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IMAGE BASED DETECTION OF COATING WEAR ON CUTTING TOOLS WITH MACHINE LEARNING

Wear of cutting tools is known to affect the surface integrity of the workpiece and significantly contributes to machine downtime. To establish wear-resistant cutting tools, several coating strategies have been introduced. It has been shown that the wear rate increases dramatically once the coating is worn through. Detecting coating layer loss is therefore a good indicator of the remaining useful life of the cutting tool. Based on cutting experiments conducted with a TiN/AlTiN-coated cutting tool, an image dataset was generated and pre-processed using multiple algorithms, such as Canny edge detection and Hough line transforms. For the classification task four machine learning Algorithms consisting of Random Forests, Decision Trees, Support Vector Machines and a Feed Forward Neural Network were implemented. The results demonstrate that all four algorithms lead to a good classification performance, with Decision Trees showing the best performance with a F1-score of 0.95. Therefore, this research provides an efficient data processing and classification framework for detecting coating wear on cutting tools.

1. INTRODUCTION

Subtractive manufacturing processes like milling, drilling or turning are characterized by removing material of a workpiece with a geometrically defined cutting edge. Besides the accuracy and stiffness of the machine itself, the interaction of the tool and the workpiece is key for an economically and technologically advanced production. The importance of the tool is highlighted by the fact that up to 20% of machine downtime is caused by tool failure [1]. In addition to economic implications wear of cutting tools causes continuously changed process state variables such as cutting forces and temperatures [2], causes dynamically worse process conditions which affect the workpieces surface integrity and ultimately causes deviation from the target geometry [3]. Developing wear-resistant tools and coatings to delay the tool failure significantly improved the lifetime of tools. Coated cutting tools are now state of the art. The coating works as a barrier for heat transfer to the underlying substrate, lowers the friction coefficient and thus the amount of the thermo-mechanical loads. Coatings have

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evolved from a simple titanium nitride (TiN) coating to mostly aluminium titanium nitride (AlTiN) coatings. Developing better coatings and strategies such as multi-layered coating systems is still an active research topic. Wear of cutting tools follows a so called S-curve, which manifests itself as a comparably rapid wear development which then transfers into a steady wear development and finally into a rapid wear development again until the tool breaks down. Detecting the loss of a coating with its superior wear resistant is therefore an important task to predict the remaining tool life.

Recently researchers focused on the development of wear detection and prediction techniques [4] for an implementation of accurate predictive maintenance. The latter also contains Finite Element Analysis (FEA) of the cutting process, where the nodes of the tools mesh are displaced based on calculation of the thermo-mechanical loads and a pre-determined wear-equation of which the Usui-equation is most widely adopted. The approach was successfully implemented for multiple processes in 2D [5, 6] and 3D [7, 8]. The benefit of this approach lies in the explain ability of the wear progress. However, the downside of FEA for wear detection and prediction is the significant computational resources required, which can still take multiple hours even for 2D simulations. In addition, complex models like the Johnson-Cook material model and friction models for the workpiece and tool material need to be available. Thus, FEA is not widely adopted in industrial applications for wear prediction.

Data-driven models, in contrast to FEA, often do not provide insights into the rules leading to their decisions, but they are much more computationally efficient and easier to incorporate into industrial use. Prerequisites are a dataset for training which features the worn and unworn state of the tool. In the past, as listed below several researchers focused on capturing tool wear with these methods. Time series classification play a major role in these efforts, as they are easy to collect and come with the benefit of an in-situ collectable data source. In [9], a tool wear classification approach was presented which transformed scaled time series data of a dynamometer for force measurement into images based on Gramian Angular Summation Fields which is a transformation from Cartesian coordinates to polar coordinates succeeded by an encoding to a matrix. Following this pre-processing technique, a Convolutional Neural Network (CNN) based on the CIFAR-10 architecture is trained. The authors achieved a correct classification of tool wear by up to 80%. Force signals are considered to be the most effective signal type due to a high correlation with the wear state of the tool [10]. However, dynamometers for high precision force measurement are expensive which hinders the application in industry. Measuring the cutting forces indirectly by using machine internal control data and using their time series as input for machine learning algorithms was applied in multiple articles such as [11], where an additional edge device collected the necessary data. A more cost-efficient alternative are vibration sensors. However, they are reported to have sensitivity issues, particularly in distinguishing between multiple sources of machining, which is especially problematic in an industrial context [12].

