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Holistic process monitoring with machine learning classification methods using internal machine sensors for semi-automatic drilling

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Abstract

Since one third of rivet holes during aircraft assembly are produced with semi-automatic drilling units, in this work reliable and efficient methods for process state prediction using Machine Learning (ML) classification methods were developed for this application. Process states were holistically varied in the experiments, gathering motor current and machine vibration data. These data were used as input to identify the optimal combination of five data feature preparation and nine ML methods for process state prediction. K-nearest-neighbour, decision tree and artificial neural network models provided reliable predictions of the process states: workpiece material, rotational speed, feed, peck-feed amplitude and lubrication state. Data preprocessing through sequential feature selection and principal components analysis proved to be favourably for these applications. The prediction of the workpiece clamping distance revealed frequent misclassifications and thus, was not reliable.

Keywords: Semi-automatic drilling; Process monitoring; Efficient Machine Learning; Classification; Internal sensors; Data dimensionality reduction

1. Introduction

Since the structure of aircrafts is mainly joined by rivets, there is a high demand for boreholes, e.g. 250,000 per medium-sized aircraft [1]. One third of the boreholes is produced with semi-automatic drilling units (ADUs). The ongoing conversion from pneumatic to electric and sensor-integrated ADUs provide the opportunity of automatic process monitoring by recording process data, which leads to reduction of manual control and rework [2]. For the sensor-based, indirect control of the process state, tool and workpiece condition various approaches have been applied so far. *Expert Systems* use the physical and experience-based knowledge of the technicians to set up routines for individual plants, which evaluate the process by means of tolerance bands, trend analysis, fixed thresholds etc. [3, 4].

Machine Learning (ML) methods evaluate Big Data systems and predict response variables for highly complex cutting processes learning from gathered data without the need of being explicitly designed for an individual application [5, 6]. Hence, ML-based research in the production technology started decades ago, e.g. predicting tool wear during turning using artificial neural networks (ANN) [7]. Current research focuses on process state monitoring, for example in [8] material identification during turning was implemented, setting up various ML models, which show varying classification results. Cutting forces during machining were predicted in [9] also applying ANNs. External and internal sensors were used for the evaluation of workpiece quality in drilling processes of CFRP and Ti6-Al-4V in [10, 11, 12]. ML-based tool wear monitoring was introduced in [13, 14], processing dimensionally reduced sensor data. Thrust force and cutting torque in semi-automatic drilling were calculated in [15]. Also in other fields, as drilling in the oil industry, ML methods are applied in order to monitor and optimise drilling operations [16].

Most actual research focuses on certain data preparation and ML methods, often using external sensor data and focusing on few response variables. The aim of this paper's research was to develop and compare reliable and efficient methods for the process state prediction during semi-automatic drilling by using only internal machine sensor data. These data were processed in combinations of five feature preparation and nine ML classification methods to identify the optimum method for predicting each of the seven process states. The term "process state" covers the cutting parameters (revolution, feed, peck-feed amplitude)

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and the external conditions (workpiece material, lubrication, workpiece/machine contact, workpiece clamping distance).

Nomenclature

CC	concentric collet
$a_{X/Y/Z}$	machine acceleration in X/Y/Z-direction [g]
A_{PF}	peck-feed amplitude [μm]
d_c	clamping distance [mm]
f	tool feed [mm]
$f_{s,ADU}$	sampling freq. SmartADU's intern. sensors [Hz]
$I_{FM/SM}$	feed/spindle motor current [mA]
L	lubrication state [%]
n	rotational speed [rpm]

