free motor running was relatively short and is not user dependent, a third operator was asked to perform these operations specifically in two separate trials to generate more diverse training data for the recognition of the class "not in process." To compensate for this, only the manual activity was measured for the third operator, without the "not-in-process" before and after the actual activity.

We chose two different cordless angle grinders from two different manufacturers, the GWS18 (GWS18-125 V-LI, Robert Bosch GmbH, Leinfelden-Echterdingen, Germany) and the CCG18 (CCG18-125 BL, C. & E. Fein GmbH, Schwäbisch Gmünd, Germany), for the experimental study. Both work with 18-volt battery packs.

For data collection, data loggers, which are mounted between the battery and angle grinder, were used for both cordless angle grinders GWS18 and CCG18. The concept of the data logger was already published [22,23]. The data logger includes a microcontroller, an IMU, a current sensor, and a voltage sensor. In total, 11 sensor signals can be measured with the data logger: acceleration in three-dimension, angular velocity in three dimensions, magnetic field in three dimensions, current, and voltage of the battery. Due to three different variations of the data logger in the study, different sensors and sampling frequencies were used. In addition, two different test setups with three different workpieces were used to account for diverse trials as well. The first test setup T1 is shown in Fig. 1. The data loggers for both cordless angle grinder GWS18 and CCG18, as well as test setup T2, are shown in Fig. 2.

The experimental study design to collect measurement data on diverse trials with three operators can be summarized in Table 1. A total of 26 trials were conducted. Two trials contain only the "not-in-process" class and the remaining trials contain a combination of the manual activity class and, to a small extent, the "not-in-process" class.

2.2 Data Processing. In data processing, the sensor signals were resampled to 1000 Hz using linear interpolation. The labeling was done manually after data collection. The distinction between an activity (class 2–5) and class 1 "not in process" was made based on the current signal.

For segmentation, we used successive sliding windows with a length of 2 s and a 75% overlap. This amount of overlap promised a slightly better accuracy in HAR [24].

We decided to balance the "not-in-process" class because this class was highly overrepresented (~7500 segments) and the easiest way to classify. Since the dataset size of the other classes is very close, we did not balance them as this would have resulted in a reduction of the valuable dataset. The amount and distribution

Fig. 2 Left side: CCG18 with datalogger and test setup T2 with the workpiece for grinding with an abrasive flap disc. Right side: GWS18 with datalogger and test setup T2 with the workpiece for roughing setup with abrasive roughing disc.

Table 1 Different aspects of the experimental study to generate diverse trials

Angle grinder	Operator	Data logger	Sampling frequency (Hz)	Test setup	Total time (min)	Trials with manual activities	Trials for class "not-in-process"
GWS18	1	V1	1000	T2	26	2×4 activities	2
GWS18	2	V1	1000	T1	49	2×4 activities	–
GWS18	3	V2	300	T2	45	2×4 activities	–
CCG18	1	V3	1000	T2	51	2×4 activities	2
CCG18	2	V3	1000	T1	53	2×4 activities	–
CCG18	3	V3	1000	T2	38	2×4 activities	–

of the segments of the five classes for manual HAR, consisting of the four manual activities and the "not-in-process" class, are presented in Table 2. It is shown that the classes are equally distributed.

For feature extraction, 62 defined features were created for each of the 11 sensor signals, since for angle grinders, manually defined features are equivalent to better than automatic features when some domain knowledge is utilized [19]. In total, we created 682 features for every window. Among those features are:

- sum, minimum, maximum, mean, median of the absolute values,
- variance, root mean square, interquartile range, several percentiles, skewness, kurtosis,
- zero-crossing rate, mean crossing rate,
- root mean square of several Daubechies wavelets,
- mean frequency, median frequency,
- value of the three highest peaks in the amplitude spectrum, and
- spectral energy in defined sections of the amplitude spectrum between 0.5 Hz to 25 Hz and 80 Hz to 150 Hz.

The result of the feature extraction is a feature table with 682 features and a corresponding label for each segment. All data processing and classification were done in MATLAB R2020b (The MathWorks, United States).