With the disadvantages of the above-mentioned sensor signals and the goal to find an easily transferable sensor signal, one can conclude that images yield benefits in comparison to time series signals as they capture the state of the wear without interference from external signals such as noise of vibration from other processes and peripheral systems of the machine. That is why multiple researchers focused on this signal type as an input to their machine learning models. Deep Learning employing Convolutional Neural Networks (CNN) played a crucial role in this effort. In [2], a Deep Learning-based method for the automatic detection of wear in drilling, end milling, and ball milling tools is proposed. Although CNNs typically achieve high accuracy in detecting wear, they come with a downside of requiring a significant amount of training data, which is costly to collect [13]. To overcome this challenge and enhance the robustness of the CNN, data augmentation techniques were applied [14]. A multi-stage deep learning pipeline consisting of a CNN for tool detection, followed by a Tool wear segmentation step with a U-Net architecture based on a Fully Convolutional Network is applied to detect the tool wear on the cutting edge and succeeded by a rule based algorithm to detect the flank wear [15]. Transferring the knowledge gained by training a CNN on a generated dataset to a new cutting tool is challenging and still part of ongoing research [16]. Transfer-learning is commonly used with pre-trained CNN architectures that have initialized weights and biases. However, transferring the ability to detect tool wear with altered features – such as coating color, shape, background, or light intensity – using a small dataset for retraining is challenging.

When considering the literature about tool wear, it becomes obvious that most researchers didn't focus on the coating of the tool when collecting their dataset. Thus, this important milestone didn't get much attention in predicting the remaining tool life. After reviewing the existing approaches and keeping the applicability and transferability of a tool wear detection algorithm in mind, the following statements can be drawn:

Tool wear is a significant technologic issue when accurate parts need to be machined and is further an economical issue when considering machine downtime. Capturing a coating loss is key to predict an increase in the wear rate. For a further self-optimizing manufacturing systems proposed by Möhring [17], a low-cost, explainable and to other processes transferable solution for wear detection is necessary. Therefore, there is a need to study simple yet efficient data-driven methods and algorithms to detect coating layer loss, which is equivalent to detecting the substrate.

2. MATERIALS AND METHODS

2.1 DATASET GENERATION

Turning operations are characterized by a spinning workpiece and a clamped tool. Relative movement is provided by the axis of the turning machine. A process which belongs to these operations is grooving. The process aims to directly transfer the negative form of the cutting edge onto the workpiece. In this study, the profile of the cutting is parallel to the workpiece axis. The used tools cutting edge is 10 mm long. They are coated via Physical vapor deposition (PVD) with an AlTiN coating with a black appearance. An additional TiN layer with a golden appeal was added via PVD. The workpiece is made of normalized AISI 1045. The materials composition is listed in Table 1.

Table 1. DIN EN ISO 683-1 of used normalized AISI 1045

C	Si	Mn	P	S	Cr	Mo	Ni	Al	Cu
0.431	0.233	0.653	0.011	0.024	0.124	0.005	0.018	0.029	0.029

The experimental setup is depicted in Fig. 1. The depth of cut was set to 0.1 mm and the cutting speed was 150m/min. Machining takes place without any coolant or lubrication. In compliance with the tool manufacturer Paul Horn GmbH, the depth of the groove was set to 3.5 mm. Given that the tool's geometry is unprofiled, leading to the assumption of orthogonal cutting, only the upper 3 mm of the cutting edge were used for cutting to ensure efficient material usage. Thus, after each cutting operation the workpiece was repositioned 3 mm along the z-axis as depicted in Fig. 1 (right). In total 1000 cutting operations were performed to cause a worn through coating.