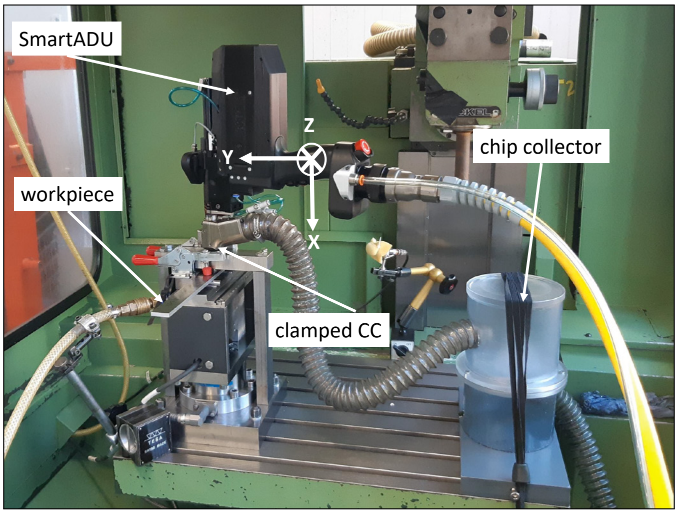

Fig. 1. SmartADU on the test rig

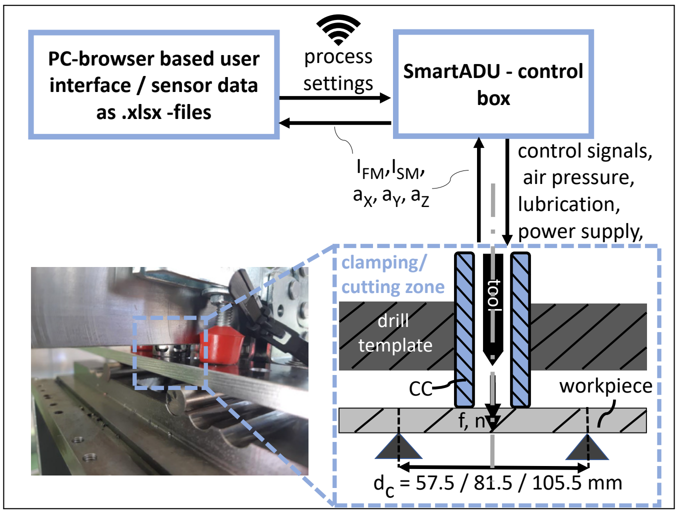

Fig. 2. Workpiece clamping and sensor data transmission

2. Experimental setup and approach

2.1. Test Rig for the advanced drilling unit (ADU)

The experiments were carried out with the SmartADU, an electrically-driven semi-automatic drilling unit developed by *Luebbering*, shown in figure 1. The machine offers position- and process data-monitoring. Spindle (I_{SM}) and feed motor (I_{FM}) currents as well as machine vibration (a_X, a_Y, a_Z) with sampling frequency $f_{s,ADU}$ of 100 Hz are internally recorded. Its cutting and lubrication parameteres are adaptive. Chip extraction and built-in vibration assisted drilling technology (="peck-feed") with an adjustable tool amplitude A_{PF} and fixed frequency ratio of 1.5 relative to the spindle speed are integrated [2].

The ADU was utilised in a test rig designed to be similar to the real production environment, shown in figure 1 and 2. The machine is fixed in a drilling template through a locking system, the *concentric collet* (CC), which is spread and contracted pneumatically. Thus, different vertical positions with or without workpiece contact of the ADU are possible. The clamping distance d_c of the workpieces is variable to account for different local stiffness situations in practise. The SmartADU-internal data is stored in the ADU-control box as a .xlsx-file. The further processing was carried out on a PC (CPU: AMD Ryzen 5(2 GHz); RAM: 8 GB; onboard GPU) using the Software *MATLAB*.

2.2. Workpiece materials and tool

The tests were carried out on four different aerospace-relevant materials, whose specifications are shown in table 1 and figure 3.

Each drill hole was produced with the same carbide tool type *KS-HB-04937-01* of *CERATIZIT Balzheim*, shown in figure 3. Every material type was drilled with an individual tool specimen as written in table 1.

Table 1. Tested materials

Material (identifier)	Tool-ID
aluminium 2024 (Al)	I
titanium Ti-6Al-4V (Ti)	II & III
CFRP - epoxy matrix (CFP - E)	IV
CFRP - thermoplastic matrix (CFP - T)	V

2.3. Experimental design

Drilling experiments were carried out with a holistic variation of the following process parameters, also shown in table 2: workpiece material, rotational speed n, feed rate f, peck-feed amplitude A_{PF}, minimum quantity lubrication state L (100/1/0), concentric collet/tool contact ("yes/no") and clamping distance d_c. These process-describing values correspond in the ML classification terminology to the response variables or the classes. The values of L are defined as follows: 100 ≙ "lubrication and air pressure"; 1 ≙ "only air pressure"; 0 ≙ "no lubrication / no air pressure". 20 drill holes per parameter set

