Machine Learning-Based Selection of Measurement Technique for Surface Metrology: A pilot study

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Abstract

The study introduces the application of machine learning (ML) for surface texture metrology in decision-making support for measurement system preliminary selection. The paper delves into the intricate data filtering considerations and the diverse metrological parameters involved across different measurement techniques. Tailored to the specifics of the measuring object, surface texture parameters, and factors such as measurement technique and uncertainty, the algorithm developed offers predictive capabilities. Drawing from a database of available metrological devices streamlines the operator's task by predicting the appropriate system before conducting measurements. Preliminary results from the validation of prediction models are also provided.

1. Introduction

In 1950 mathematician and codebreaker Alan Turing published a paper on the fundamental discussion of artificial intelligence [1]. He also asked questions about learning machines, such as where to start with machine learning. Based on this inspiration, enormous progress has been made with AI. Today, we use machine learning for decision-making support, big data processing, and physical and chemical computing, from medical to mechanical engineering applications. It is also applied successfully for metrology.

1.1. AI in tactile surface measurements

In manufacturing metrology, tactile systems are still the first choice for measuring high-precision parts. Its well-known and established technique guarantees an easy way to compare the results with accuracy that is still acceptable to the manufacturing tolerances. Moreover, the physics of the probe-surface interaction is well described by the non-complex Newton equation, while the optics are still quite complex with Maxwell's. These provide straightforward data processing and simulation verifications with tactile measurement systems, while optical signal processing may be complicated. In the age of production automatisation and informatisation, AI solutions are also used in these techniques for making measurements faster, more reliable and with reduced error influences.

A. Eser et al. introduced the AI application for roughness parameter (Ra) estimation of an aluminium alloy after milling using carbide cutting tools coated with CVD-TiCN in dry conditions [2]. They used cutting speed, depth of cut, and feed rate for predictive model classes. They used the Mahr Marsurf PS 10 surface roughness tester to measure the surface roughness of the machined surfaces. The authors declared the R^2 = 95.6 % for testing data.

Similar work was presented by I. Abu-Mahfouz et al. [3]. AI was applied to predict surface roughness in turning based on a vibration signal analysis.

In their study, U. Adizue et al. introduced an artificial intelligence (AI) powered predictive model for surface roughness in micro-milling hard materials [4]. They employed a feedforward artificial neural network (ANN) model, which underwent training, validation, and testing with experimental data. The resultant trained model demonstrates proficient prediction capabilities for surface roughness, attaining a Root Mean Square Error (RMSE) of 0.019.

The AI proposal application for wear-surface prediction was made by A. Bustillo et al. [5]. They proposed parameters and the level of isotropy of the surface of the samples determined using a Talyscan 150 measuring machine (Taylor Hobson). The dataset was generated from a friction process experiment for 4 different outputs: relative loss in mass (Δm), roughness as a root mean square profile (*Rq*), roughness as reduced peak height of profile (*Rpk*) and roughness as an arithmetic mean of the profile (Ra).

The machine learning application for real-time manufacturing control was proposed by D. Pimenov [6]. They introduced methods for real-time surface roughness prediction, depending on the main drive power and considering tool wear. They postulated, with experiments, that the Random forest model has the highest accuracy in surface quality prediction. A similar approach was described by V. Dubey et al. [7] to use machine learning in cutting fluid to estimate the surface roughness and compare the experimental value to the predicted values.

Application of artificial intelligence for additively manufactured components metrology was comprehensively reviewed by T. Batu, H.G. Lemu and H. Shimels in [8]. The authors discussed the limitations, challenges, and future directions for applying AI in surface roughness prediction. They discussed machine-learning approaches.

An interesting application of Artificial Neural Networks in additive surface metrology was introduced by D. Soller et al. [9]. The model for surface roughness *Ra* prediction of additively manufactured parts was proposed and proven with experimental results. Specimens produced by SLM with surface treatment by blasting and electropolishing were measured using Taylor-Hobson Talysurf-Intra 50 mm profilometer. The described algorithm gives a chance to improve the surface roughness roughly by 60 %.