2.3 Machine Learning Framework. The classification is machine specific, which means that one machine learning model is used for one angle grinder. This corresponds to the application in manufacturing since one would also employ one machine learning model per machine due to different gearing or control algorithms.

To estimate the machine learning model's ability to generalize across more diverse trials, we used two validation methods: A classic CV, in which folds are resampled randomly on all trials, and a LOTO CV, in which a fold consists of one trial alone. For better comparability, the number of folds for CV is chosen to be 26 to match the number of trials. Therefore, the only difference between the two validation strategies is how the fold used to validate the machine learning model is drawn from the data set. The classical CV is a common validation strategy to investigate if the classes are separable on, for the model unknown, data based on the data provided by the datalogger. The LOTO CV is used to estimate how well the created models will perform on unknown data from a full diverse trial, which is probably skewed due to the lack of process consistency [20] and disturbance variables. The assignment of the folds is illustrated for CV and LOTO CV in Fig. 3.

For better prediction performance and learning efficiency, as well as a higher probability of avoiding overfitting, we used feature

Table 2 Classes for classification and the segment distribution by angle grinder

Angle grinder \ Class	Not-in-process (class 1)	Grinding with a flap disc (class 2)	Roughing with a fiber disc (class 3)	Roughing with a roughing disc (class 4)	Cutting with a cut-off wheel (class 5)
GWS18	2559 segments	2559 segments	2533 segments	2528 segments	2363 segments
CCG18	2918 segments	2918 segments	2691 segments	2886 segments	2562 segments

Table 3 Accuracy of the classical 26-fold CV and the LOTO CV in % for GWS18 and CCG18 angle grinder

	Angle grinder GWS18				Angle grinder CCG18			
	Classical 26-fold CV		LOTO CV		Classical 26-fold CV		LOTO CV	
Accuracy (%) Classifier	Mean of accuracy (%)	Standard deviation (%)	Mean of accuracy (%)	Standard deviation (%)	Mean of accuracy (%)	Standard deviation (%)	Mean of accuracy (%)	Standard deviation (%)
EL	97.87	0.49	72.29	31.06	97.50	0.84	68.67	35.17
kNN	94.55	1.45	62.76	28.96	89.21	2.32	61.84	31.36
SVM	94.91	2.02	68.08	26.98	86.29	4.66	60.65	29.23
MBC	98.09	–	69.89	–	97.11	–	71.49	–

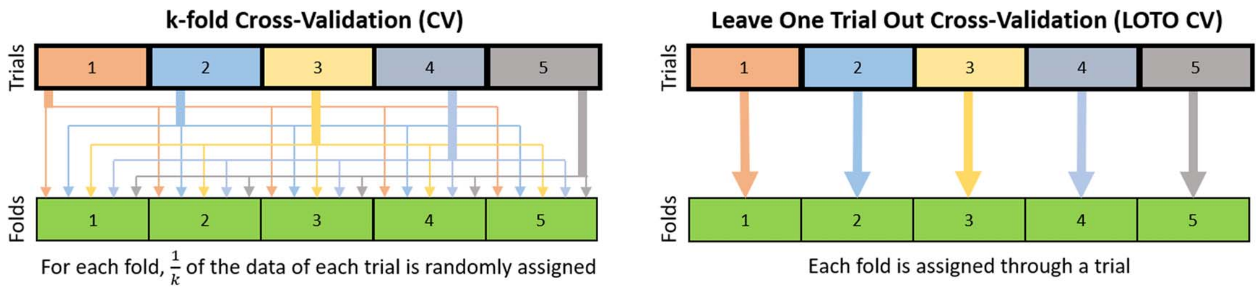

Fig. 3 Assignment of the folds is illustrated for CV and LOTO CV

selection by the minimum redundancy maximum relevance (MRMR) algorithm [26]. With the MRMR algorithm, we filter the 682 extracted features into the 50 most important features. To improve the performance of the classification we used an automated Naive Bayes hyperparameter optimization. The integration of feature selection and hyperparameter optimization was solved with a nested CV approach. This means that for each of the outer 26-fold CV loops, an inner 10-fold CV loop for feature selection and hyperparameter optimization was performed. The nested CV approach is shown in Fig. 4. Within the loops, the training data are shown in green and the test data in orange.