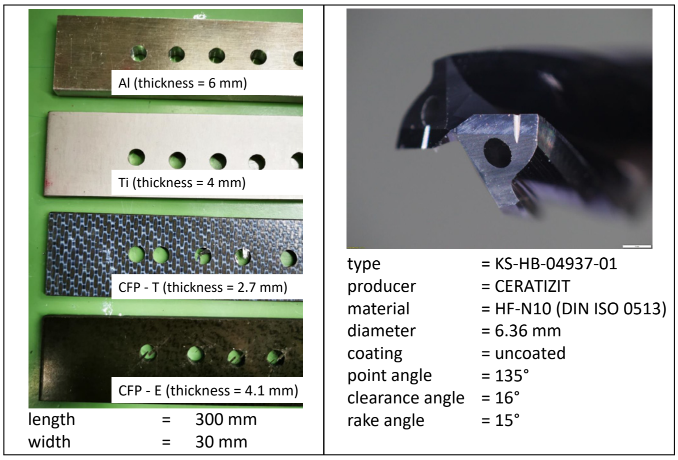

Fig. 3. Workpiece materials and tool

were conducted. The created data contains all relevant process conditions and is numerically sufficient. However, the effect of unbalanced data distribution is challenging.

Table 2. Experimental design (bold: varied parameteres within a group)

Group (Tool)	Mat.	n [rpm]	f [mm]	A_{PF} [μm]	L [%]	CC	d_c [mm]
1(IV)	**CFP-E**	**1000**	0.05	125	**1**	no	57,5
1(V)	**CFP-T**	**1000**	0.05	125	**1**	no	57,5
1(II)	**Ti**	**1000**	0.05	125	**1**	no	57,5
1(III)	**Ti**	**750**	0.05	125	**100**	no	57,5
2(I)	Al	**1000**	0.05	125	1	no	57,5
2(I)	Al	**2000**	0.05	125	1	no	57,5
2(I)	Al	**3000**	0.05	125	1	no	57,5
3(I)	Al	2000	**0.03**	125	1	no	57,5
3(I)	Al	2000	**0.08**	125	1	no	57,5
4(I)	Al	2000	0.05	**62.5**	1	no	57,5
4(I)	Al	2000	0.05	**0**	1	no	57,5
5(I)	Al	2000	0.05	125	**0**	no	57,5
5(I)	Al	2000	0.05	125	**100**	no	57,5
6(I)	Al	**1000**	0.05	125	1	yes	57,5
6(I)	Al	**2000**	0.05	125	1	yes	57,5
6(I)	Al	**3000**	0.05	125	1	yes	57,5
7(I)	Al	2000	0.05	125	1	no	**81.5**
7(I)	Al	2000	0.05	125	1	no	**105.5**
8(I)	Al	1000	0.08	125	1	yes	81.5

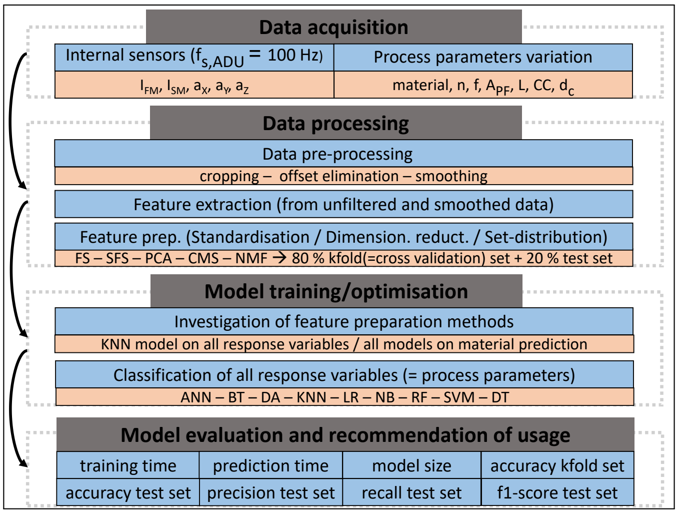

Fig. 4. ML-based workflow

Table 3. Feature examples (in total 203 features)