1.2. AI in optical surface measurements

Optical measurement systems (e.g. laser scanner, photogrammetry or fringe projection systems) provide contactless surface measurements with sub-μm resolution. Damage to the surface is easily prevented, and wear and tear, known from tactile measuring systems, also cannot occur with these systems. Massive progress in AI application for optical surface measurements is observed.

In the realm of surface texture measurement, light scattering is classified among area-integrating techniques. Unlike traditional approaches that involve coordinate measurements of individual surface points, light scattering methods delve into specific surface areas, providing parameters reflective of the overall texture in that region. Examples of measurable aspects resulting from light scattering, such as specular beam intensity, angle-resolved scatter, and angle-integrated scatter, offer valuable insights into the characteristics of the surface texture as a whole [10]. M. Liu et al. proposed a surface defect detection system based on light scattering and a supervised deep learning model [11]. They showed a deep convolutional neural network trained using a large scattering dataset. This way, surface defect information may be predicted using the scattering signal. The proposed technique is promising for on-machine defect detection of surfaces with high speed and robustness.

Digital holographic microscopy (DHM) is an interferometric method that captures 3D surface details from a single image in mere microseconds. Capitalizing on this speed, DHM excels in real-time measurements, achieving speeds of up to twenty frames per second in live mode. Its primary limitation lies in the camera's acquisition rate during post-processing. A stroboscopic module designed explicitly for periodic movements enables 3D displacement measurements at frequencies reaching 25 MHz, utilizing brief laser pulses lasting 7.5 nanoseconds. Like traditional optical microscopes, the lateral resolution of DHM is determined by the numerical aperture of the microscope objective. Remarkably, DHM avoids mechanical scanning and instead utilizes wavelength for vertical calibration. This approach showcases remarkable resistance to vibrations, resulting in an impressive vertical resolution of 0.1 nanometers and a repeatability of 0.001 nanometers. With these capabilities, DHM finds its niche in certification metrology and proves invaluable for rapid topographic imaging across diverse applications, including surface texture quality control and measuring the height and displacement of MEMS and MOEMS devices [10].

F. Pan et al. presented an interesting application of machine learning to digital holography interferometry [12]. They demonstrated for the first time the application of machine learning for assisting the sub-apertures stitching processes in holographic and interferometric systems. Compared to state-of-the-art instruments, the method may potentially address rapid surface quality measurement in realistic workshop conditions with high precision and low cost.

A fundamental optical technique is interferometry. Variations in fringe visibility associated with optical coherence in an interference microscope, contingent on height, present a robust and non-contact sensing mechanism for 3D measurement and surface characterization. Coherence scanning interferometry expands the application of interferometric techniques to intricate surfaces featuring roughness, steps, discontinuities, and complex structures like transparent films. Noteworthy advantages encompass an autofocus equivalent at every point within the field of view and the mitigation of unwanted interference arising from scattered light.

C. Zuo et al. presented a comprehensive overview of machine learning (ML) applications in optical metrology [13]. The authors described many ML applications for analysis, pre-and post-processing images in optical measurements.

For manufacturing metrology, O. Obajemu et al. presented a new machine learning approach for modelling the surface metrology parameters of manufactured components [14]. Such a modelling approach can allow one to better understand and, as a result, control the manufacturing process so that the desired surface property can be achieved whilst manipulating the process conditions. They used an ALICONA interferometric instrument for areal surface measurements.

1.3. AI for decision making-support in metrology

New findings about AI and ML applications are mainly based on data evaluation and image processing but not so representatively on a complex application for the AI decision-making support of an operator in the measurement process chain, such as what type of system should be used or what level of filtering should be applied. An exciting application was presented by S. Mian et al. for the evaluation of cylindricity [15] measured by a coordinate measuring machine (CMM). The proposed approach utilized three distinct inputs: point distribution schemes, the overall quantity of points, and form assessment algorithms. These inputs assessed two key outputs: cylindricity and measurement duration.