Three classical machine learning algorithms were considered for classification: ensemble learning (EL) classifier, k-nearest neighbor (kNN) classifier, and support-vector machine (SVM). In our work, the EL is restricted to tree-based models, which are then aggregated by bagging or boosting methods. Due to the size of the datasets, we decided against using deep learning methods such as neural networks because these require significantly more data. In addition to the three classical multiclass classifiers, we evaluated a newly adapted approach called multistage binary classification (MBC). MBC has been introduced to improve accuracy by incorporating domain knowledge and to account for the varying difficulty of recognizing individual manual activities. The approach corresponds to the concept of various algorithms to convert a multiclass classification problem into multiple binary classification problems [27]. The main idea is to extract the two most distinguishable classes from the rest. Thus, it is possible to perform a classification at a rough level, such as cutting versus grinding/roughing, with higher accuracy, and to perform a classification at a more precise level, such as different tools for roughing, with lower accuracy within the same machine learning model. The binary classification at each stage in the MBC framework was performed with the EL classifier. The MBC framework with the five classes is shown in Fig. 5.

The first stage exists to separate the "not-in-process" segments (class 1) from the in-process segments (class 2). This binary classification was chosen because it can be based on the current signal, which correlates to the additional load due to contact of the grinding disc with the workpiece. In the second stage, the previously in-process classified segments should be distinguished into cutting and grinding/roughing. This binary classification was