Name	Domain	Sensor
max	time	I_{FM}, I_{SM}, $a_{X/Y/Z}$
mean	time	I_{FM}, I_{SM}, $a_{X/Y/Z}$
skewness	time	I_{FM}, I_{SM}, $a_{X/Y/Z}$
$\text{slope}_{\text{in/out}}$	time	I_{FM}, I_{SM}
$\text{peak}_{freq1\ ...\ freq5}$	frequency	I_{FM}, I_{SM}, $a_{X/Y/Z}$
range	frequency	I_{FM}, I_{SM}, $a_{X/Y/Z}$
...	...	...

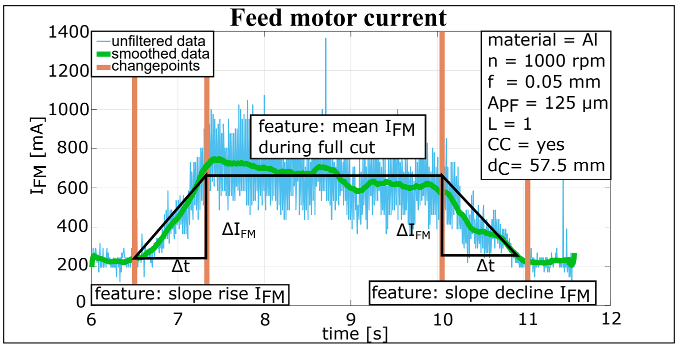

Fig. 5. Feature examples of I_{FM}

3. Data processing and ML-based process monitoring

The total workflow is shown in figure 4 and described below.

Data pre-processing and feature extraction: The sensor data pre-processing was followed by feature extraction in time and frequency domain separately from unfiltered and smoothed data, which resulted in *203* features per drill hole, respectively. For smoothing, the *moving average* filter [17] with a window size of 5 % of the data points was used. Examples for features and sensor data are displayed in table 3 and in figures 5 and 6.

The features were standardised [18] and summarised to the feature-label matrix where each drill hole corresponds to a row and the metadata (e.g. tool number), features and labels to the columns. The labels contain the seven response variables. Hence, the feature-label matrix of the experiments has the size of 371 × 218 (9 data sets were invalid).

Feature preparation: *Feature scaling* (FS) was conducted by data standardisation. Four dimensionality reduction methods, summarised with their abbreviations in table 4, were applied on the standardised features. The output of the SFS method is a significance score of present features in respect of the labels, which is a response-oriented approach [19]. By applying CMS on a m-dimensional feature space the output is a lower-dimensional representation preserving the characteristic dissimilarities of the data. NMF transforms the feature matrix in a lower dimensional space by its decompostion in a product of lower rank-matrices [22]. To use SFS, CMS and NMF,

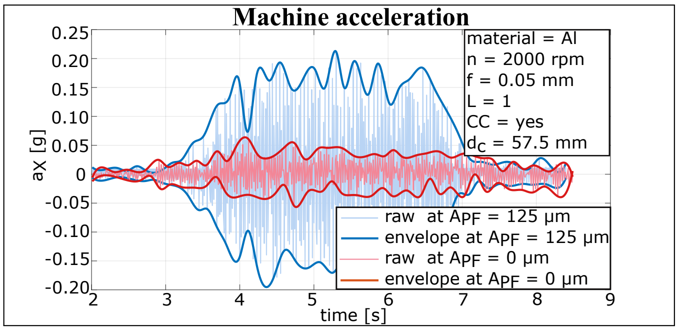

Fig. 6. Time Series of machine acceleration

the target dimension of the feature space must be provided [20]. The conducted PCA projects the feature space on a lower dimension covering 95% of the variance and is not response variable-oriented [21]. Further, FS, SFS, PCA, CMS and NMF are named as "feature preparation methods". Applying them reveals whether data dimensioanality reduction benefits the results.