The adaptive form verification in coordinate metrology was described by S. Raman et al. [16]. They showed that kernel methods might be successfully applied to recover deformation patterns on the surface of parts and compute minimum zones.

The theoretical consideration of AI decision-making support in surface metrology was discussed by M. Wieczorowski et al. in the published articles [17], [18]. They described ML-based AI applications for tactile and optical systems for data processing support and the idea of the AI application for decision-making support in the measurement scenario preparation: prediction of measurement system type to be used, data filtering, and more.

In this paper, we propose the experimental answer to a Turing-like question: Can a machine predict and offer a measurement scenario for an operator? Here, the practical application of machine learning (ML) for surface metrology is proposed for the first time in the literature in this scale for surface topography measurements using many different measurement systems, tactile and non-tactile. The proposed approach describes the Ml-based AI algorithm for prediction of the measurement system type to be used when input parameters are known: material type of the surface, data filtering, type of the object (reference or not), topography parameters (*Ra*, *Rz*, *RONt*) with their uncertainties. The algorithm for system type prediction is freely available on the internet and developed in the GitHub group https://github.com/dawidkucharski/AI_for_surface_metrology

2. Method

The prediction algorithm is based on the R. R is a programming language and environment for statistical computing and graphics. Developed at Bell Laboratories, R is influential in statistics and image processing and is highly extensible via packages [19]. It is highly competitive with Python and also provides AI application packages: caret [20], keras [21], tensorfFlow [22]. The prediction algorithm is supplied with an extensive dataset (comprising 1143 total measurements) gathered from diverse surfaces utilizing both contact and non-contact methods. This dataset is enriched with multiple measurement parameters and outcome-filtering protocols. Each sample underwent 50 measurements under identical parameters to assess uncertainty. Monte Carlo (MC) simulation was employed to estimate measurement uncertainties for surface irregularities, serving as input parameters for the algorithm. The MC measurement function was adapted from [23] by [24]. The presented algorithm is proposed to support the operator's decision-making to determine which type of measurement system may be used when other information is known.

2.1. Data processing, Experimental Workflow

The data was collected using measurement systems: tactile profilometer (TP), coordinate measuring machine (CMM), round-tester (RoundScan), phase grating interferometry (PGI), and non-contact profiler, coherence correlation interferometry (CCI). As the samples, referenced surfaces (roughness and form standards) were used (see eg. figs. 1 and 2), and machined ones (see eg. fig. 3).

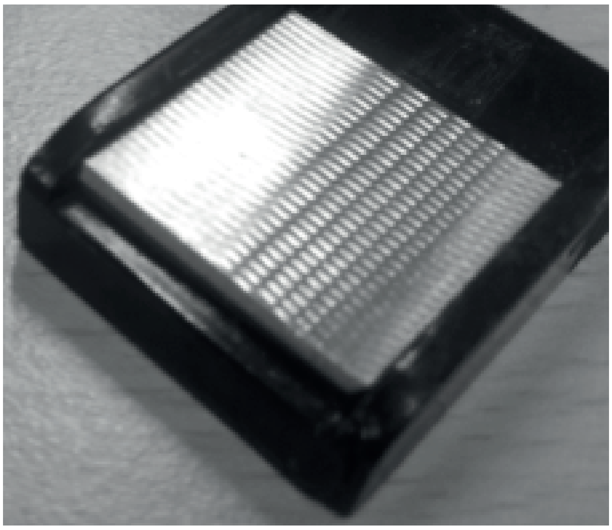
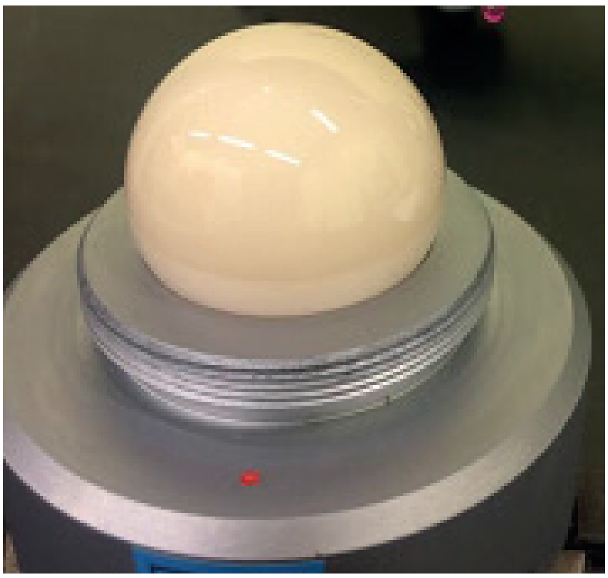