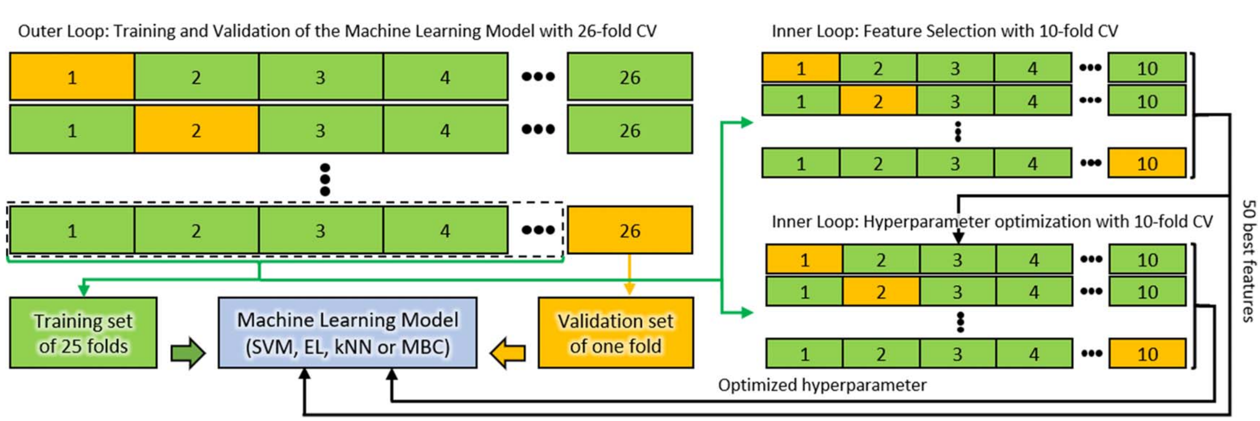

Fig. 4 Machine learning framework with nested CV approach

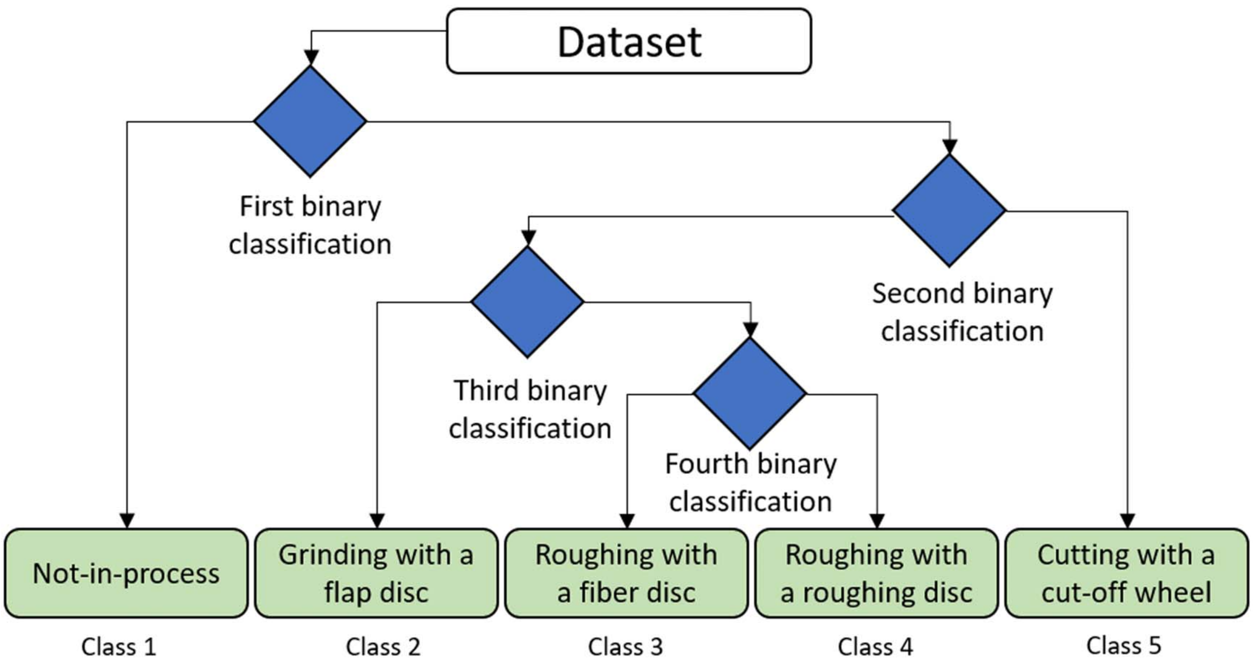

Fig. 5 The MBC framework

chosen due to the activity "cutting with a cut-off wheel" taking place mostly in a vertical plane. In the third stage, the grinding and roughing should be distinguished. This binary classification was chosen since the activity grinding is performed in a more two-dimensional way rather than in a linear way as is the case in the roughing of a weld. In the fourth and last stage, the roughing application segments are examined to differentiate between the activity "roughing with a fiber disc" and the activity "roughing with a roughing disc." For comparison with other classifiers, we perform a binary classification at each stage, taking into account only those classes that were not separated in a previous stage.

As a performance metric, we use accuracy due to having relatively balanced datasets. For the classical 26-fold CV as well as the LOTO CV, we extracted the mean of the accuracy and the standard deviation between the accuracy of the folds.

3 Results

This section presents the performance of the chosen classifiers in each validation method. The results of the classical 26-fold CV and the LOTO CV with both angle grinders are presented in Table 3. The upper half of each table represents the GWS18 angle grinder and the lower half the CCG18 angle grinder. The mean and the standard deviation of the accuracy are shown in percent for all four classifiers. For GWS18, the mean accuracy ranges between 94.91% and 98.09% for 26-fold CV and between 62.76% and 72.29% for LOTO CV. The best accuracy (mean = 98.09%, std = 0.49%) for 26-fold CV is achieved with MBC. For CCG18, the mean accuracy ranges between 86.29% and 97.5% for 26-fold CV and between 60.65% and 71.49% for LOTO CV. The best accuracy (mean = 97.5%, std = 0.84%) for 26-fold CV is achieved with EL.

The individual accuracies of the individual stages, which are illustrated in Fig. 5, are listed in Table 4. The representation of the individual accuracies of the four stages of the MBC is done for the LOTO CV for both angle grinders with the EL classifier. The class "not in process" can be best distinguished from the rest of the classes with an accuracy of 98.42%. The binary classification in the fourth stage between "roughing with a fiber wheel" and "roughing with a roughing disc" has the worst performance with an accuracy of 75.82%.