Table 4. Applied dimensionality reduction methods [19, 20, 21, 22]

Method	MATLAB function
sequential feature selection (SFS)	fscmrmr
principal components analysis (PCA)	pca
classical multidimensional scaling (CMS)	pdist, cmdscale
nonnegative matrix factorization (NMF)	nnmf

For the model validation, a combination of *train/test split* and *5-fold-cross-validation* was realised [18]. 20 % of the data set were reserved as test set, whereas 80 % of the data were used as training set and cross-validated in five folds during the automated hyperparameter optimisation in MATLAB. Here, the *bayesian* optimisation with a maximum number of 30 iterations was applied. The procedure combines random hyperparameter search and exploration of hyperparameter sets with improving model performance. Thus, comparable tuning level for the models is assumed. The favoured model was determined through the highest k - fold accuracy [21] and also evaluated on the test set.

Most common ML classification methods were investigated, summarised and characterised in table 5. Hence, a link between a model group and classification results can be identified. Due to space restriction, we refer to the provided literature for deeper model description. Each model was individually tuned, except the ANN, which was trained with one hyperparameter set, shown in figure 8 for prediction of A_{PF}.

The models were evaluated by the following indicators, which are needed for a holistic review: model size, training and prediction time were analysed to judge the computational effort. The prediction quality was rated by the accuracy of the predictions using training and test data as well as by recall, precision and F1-Score of the predictions using test data. By this, the generalisation capability of the models can be evaluated [18]. The indicators were handled in following general assessment. First, the methods were ranked for each performance indicator. For each indicator the best approach got 5 points, the second best 4 points,..., the fifth best 1 point. The total score for a model was calculated through the addition of the points, whereby points of the prediction quality indicators were multiplied by two due to their higher relevance. Based on the total points number, a ranking was built for a chosen response variable.

Table 5. Applied ML methods [18, 21]

Method	Group/Interpretability	MATLAB func.
k-nearest neighbours (KNN)	clustering/complex	fitcknn
logistic regression (LR)	regression/simple	fitcecoc
discriminant analysis (DA)	kernel/medium	fitcdiscr
naïve bayes classifier (NB)	bayesian/simple	fitcnb
support vector machine (SVM)	kernel/medium	fitcecoc
artificial neural network (ANN)	neural networks/complex	fitcnet
decision tree (DT)	tree/simple	fitctree
boosted tree (BT)	tree/complex	fitcensemble
random forest (RF)	tree/complex	fitcensemble

Investigation of feature preparation methods: The KNN model was trained on each response variable using the data of all feature preparation methods, resulting in 35 models (= 5 feature prep. methods $\times$ 7 response variables). To check whether the results of the KNN model can be transferred to further models, all ML models were trained using all feature preparation methods on material prediction, which yielded in further 45 models (= 5 feature prep. methods $\times$ 9 ML models). Thus, the performance of feature preparation methods was identified.

Classification of all response variables: For the determination of the approach with the best performance regarding each process state (=response variable) all ML models were trained having the input of the first, second best and poorest feature preparation method determined from the above described analysis. Thus, the training of all investigated ML models (9), shown in table 5, for each response variable (7) using all feature preparation methods (5) (= 315 models) was reasonably shortened. The combinations of the feature preparation and ML methods were ranked using the above described assesment.

For the described analysis, unfiltered sensor data was used. A following study was also made using the identified best combinations of feature preparation and ML models in order to show the influence of data smoothing and data set size:

- training with smoothed I_{FM}/I_{SM} and unflitered $a_{X/Y/Z}$ data as input
- training with a dataset reduced by 50 % in its size
- training with an doubled data set by adding synthetic data created through scaling the time series and adding noise

4. Results and evaluation of the ML-based monitoring

First, the KNN method was trained and optimised using all feature preparation techniques on each response variable. The result for the material classification is shown in figure 7, reflecting the average behaviour for all response variables. The application of dimensionality reduction (PCA, SFS, NMF) shows advantages in terms of prediction and training time and models size compared to just data standardisation (FS), while the prediction quality applying PCA, SFS and FS is similar.