Figure 1. Example of roughness steel standard used for ML model training



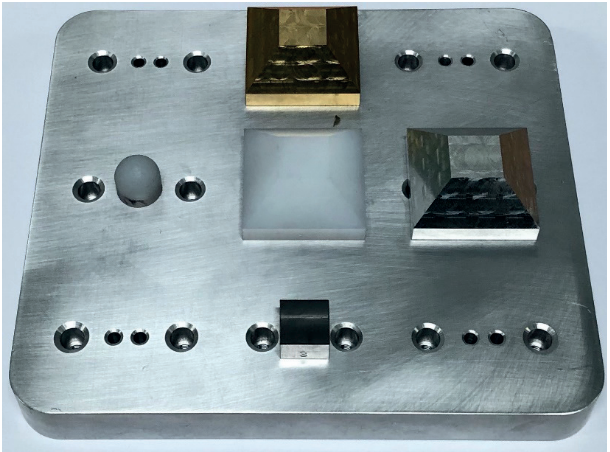


Figure 3. Steel probe plate 180x160x10 with machined samples mounted using $\phi 4$ rods

The samples are made of steel, aluminium, brass, polymer, glass, and ceramic. For attributes in ML algorithm, materials are numbered as integers 1-6. In tab. 1 first 40 rows of prepared data are shown.

For data preparation and final ML algorithm, the knitr package was used to combine R and LaTeX [25-27]. In this way, part of the data presented in the tables might change after manuscript compilation, which does not affect the numbers shown in the results. These approaches can dramatically reduce the time required to complete a research project that can be trivially replicated. Recent enhancements to RStudio streamline the entire process of output format generation via a simple click of an icon or keystroke shortcut (the minimum requirement is R). Replicability is guaranteed using the checkpoint package in R. This article was written using Markdown. The input codes are marked as blue, while outputs are green in the text.

The measurement data are stored on the iCloud disc with a link shared between contributors. The data format was not unified so the algorithm is adopted to read the extension type of the data in the folder. After that, topography parameters like Ra, Rz measured 50 times are used for Monte Carlo mean value and uncertainty calculations. For example, for Ra with uncertainty, the MC code was as follows [23]:

Which gives the result as the confidence interval from the R internal bootstrap function (eq. 1):

$$\overline{Ra} = 1.56 \pm 0.05\ m\mu\ (95\%), \tag{1}$$

where:

Ra - mean Ra; 0.05 "mμ – uncertainty; 95 % – confidence interval. The collected data partially shown in tab. 1 are used for machine learning steps (see fig.4).