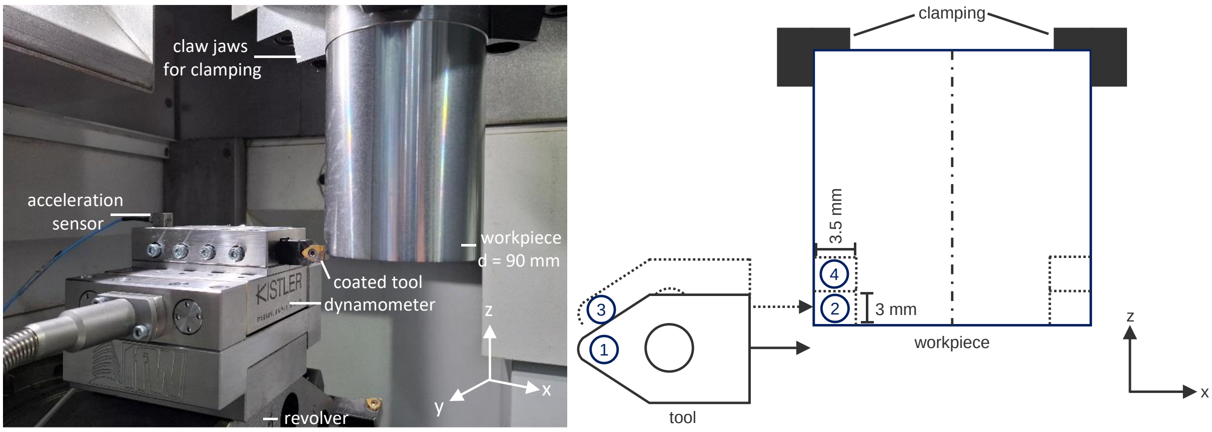

Fig. 1. Experimental setup for grooving (left) and schematic drawing (right)

To monitor the tool's condition throughout its lifetime, a USB-Camera with a custom made, 3D printed fixture for a repeatable positioning was implemented in the VLC 250 vertical lathe machine by EMAG. The used camera is a TOOLCRAFT USB microscope with five mega pixels, remote LED lighting rings and is connected to a laptop. A distinct challenge in monitoring the condition of the tool with images instead of time-series signals like cutting force or acceleration is the necessity to closely access the tool with the camera. On the one side, the process conditions in machining are harsh were different sized chips with temperatures of several hundred degrees and considerable kinetic energy are produced. Furthermore, wear occurs in exactly these subsections of the rake surface and flank surface of the tool, where it is in contact with either the workpiece or the chip. Thus, an in-situ observation becomes very difficult. To overcome these difficulties, the camera was positioned on a sphere, accessible by moving the machine's revolver with the mounted cutting tool. This way, the camera was places outside the region where hot chips could potentially damage the equipment. Moving the revolver was automated by implementing a loop in the G-Code. Images were taken every five, cuts which resulted in a database of 200 pictures. To guarantee an easier distinction between the background of the machine and the tools surface, the light in the machine was turned off for the duration of capturing the image. A variety of recorded images is depicted in Fig. 2 where the virgin tool (top left) features a clear golden colour from the TiN coating. The other images have a large grey appearing part on the right side of the images in common. However, these surfaces were not actively taking part in the cutting process, since only the left third was used for cutting. The actual wear for the tool therefore takes place in these areas. The wear of the coating then progresses with each cut until a full coating layer loss is achieved after 1000 cuts (bottom right). The area of the rake face, which is in contact with the chip, is marked in Fig. 2.