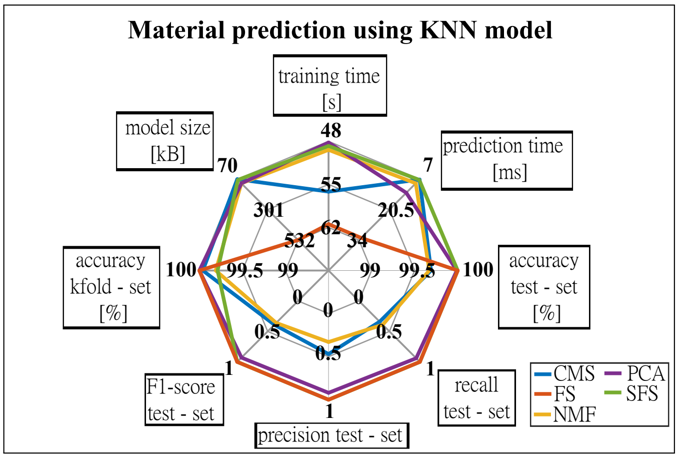

Fig. 7. Comparison of feature preparation methods with the KNN model

Next, all ML methods were applied to the material prediction to verify the described dependence on the feature preparation methods with results shown in table 6. The outcome confirms the previous diagnosis (note in table 6: the approaches are compared isolated for each ML model type and hence the ranking points are assigned separately within a column). The averaged ranking of feature preparation methods reveals following order, beginning with the best approach: SFS, PCA, FS, CMS, NMF. Hence, the best performing feature preparation methods (SFS, PCA) were used with the aim of developing a holistic process monitoring. It was also tested whether NMF performs poorly on all response variables with all ML models.

Table 6. Ranking results for workpiece material prediction using all feature preparation and ML methods (**bold**: highest scores for each ML method)

Feature prep.	Scores ML methods KNN	LR	DA	NB	SVM	ANN	DT	BT	RF
FS	45	38	46	46	46	**48**	50	46	51
SFS	**50**	**51**	50	**53**	**50**	42	**52**	**54**	**56**
CMS	30	32	29	30	32	30	34	27	27
PCA	42	46	**52**	48	48	43	42	48	42
NMF	20	20	17	16	19	22	17	20	19

Figure 8 summarises the performance of seven best combinations of a feature preparation and ML method for each process parameter. The evaluation indicators with their position and unit in the spider plots are described in figure 7, whereas in figures 8 and 9 due to visibility reasons these are just labelled with their values. The specification of the approaches with best overall performance and their confusion matrix of the test set data are also presented.

Despite the unbalanced classes, the predictions are accurate for material, n, f, A_{PF}, L and acceptable for the CC contact. The results for d_C are imprecise. Process states with an impact on the process forces and hence on the sensor signals are well-captured by simpler models such as KNN. The ANN model is favourable for the highly complex process states A_{PF} and d_C. In general, the prediction durations are short and the models' memory usages low.