Table 1: First 40 lines of collected data. Surface parameters are calculated as an average from 50 repeated measurements. The uncertainties are calculated with the Monte Carlo method. F = 0 or 1 means the data were filtered or not. Standard = 1 when the surface was collected from reference object

system_type	Ra	Ra_uncert	Rz	Rz_uncert	material	RONt	RONt_uncert	standard	F
TP	7.14	0.05	28.60	0.05	1	0.00	0.00	1	1
CCI	0.84	0.05	2.06	1.05	1	0.00	0.00	1	1
TP	3.36	0.05	12.41	0.05	1	0.00	0.00	1	1
TP	2.91	0.05	12.17	0.05	1	0.00	0.00	1	1
TP	0.24	0.05	1.48	0.05	1	0.00	0.00	1	1
TP	0.12	0.05	0.48	0.05	1	0.00	0.00	1	1
TP	7.29	0.05	31.04	0.05	1	0.00	0.00	1	1
TP	0.39	0.05	3.10	0.05	1	0.00	0.00	1	1
PGI	0.08	0.05	0.22	0.05	1	0.00	0.00	1	1
TP	1.67	0.05	6.91	0.05	1	0.00	0.00	1	1
TP	1.67	0.05	11.46	0.06	1	0.00	0.00	1	1
CCI	0.07	0.05	0.09	0.05	1	0.00	0.00	1	1
TP	0.67	0.05	4.49	0.05	1	0.00	0.00	1	1
TP	1.17	0.05	6.27	0.05	1	0.00	0.00	1	1
TP	5.89	0.05	21.00	0.05	1	0.00	0.00	1	1
TP	19.36	0.05	84.77	0.05	1	0.00	0.00	1	1
TP	19.36	0.05	84.77	0.05	1	0.00	0.00	1	1
TP	5.77	0.05	32.41	0.05	1	0.00	0.00	1	1
TP	5.91	0.05	22.94	0.05	1	0.00	0.00	1	1
TP	1.66	0.05	7.60	0.05	1	0.00	0.00	1	1
TP	0.48	0.05	3.04	0.05	1	0.00	0.00	1	1
TP	0.28	0.05	1.41	0.06	1	0.00	0.00	1	1
TP	1.81	0.05	6.85	0.05	1	0.00	0.00	1	1
TP	0.07	0.05	0.12	0.05	1	0.00	0.00	1	1
TP	0.78	0.05	4.84	0.05	1	0.00	0.00	1	1
TP	5.96	0.05	24.41	0.05	1	0.00	0.00	1	1
CMM	0.00	0.00	0.00	0.00	1	2.40	0.08	1	1
TP	0.08	0.05	0.18	0.05	1	0.00	0.00	1	1
TP	4.88	0.05	19.49	0.05	1	0.00	0.00	1	1
TP	2.47	0.05	10.92	0.05	1	0.00	0.00	1	1
RoundScan	0.00	0.00	0.00	0.00	1	1.37	0.07	1	0
TP	11.06	0.05	41.86	0.05	1	0.00	0.00	1	1
TP	1.73	0.05	10.71	0.05	1	0.00	0.00	1	1
TP	2.88	0.05	15.33	0.05	1	0.00	0.00	1	1
TP	0.18	0.05	1.07	0.05	1	0.00	0.00	1	1
TP	0.07	0.05	0.15	0.05	1	0.00	0.00	1	1
TP	0.40	0.05	2.94	0.05	1	0.00	0.00	1	1
PGI	0.15	0.05	0.71	0.05	1	0.00	0.00	1	1
TP	6.11	0.05	22.07	0.05	1	0.00	0.00	1	1
RoundScan	0.00	0.00	0.00	0.00	1	1.37	0.07	1	0

```
> x <- c(wzNr93szlifScierTasm1_6_VP_031nr6\$Ra*1000) # example Ra data in the micron scale
> Nx <- length(x) # number of data points in x
> P <- 0.95 # confidence level
> R <- 10^5 # number of times to resample the data
> bLin <- 0.01 # linearity error
> bRep <- 0.01 # repeatability
> bCal <- 0.005/2 # calibration error
> bProbe <- 0.01 # Probe error
> boot.r <- numeric(R) # vector for r values
> for (i in 1:R) {
+   boot.sample.x <- sample(x,size=Nx,replace=T) # resampling pipe
+   beta1x <- rnorm(n=1,mean=0,sd=bLin) # linearity error function
+   #(normally distributed)
+   beta2x <- runif(n=1, min = 0, max = 0.1) # repeatability error function
+   #(normally dostributed)
+   beta3x <- rnorm(n=1,mean=0,sd=bCal) # calibration error function
+   beta4x <- bProbe # Constant probe error
+   xs <- mean(boot.sample.x)+beta1x+beta2x+beta3x+beta4x # measurement function
+   boot.r[i] <- xs # r vector
+ }
> quant<-quantile(boot.r, probs = c((1-P)/2,(1+P)/2))
> uncert<-mean(boot.r)-quant[[1]] # uncertainty based on quantile
> Ra<-round(as.numeric(mean(boot.r)),digits=2); # Ra
> Ra_uncert<-round(as.numeric(uncert),digits=2); # Ra uncertainty
```