4 Discussion

The results of the classical 26-fold CV, which contains all three operators and all 26 trials, reached a very high accuracy for the angle grinder GWS18 (mean = 96.36%, std = 1.32%) and for the angle grinder CCG18 (mean = 92.53%, std = 2.61%). The small standard deviation shows that the accuracy is consistent for each fold. This means that the recognition of the four chosen manual manufacturing activities with an angle grinder is feasible with data measured by a data logger attached to the machine. The comparison with the study of [18] regarding the binary classification of

Table 4 Accuracy of the stages in the MBC framework for the LOTO CV validation approach

Class	Not-in-process	Cutting with a cut-off wheel	Grinding with a flap disc	Roughing with a fiber disc	Roughing with a roughing disc
Stage	1. Stage	2. Stage	3. Stage	4. Stage	
		Angle grinder GWS18			
Mean of accuracy (%)	98.52	96.41	76.91	70.90	
Standard deviation (%)	2.69	11.42	37.05	35.94	
		Angle grinder CCG18			
Mean of accuracy (%)	98.33	99.02	69.77	80.73	
Standard deviation (%)	3.69	2.18	32.27	26.13	

the activities "in process" and "not in process" of a handheld grinder achieved an accuracy of 93.15%. As shown in the MBC in Table 4, a slightly better result of 98.53% was achieved in this work. The comparison with the study of Ref. [17] using laboratory measurement techniques achieved an accuracy of up to 100%. Although a very high accuracy was achieved for six activities, the data were recorded with a sampling frequency of 25 kHz, special metrics such as the shaft displacement of the drive train were collected, the data contain only one operator and a 70:30 split was used for the validation/test data. Therefore, a direct comparison of the accuracies due to the inferior validation approach is not possible. The comparison with the results of the preliminary study by the authors [19], which achieved an accuracy of 85% on the test set for the angle grinders, indicates a better accuracy in this work although one application was added and the experimental study for data collection included several operators. In addition, this study investigated cordless grinders instead of corded grinders, resulting in a new disturbance variable of battery charge level. The observed improvement in accuracy can be explained by a more sophisticated and superior machine learning approach that includes more comprehensive feature extraction, hyperparameter optimization, and a nested CV approach.

The results of the LOTO CV reached worse mean accuracies than the results of the classical 26-fold CV for the angle grinder GWS18 (mean = 68.36%, std = 29.00%) and for the angle grinder CCG18 (mean = 65.66%, std = 31.92%). The large standard deviations show that the classification is very different for each individual trial. The variance of the LOTO CV is affected by the uneven distribution of the "not-in-process" class among the trials. To some extent, the variance of the results with LOTO CV in Table 3 can be explained by the uneven distribution of the "not-in-process" class among the trials. However, the uneven distribution between trials only affects the "not-in-process" class that is easiest to classify. The breakdown of accuracy using MBC in Table 4 allows an analysis of the variance excluding the first stage of the "not-in-process" class. It shows that the variance is mainly due to the difficulty of classifying stage 3 and stage 4. While high accuracy was achieved in some trials, it was not feasible to recognize the correct activity in other trials. This indicates that the recognition of the manual manufacturing activities on a full unknown trial depends on how much the trial deviates from the reference training data.

This is consistent with the expected result since the experimental study for data collection included many disturbance variables and influencing factors. These are, for example, strongly varying pressure forces due to expertise and fatigue of the operators, different working methods of the operators, wear of the grinding discs, and the changing geometry and heating of the workpiece. A large disturbance variable was the heat development of the drive train of the angle grinders, which in various trials led to a brief shutdown or a termination of the trial. Another large disturbance variable was the battery state of charge of the cordless angle grinders, which has a significant effect on the voltage measurement and current measurement, especially since they were changed during the trials. Another reason for the high standard deviation is that the experiments contain only one application and, to some extent, the "not-in-process" class. Since the classification of the application varies in difficulty, as explained in the MBC framework, this also contributes to the deviation in accuracy. However, this corresponds to the real-world application since the use of the angle grinder in manufacturing usually contains only one application over one evaluation phase.