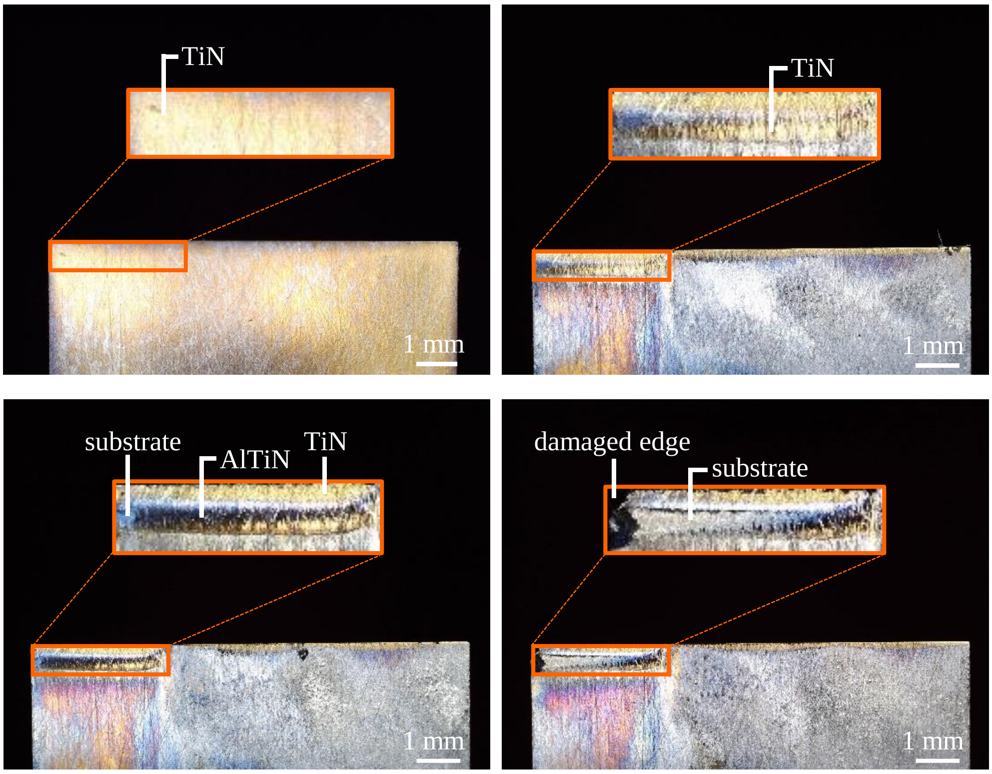

Fig. 2. Examples of recorded images. Virgin tool (top left), after 335 cuts (top right), after 675 cuts (bottom left) and after 1000 cuts (bottom right)

2.2 DATASET PREPARATION

An important step in training machine–learning algorithms is to prepare the dataset. In this case a manual labelling of the images was executed in two distinct classes. One class resembles an unworn coating and the other one a worn through coating, where the substrate of the tool is noticeable. The following steps were taken. First, the image is converted to a binary image, meaning that it consists only of black and white pixels by carefully setting a threshold. Since the images feature an excellent black background this can be done with perfect sensitivity. In the next step, the edges of the tool were detected via a Canny edge detection algorithm. This algorithm is one of the most used edge detection algorithms. The algorithm follows a multi-stage process, where the first step involves convolving the image with a Gaussian kernel G, as stated in equation 1, for noise reduction.

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1}$$

The intensity gradients of the image are then calculated via a Sobel operator for calculating the horizontal and vertical derivative of an image I. The operator is shown in equation 2. Then the edge gradient and the direction can be calculated as shown in equation 3.

$$\boldsymbol{G}_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * I \qquad \boldsymbol{G}_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I \tag{2}$$

$$\boldsymbol{G} = \sqrt{{\boldsymbol{G}_x}^2 + {\boldsymbol{G}_y}^2} \qquad \Theta = \arctan2(\boldsymbol{G}_y, \boldsymbol{G}_x) \tag{3}$$

When determining the location of the upper left corner of the tool, the next step is to identify lines on the detected contours. To achieve that, a Hough transform was applied to the output of the Canny edge detector. Due to the tools good alignment with the camera, only focusing on horizontal and vertical lines is expedient. A line in an Euclidian space of dimension two $\mathbb{E}^2$ is usually represented in cartesian coordinates with the slope m and an offset c. However, when defining lines which are close to being vertical, these parameters obtain large values. Thus, as shown by Duda and Hart [18], using the polar coordinate system yields benefits and leads to the formulation in equation 4, where ρ is the algebraic distance from the origin while θ is the angle of the lines normal.

$$\rho = x cos\theta + y sin\theta \tag{4}$$

Edges of the tool then were found by a determination of the intersection between the determined lines. Lastly, the image was automatically cut to only contain the information required for wear determination while leaving out all sections were no contact between chip and tool takes place. This process was iterated with each image of the dataset. The OpenCV library was applied for all tasks requiring image processing [19].