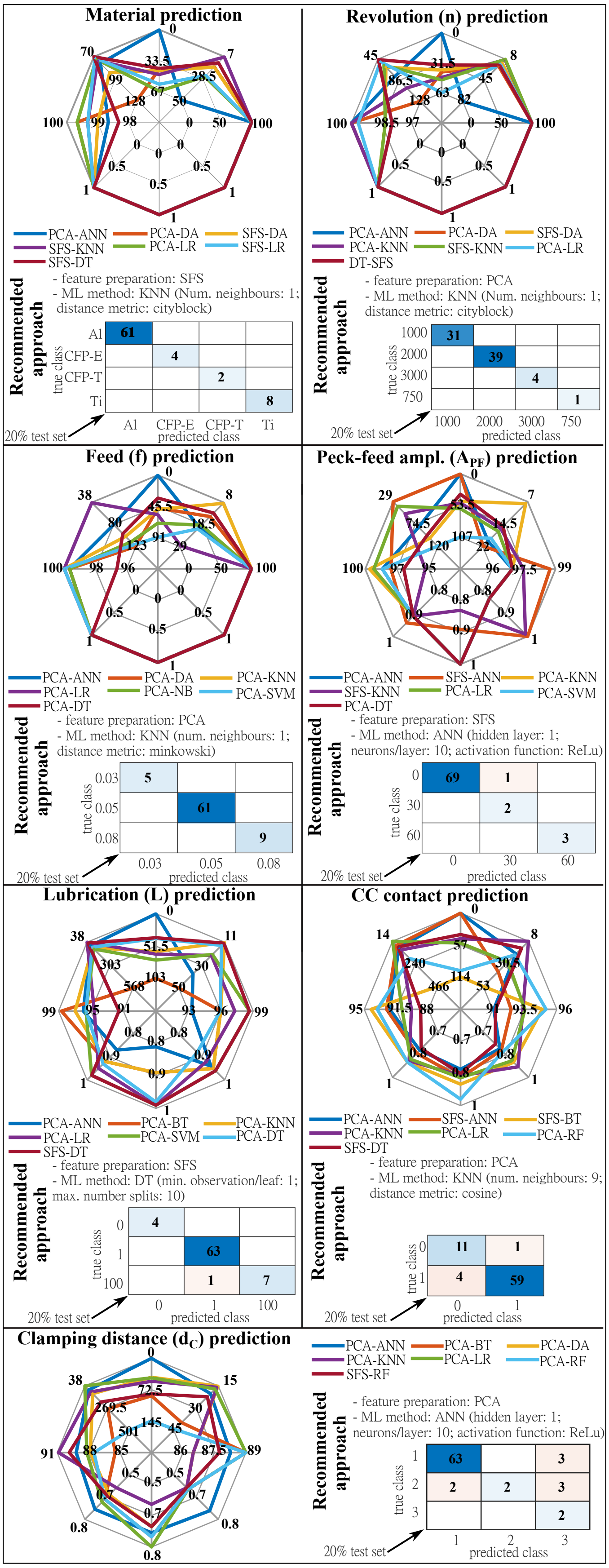

Fig. 8. Prediction for each response variable (axes/units description in fig. 7)

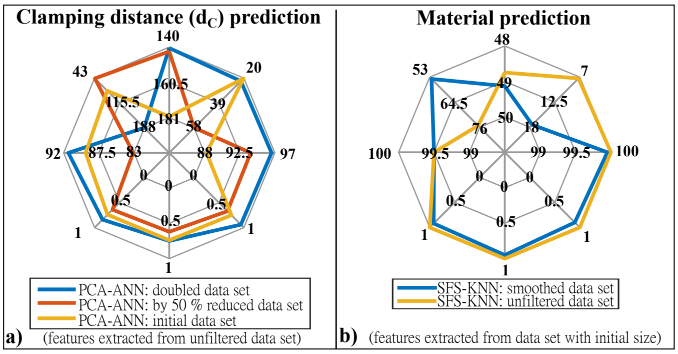

Fig. 9. Evaluation of the influence of data set size and smoothing

Figure 9a reveals the exemplary impact of data set size on the model performance (the indicators and units are analog to figure 7, except the training time is presented in *ms* for a better camparability). Here, the most challenging prediction of d_C is shown. Adding of further synthetic data improves the prediction quality. Smoothing of I_{SM} and I_{FM} before feature extraction decreases the model performance, which is exemplary shown in figure 9b (the indicators and units are analog to figure 7) on the material prediction. This can be explained by the induced data loss.

5. Conclusion and outlook

A holistic development and evaluation of optimal approaches, consisting of feature preparation and ML classification methods, for the process state monitoring during semi-automatic drilling was carried out. Only internal machine sensor data of spindle and feed motor current and machine acceleration was used for the analysis. For the process state prediction of workpiece material, drill revolution, feed rate, peck-feed tool magnitude, lubrication state and workpiece-CC (=machine) contact, reliable methods were presented. For the clamping distance prediction, further improvements must be worked out, which is possibly done by including further sensors or developing other features from the currently used data. The prediction quality improves by enlarging the data set with synthetically created training data and deteriorates through the motor's current data smoothing. The following production errors can be detected through the presented monitoring of the process states:

- material: borehole position, material stack setup
- drill revolution/feed rate/peck-feed tool magnitude: process parameter setting
- lubrication state: process parameter setting/lube fill level
- workpiece-CC-contact: machine position/ air pressure supply of CC
- clamping distance: material defects/borehole position

In future, the implementation of the investigated methods on an edge or cloud computing device and testing of the real-time prediction capability is necessary. The prediction time of the developed ML models is low, which means the bottleneck in the computing chain could be the data pre-processing. Furthermore, possible advantages of the use of additional sensors (e.g. acoustics and workpiece vibration) must be evaluated.

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