The comparison of the classifiers shows that all four classifiers have a comparable performance. However, it can be stated that EL seems to perform best except for two exceptions. In this work, we varied between several approaches to improve accuracies, such as a different classifier and an automatic Naive Bayes hyperparameter optimization. Therefore, we assume that the accuracy of this data set is already well exploited. For our collected dataset, we strongly hypothesize that the small size and lack of diversity across all trials in the dataset are the major cause of the declining accuracy of the LOTO CV compared to the CV.

It is possible that other methods, such as hidden mark models or neural networks, could improve the accuracy significantly. However, the use of neural networks requires a much larger amount of data. Furthermore, neural networks are more difficult to transfer to a similar problem. Last but not least, neural networks require a significantly higher computation time. This is a problem for an application in the field of manual manufacturing in the industrial sector, since often only few data are available, the computation is partly done on less powerful hardware and the classification models have to be retrained for different devices and application areas.

While the classification with LOTO CV already works well for the first two levels of MBC, it remains unclear whether the classification of deviating activities at a more precise level such as "roughing with a fiber disc" and "roughing with a roughing wheel" shows a better performance with a larger and more diverse training set. It should also be investigated how accurate the recognition of other manual activities in manual grinding, such as different workpieces and grinding discs. In addition, other manual activities and workpieces for a specific area in manufacturing should also be investigated in further studies.

For the application of the presented HAR, training data must be recorded for each power tool type to train a power tool-specific machine learning model. In our experiments, we used one grinder for all trials of GWS18 and one grinder for all trials of CCG18. It remains unclear to what extent an angle grinder of the same type with possibly more wear represents a disturbance variable. An interesting research direction is the transfer and adaptation of machine learning models, for example, from GWS18 to CCG18, so that less training data need to be collected for each specific power tool type.

When integrating the recognition of the manual manufacturing activities of handheld grinders into the IoT in a manufacturing system, the data rate for communication must be considered. To reduce the data rate, a research direction would be to reduce the measurement data by using fewer signals or a low sampling rate for recognition. Another research direction is to employ feature extraction or machine learning classification on a microcontroller inside a handheld angle grinder. A very important research direction for integrating manual manufacturing recognition into the IoT in manufacturing systems is the speed and real-time capability of the classification. There is further relevant information for manual grinding in Industry 4.0, such as wear [28], the tool force [18,21], which can be linked to productivity [25], or the hand-arm vibration value [12,25,29,30], which describes the permissible vibration value for an operator. The prediction of the information is based on the recognized activity, which underlines the importance of HAR in Industry 4.0.

5 Conclusions and Future Work

As the recognition of manual activities within power tools offers great potential for the IoT in manufacturing, we investigated the feasibility of using a datalogger and machine learning for the recognition of manual manufacturing activities on angle grinders. An experimental study with two angle grinders with attached data loggers and three operators was conducted to collect measurement data from four manual manufacturing activities over a machining time of 5 h. We evaluated four classifiers including a multistage gate binary classification (MBC) approach to improve accuracy by incorporating domain knowledge and to account for the impact of increasingly precise activities on accuracy with a CV and a LOTO CV. Results show very good accuracies (97.68%) for CV and worse accuracies (70.48%) for LOTO CV with the EL classifier. This means that recognition of the four chosen manual activities within an angle grinder is feasible but depends on how much the trial deviates from the reference training data.

For further research on activity recognition in manufacturing and power tools, we propose the explicit consideration and evaluation of disturbance variables and diversity in data collection for the creation of the machine learning model.

In the future, recognition of activities within one grinder with LOTO CV should be investigated in a larger training dataset with more diversity across all trials. Another research direction is the transferability and adaption of machine learning models for a specific grinder to another grinder. For integration into the IoT, the computational time and real-time capability of activity detection to reduce the data rate should be investigated. An alternative approach is edge computing on a microcontroller inside the grinder.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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