After applying the above-mentioned algorithms the image dimensionality is further reduced by extracting meaningful features for the classifiers. Since wear can not only be detected due to edges and challenging image processing, the authors decided to extract the mean and standard deviation of the RGB color space by calculating a histogram of the intensity of the basic colors over each pixel. This reduces the input parameters of the classifier to just six parameters.

2.3 APPLIED ALGORITHMS FOR WEAR DETECTION OF COATED CUTTING TOOLS

Classifiers try to capture the function between input and output parameters. In this case the input vector x consists of six features while one output is defined which features two classes (worn/unworn). For high dimensional input data machine–learning algorithms can effectively achieved this. Since the acquired dataset is limited in its size, algorithms such as CNNs which were introduced in Chapter 1 are not considered. Moreover, the implementation of well established algorithms for small datasets were taken into account. Due to an easy to label dataset supervised machine learning techniques were chosen.

Tree–based machine learning algorithms are known to deliver good results in classification tasks, even when compared to more complex algorithms [20]. They have the ability to handle continuous and discrete data, can learn non-linear relationships between attributes, need comparably low computational resources and are of a non-parametric design [21]. A Decision Tree splits the data into homogenous subsets by selecting a promising feature. The quantification of the splits accuracy is then performed via the Gini Impurity.

Another tree–based architecture studied in this context are random forests. This algorithm is a classifier based on a tree-structured classifier consisting of multiple classifiers $\{h(x, \Theta_k)\ k = 1,\dots\}$with independent distributed random vectors $\{\Theta_k\}$ [22]. The algorithm builds an ensemble of decision trees [23]. By drawing a subset of the training data with replacement, multiple trees are created, followed by a vote to determine the best decision tree based on a new data input [24].

Support Vector Machines (SVM) were implemented for the classification as well. The technique was developed by Vapnik for classification and regression tasks. SVM have been widely used for classification tasks due to their good generalization capability [25]. SVM classifiers are based on the mapping of an input vector $\boldsymbol{x}_i$ by the function ϕ to a higher dimensional feature space where a hyperplane separates the two classes [26]. Key aspect is finding a hyperplane that maximizes the distance, also called margin, between the closest data points of the classes and the hyperplane. Finding this hyperplane requires the solution of the optimization problem [27] stated in equation (5), where C corresponds to the penalty term. A linear kernel was implemented.

$$\begin{gathered}\min_{w,b,\xi}\ \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{l}\xi_i \\ \text{subject to}\quad y_i(\boldsymbol{w}^T\phi(\boldsymbol{x}_i) + b) \geq 1 - \xi_i, \qquad \xi_i \geq 0\end{gathered} \tag{5}$$

As a last approach, a Feed Forward Neural Network (FFNN) is implemented. The basis of FFNN are perceptrons, which are connected to each other [28]. During training weights $\boldsymbol{w}_i$ with i∈[1,n] are updated via backpropagation [29]. Non-linear behavior is introduced via activation functions such as Rectified Linear Units (ReLU). When considering one neuron with input $\boldsymbol{x}_i$ and the bias b, the output y is calculated according to equation (6).

$$\begin{gathered}y = ReLU\left(\sum_{i=1}^{n}\boldsymbol{w}_i\boldsymbol{x}_i + b\right) \\ \text{with}\quad ReLU(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0\end{cases}\end{gathered} \tag{6}$$

The chosen network architecture consists of an input layer with six neurons, each corresponding to an extracted feature, a hidden layer and an output layer with two neurons, utilizing the softmax activation function. Only one hidden layer was chosen to keep the training parameters at a manageable range considering the size of the dataset. To find the optimal hyperparameters of the network for the classification task, a grid search was implemented regarding the optimum parameters for neurons in the hidden layer (4, 8, 12, 16, 32), the activation function (ReLU, tanh) and the batch size (10, 20, 40). An adam optimizer was used with a learning rate of 0.001 and the loss function is binary cross-entropy.

To evaluate the algorithm's performance on the classification task, the dataset was divided into subsets, with 80% used for training and 20% for testing. In the case of the neural network, the training dataset was again split into training (80%) and validation (20%) subsets. Before generating the subsets, the original dataset was shuffled.