The approach is based on a simple proposal by J. Brownlee applied to machine learning-based iris flower recognition [28].

The data are split into two parts. 70 % is used for training and model testing, and 30 % is used as a validation dataset (not seen by models). Statistics are used to monitor the interaction between attributes and classes, such as the dimensions of the dataset, the types of attributes, the levels of the class attribute, and a statistical summary of all attributes (see eg. fig. 5).

A 10-fold cross-validation test harness is applied to create data models and estimate their accuracy. The accuracy is a ratio of correctly predicted instances divided by the total number of instances in the dataset multiplied by 100 to give a percentage.

The data (70 % of the total) are split into ten parts: train in 9, test on 1, and release for all combinations of train-test splits. The process is repeated three times for each algorithm, with different data splits into ten groups to get a more accurate estimate. Six models were tested:

1. LVQ – Learning Vector Quantization,
2. CART – Classification And Regression Tree,
3. KNN – k-Nearest Neigbor Algorithm,
4. GBM – Generalised Boosted Regression Models,
5. RF – Random Forest.

3. Results

The calculations of the models without optimisation gives 98.63 % accuracy for Random Forest Model (see fig. 6) with Kappa parameter equal 95.08 %. Kappa or Cohen's Kappa is like classification accuracy, except that it is normalized at the baseline of random chance on dataset. It is a more useful measure to use on problems that have an imbalance in the classes (e.g. 70-30 split for classes 0 and 1 and we can achieve 70 % accuracy by predicting all instances are for class 0). In fig. 6 the models comparison is presented.

The accuracy of the Random Forest model validation, for first tests, is on the level of 97.65 % with Kappa 91.61 . The confusion matrix for measurement system predictions is shown in tab. 2.

The first results showed a high accuracy of the machined learned models and predictions in the preliminary selection of measurement system type. It is basically due to using precisely machined surfaces and reference objects for training and validation. It means ongoing research to expand the data source used for more accurate AI application in metrology is relevant with more random objects, and here, the possibility of AI in decision-making support in metrology is presented for the first time in literature on this scale.

The prediction models are nonlinear. At first statistical look, no particular relation may be seen between