3. RESULTS

Preparing the image so it explicitly contains areas of interest for the chosen algorithms is key to ensure decision making solely based on the contact length on the rake face. Figure 3 shows the results from the described approach in Chapter 2.2. It starts by a defining successful threshold for the input image to a binary image. A threshold of 10 out of 256 delivered good result (left). The successive Canny edge detector finds the edges of the tool with high repeatability (middle). However, as it is shown, an unwanted outline is detected, when small particles are attached to the tool. To tackle the issue of small segments being detected as an independent line by the following Hough transform, a threshold of the minimum edge length considered for line detection had to be set. This lead to a satisfactory line determination (right).

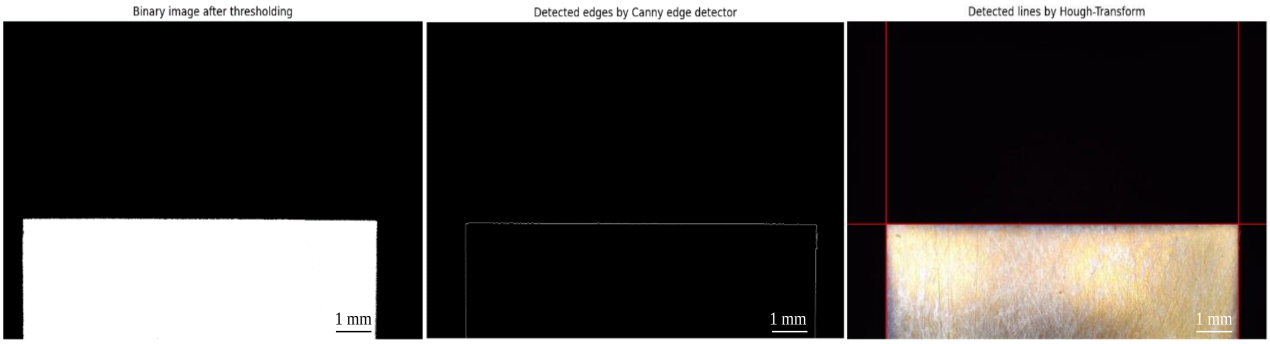

Fig. 3. Result of the data pre-processing with the proposed methods

The dataset pre-processing is a vital step in reducing the input vector of the image from thousands of pixels to a representative vector with smaller dimension. This was executed by finding the standard deviation and mean of the colors red, green and blue. The results of this step are depicted in Fig. 4. The difference of the color histogram of a tool with 10 cuts (left) and 1000 cuts (right) is visible, which proves that a correlation between color change and wear of the tool exists. The x-axis represents color intensity based on RGB color–coding, with 0 meaning the absence and 255 meaning maximum intensity of that color. It should be noted that no cutting fluid was used in these experiments, which improved image quality by eliminating light reflections caused by lubricants attached to the tools surface. If the proposed approach is applied to a process where lubricants are used, we recommend removing lubricant droplets before capturing the image. One way to achieve this could be by using compressed air to clean the tool's cutting edge, a step that can also be automated within the process.

Regarding the outcome of the trained algorithms, it becomes clear that all of them are up to the task of classifying the labeled and pre-processed dataset. The decision tree achieved an F1 score of 0.95. The Random Forest algorithm could classify a test dataset with an F1-score of 0.9. The FFNN achieved an F1-score of 0.89 while SVM resulted in the classification performance with an F1-score of 0.86.

The conducted grid search delivered the best F1-score with a hidden layer of 12 neurons, ReLU as the activation function and a batch size of 10. The depth of the used decision tree is six. The number of decision trees in the random forest was 100.

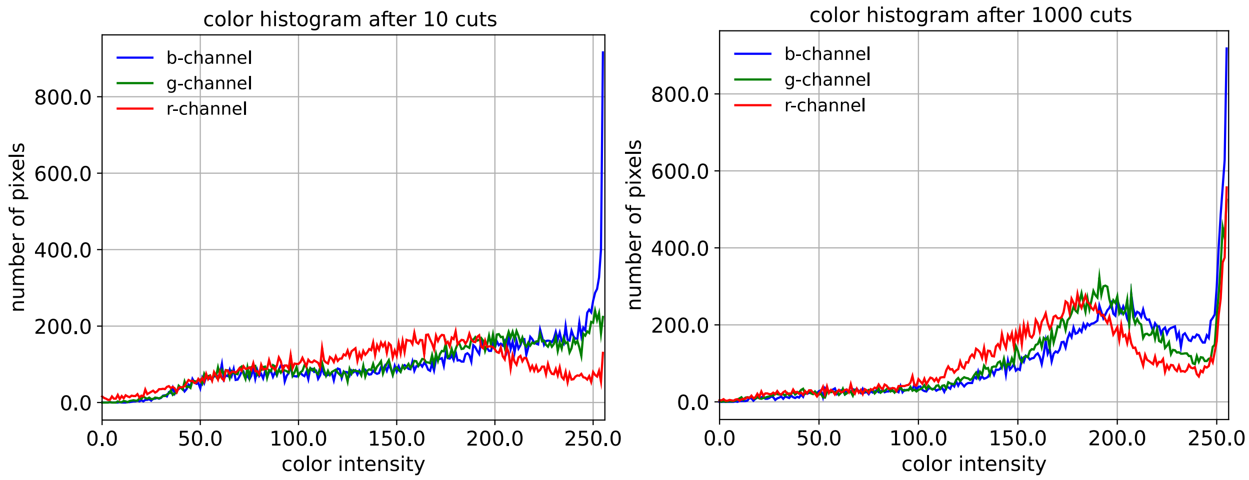

Fig. 4. Resulting histogram for tool after 10 cuts (left) and after 1000 cuts (right)

Although the decision tree is one of the simplest machine learning methods for this classification task, it yielded the best results. The results of training the algorithms are summarized in table 2, where the metrics precision and recal, which lead to the F1-score are also listed. The precision corresponds to the accuracy of positive predictions by the models, while the recall measures how well the models capture the actual positives.

Table 2. Classification performance of the chosen machine learning algorithms on a test dataset.

Metric	Decision Tree	Random Forest	SVM	FFNN
Precision	0.95	0.86	0.86	0.89
Recall	0.95	0.95	0.90	0.85
F1-score	0.95	0.90	0.88	0.87

The data leading to the above mentioned metrics are displayed in Table 3. It can be seen that the false-positive rate of Random Forest and SVM is higher compared to the Decision Tree and FFNN.

Table 3. Confusion score of the implemented algorithms.

	True Positive	True negative	False Positive	False Negative
Decision Tree	19	19	1	1
Random Forest	19	17	3	1
SVM	18	17	3	2
FFNN	17	18	2	3

4. CONCLUSION

Detecting the loss of a tool's coating is crucial for predicting its remaining lifespan, as the wear rate increases significantly from that point onward. Detecting this point in time comes down to a classification problem. Despite existing machine learning-based wear detection techniques, it remains challenging to develop robust methods that are easily transferable, cost-efficient, and capable of providing good classification performance even with small datasets. Therefore, this study proposes an approach containing two steps. First a dataset prepossessing for extracting meaningful features in the form of mean and standard deviation of each color channel. This step is succeeded by training of multiple machine learning algorithms. In total four algorithms were tested on the image dataset of a TiN/AlTiN coated cutting tool. Amongst Decision Tree, Random Forest, Support Vector Machines and Feed Forward Neural Networks, the Decision Tree proofed to classify a worn through coating on the rake surface with the highest F1-score of 0.95. This study successfully provided an efficient data pre-processing framework and suggests a machine–learning model to tackle the issue of detecting coating layer loss with a cost-effective sensor method. For a more industrial friendly application of the proposed approach, the authors suggest to implement an inductive sensor to trigger capturing of the image if the tool is present in front of the camera. Furthermore, an industrial computer (IPC) in combination with a cost-effective sensor and camera can be implemented and retrofitted to CNC machines, making the proposed approach highly transferable. Therefore, the applicability of the findings is valuable for end-users in industry as well as for tool manufacturers, as it enables an automated testing of the wear resistance of their developed coatings over time. Future research will focus on predicting the wear progression of the coating using machine learning, by training algorithms like U-Nets for image segmentation to automatically identify the areas of wear on the cutting tool. Using the area of wear as the input, additional algorithms will be trained and evaluated for their predictive capability in relation to tool wear.

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