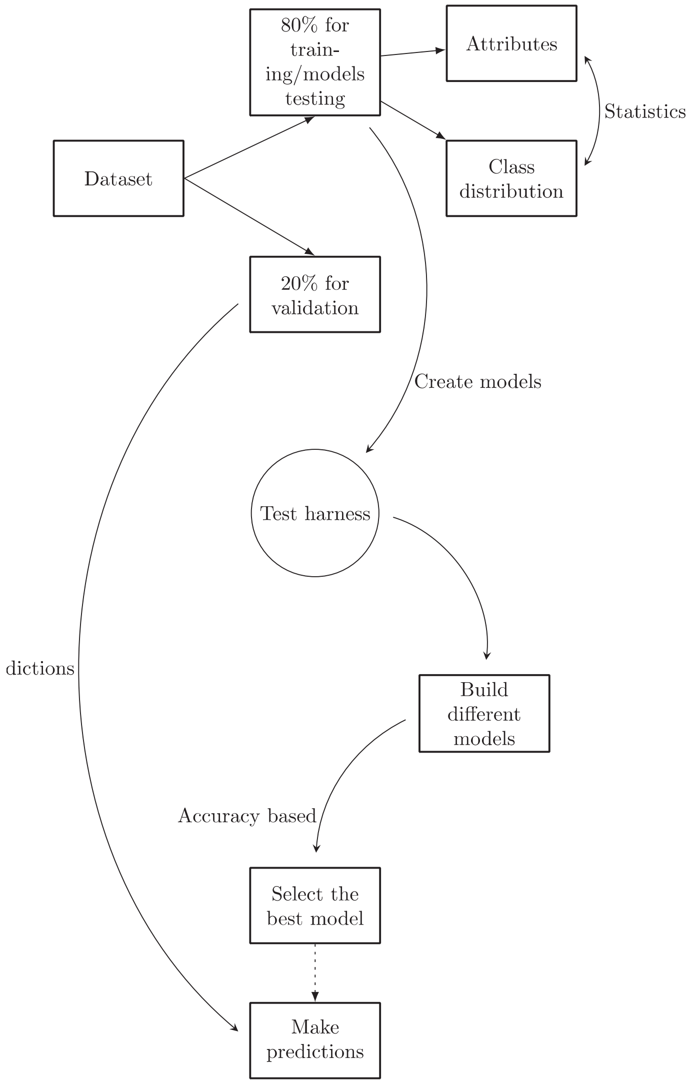


Figure 4. Flowchart of the simple machine learning algorithm

Tab. 2. Confusion matrix

	CCI	CMM	PGI	RoundScan	TP
CCI	16	0	0	0	5
CMM	0	5	0	0	0
PGI	0	0	18	0	3
RoundScan	0	0	0	10	0
TP	0	0	0	0	283

attributes and classes. A final decision-making model might be even more complicated, so the neural network with a convolutional neural network (CNN) is considered for further research. The first results with CNN are also auspicious, especially with an expanding results database.

4. Discussion and Conclusions

The paper presents the ongoing project for implementing AI decision-making support in surface metrology

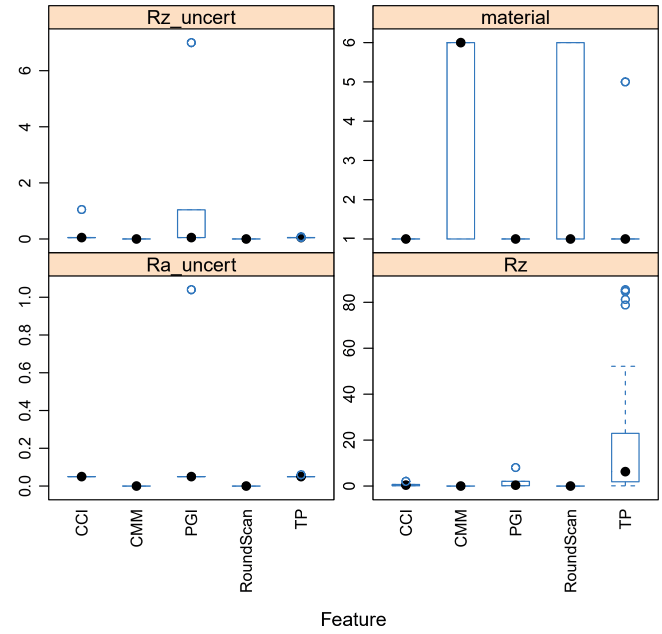


Figure 5. Boxplot for example feutures. Surface parameters are in μm

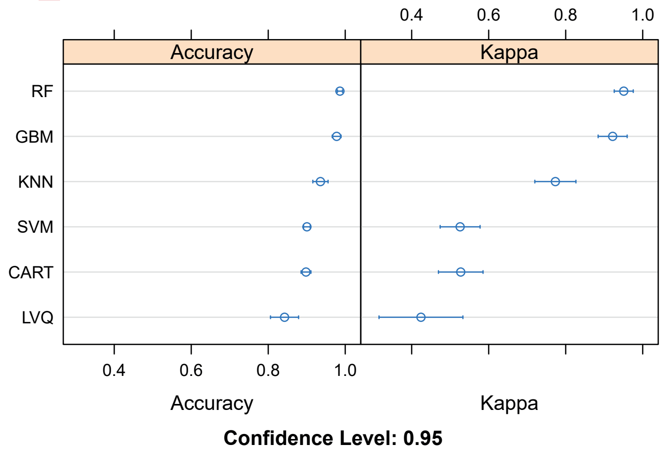


Figure 6. Prediction models comparison: LVQ - Learning Vector Quantization, CART - Classification And Regression Tree, KNN - k-Nearest Neigbor Algorithm, GBM - Generalised Boosted Regression Models, RF - Random Forest

with the first preliminary results of the machine learning application approach. The measurement system type selection was chosen as the algorithm prediction of classes based on the selected metrological attributes. The Random Forest model has been found to be the most accurate tool for the proposed machine learning application.The model will be further investigated with more measurement data. However, the prepared algorithm frame is ready to be used. The simple neural network and convolution (CNN) are now investigated, and the results will be announced to the public soon.

The results presented above yield the following conclusions:

- The proposed machine learning application introduces a commendable preliminary phase in readying the intelligent tool for decision-making support in surface metrology—a concept first introduced in the literature and complete with preliminary experimental results.
- The presented findings correspond to relatively high accuracy (with Kappa 91.61 %) of the measurement system type prediction using the Random Forest algorithm. Overlearning issues that may be related to the high accuracy level have not been investigated yet.
- The developed algorithm with ongoing updates is freely available on the internet in the GitHub group https://github.com/dawidkucharski/AI_for_surface_metrology.
- The algorithm has been tested using limited data, which will be improved with ongoing experiments with more measurement system types involved.
- The freely accessed measurement data will be expanded for further investigations with AI applications, and the presented outcomes of the paper are the first whistleblower to the public announcement.
- The observed disadvantage is the high accuracy of all the compared models, which might be connected with the overlearning issue with the data from reference surfaces, a common problem with classical machine learning. This may be overcome with the advanced deep learning approach.

In the paper, the experimental realisation of the theoretical consideration of AI decision-making support in surface metrology discussed by M. Wieczorowski et al. in the published articles [17], [18] is presented very first time in the literature in this scale. The AI-driven algorithm for a measurement system type selection has been proposed here. The outcomes of the findings may be numerically summarised as follows:

- The algorithm for system type prediction was fed by the vast amount of data (1143 of total measurements).
- The data was collected using 5 different measurement systems.
- The samples were made of 6 different materials.
- Every sample was measured 50 times with the same setting parameters.
- 6 prediction models were tested.
- The calculations of the prediction models give 98.63 % accuracy for the Random Forest Model.
- The Random Forest model validation accuracy for first tests is on the level of 97.65 %.

Further research will focus on data collection to expand significantly the database, with more material types, surface finishing, and different geometries of the samples. More tactile and optical measurement systems will be involved in the investigation. The deep learning algorithm based on Convolutional Neural Network (CNN) is currently developed based on GPU and keras [21] and tensorfFlow [22] in R. The first promising observation showed more robustness, accuracy, and independence due to the number of inputs compared to the classical machine learning approach. More details will be published in the following papers.

Declaration of Competing Interest

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