

Article

Automatic Estimation of Drill Wear Based on Images of Holes Drilled in Melamine Faced Chipboard with Machine Learning Algorithms

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Abstract: In this article, an approach to drill wear evaluation is presented. Tool condition monitoring is an important problem in furniture manufacturing and similar industries. At the same time, approaches that rely on sets of sensors, often tend to be too robust or complex for the production environment. Instead of signals acquired from dedicated sensors, presented approach uses images of drilled holes as input data. Initial pictures are processed and enhanced in order to highlight the crucial properties. A set of selected features is then calculated on the resulting images, and later used during the training of 5 state-of-the-art classifiers. Presented research also evaluates number of images for consecutive drillings that needs to be taken into account in order to produce accurate results. From the selected set, the best performing classifier was Random Forest and it achieved close to 100% accuracy.

Keywords: optical tool state recognition; artificial intelligence; drill-wear classification



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1. Introduction

The furniture manufacturing industry is a demanding field, with various challenges related to different production process stages. It is especially the case with the composite material machining, where quality problems, mainly delamination, can result in unsatisfactory products. Such defects often can appear during drilling process, where various factors can lead to undesirable effects.

Laminated panels are commonly used material in the furniture manufacturing [1–3]. Different studies show, that main reason the delamination happens in the cutting process of wood-based materials tends to be the wear of the used tool. Researchers noticed a relationship between the wear of the drill over time and the condition of the holes, which clearly degrades the material laminate. These observations became the subject of further research and analysis, the results of which are presented here. There are similar studies [2–4] based on that relation in the chipboard panel. Analyzing the work of other researchers, such as [5,6], one can notice the analysis of cutting parameters and tool geometry in assessing the impact on machining quality. They proved that the processing quality is related to feed speed, although they were based on MDF boards. In turn, [7] describes the study of laminated chipboard showing the dependence of delamination on the feed rate, emphasizing that the parameters are based on techniques used in the wood industry. However, the issue discussed in this work is an attempt to combine the degree of tool wear with the quality of drill process to determine the minimum visual resources (drill images) to infer the condition of the tool effectively.

Due to differences in material, as well as various processes that can occur, the structure of the wood products is not always easy to predict. Tool condition monitoring is an important issue, where pinpointing the right moment to exchange such element is crucial

in order to avoid delamination and poor-quality products. At the same time, this process cannot be performed efficiently without automation. Manual tool examination, without prior indication to the tool state, can result in unnecessary downtime. On the other hand, if the exchange is postponed to long, the worn tool can damage used material. There are many factors that need to be taken into account, hence it is not surprising, that the issue of automation in tool condition monitoring is widely researched in recent years [8–10].

When it comes to fundamental research in the topic of tool condition monitoring, the related research was published almost 40 years ago in [11]. The main focus was put on finding the best signals and related features in order to reliably identify tool wear during production process, without the need for downtime.

The subject of this research develops the solutions discussed in other works and studies aimed at identifying the most optimal moment of tool wear. The works [12,13] broadly discuss research into the optimal use of built-in and mounted-on sensors for a CNC machine. Similarly, Ref. [14] discusses the tooth wear of table saw blades using the wavelet transform. The use of sensors is also discussed in [15–17]. Here, the influence of time of the tools used in the wood industry (bandsaw and drill bit) on the delamination process of the material was reported. A different approach was presented in [18–20]—the tool condition was combined with the vibroacoustic analysis of the machine and the environment.

Usually such solutions require large array of various sensors to work, such as acoustic emission, testing vibrations, noise measurement, or evaluation of cutting torque or feed force [21–25]. While the obtained results are accurate, the process itself is lengthy and complex. Even setting up the initial measurements often poses an issues with sensor placement, and potential adjustments to the environment changes. Each sensor needs to be calibrated to the specific work environment before the measurement process begins. At the same time any errors in the initial setup can result in unstable and inaccurate results, even more so if it needs to be regularly folded. All those disadvantages make the sensor approach difficult to use, especially if the production environment is changing (i.e., it uses different materials, various machines can be active at the same time, the layout of used elements can vary, etc.).

Taking into account various factors affecting the overall quality of drilling, machine learning (ML) algorithms are first solution that come to mind. In recent years, generally in the wood industry such methods have gained popularity in various applications. From solutions focusing on monitoring machining processes [26–28], to algorithms focused on wood species recognition [29]—the possibilities are varied. Depending from the specific problem, there either exists a well fitted solution, or one of ML algorithms can be adjusted to it.

During research presented in this paper, the images of drilled holes were used as an input data. The main assumption was that the quality of the drilling edge can be a good indicator of the overall tool wear, and, therefore, can help pinpoint the moment, when it should be exchanged. This idea was already explored, and achieved promising results, while incorporating various algorithms and approaches. Deep and transfer learning methodologies proved to be accurate, and adjusted well to the problem [30,31]. Further evaluation showed that classifier ensembles and data augmentation can potentially improve the overall results [32,33]. Different classifiers were used and tested in this problem, showing great promise for further application, checking the decision confidence, evaluating the classification process, and checking various algorithms [34–37].

In this paper we expand on this idea, continuing with the images of drilled holes as input data for ML algorithms. It was noted that a single or a small sequence of images used in previous research, may lead to inaccurate assignment of a wear class. There is a possibility that the good drill will produce ragged edge, as well as for a worn tool to perform well occasionally. This is not the case with the proportion of “good” and “bad” holes, as it will steadily worsen while the drill blunts during usage. The overall edge quality and laceration was used to show the drill wear. Furthermore, sequences of images were evaluated to better determine the moment when the tool needs to be exchanged. Apart

from pointing that out, second task was to find the optimal number of drillings taken into account in order to accurately determine the degree of drill wear with the calculated error. Three point scale was used for tool designation.

2. Materials and Methods

2.1. Data Collection

During the tests, an automated Computerized Numerical Control (CNC) workstation by Busselato (Jet 100 model, Piovenne Rochette, Italy) was used. The use of such a system ensured experiment repeatability. Test holes were made with a drill with a diameter of 12 [mm] by FABA (model WP-01, Baboszewo, Poland, Figure 1). Drilling was performed at a rotational speed of 4500 RPM and a feed rate of 1.35 [m/min], in accordance with the drill manufacturer's guidelines. The test material was a standard laminated board used in the furniture industry by the Polish company KRONOPOL (model U 511) with a thickness of 18 [mm].



Figure 1. The FABA WP-01 drill used during experiments.

The research procedures were carried out as follows: the laminated chipboard was divided into 610 profiles (Figure 2) with dimensions $300 \times 35 \times 18$ [mm]. Each profile was drilled 14 times in the central part of the profile axis at equal distances from each other, ensuring a homogeneous work area. A total of 8540 holes was made. The drill was subjected to regular evaluation with Mitutoyo microscope (model TM-500, Kawasaki, Japan) to check its state and assign each hole to one of three classes:

- Good—a new drill that is not yet worn and can be further used;
- Worn—a used drill in a warning state that is good enough to be continuously involved in the production process, but might soon require replacement;
- Requiring replacement—a used drill in an unusable state that should be replaced immediately.

The initial ranges for each of the wear classes were assigned according to the wear parameter (W), calculated for each of the drill cutting edges. This parameter is calculated as shown in Equation (1):

$$W = W'' - W' \quad (1)$$

where the W'' denotes the width of cutting edge for the brand-new drill, measured near the outer corner in [mm], while the W' is the current width checked for the evaluated tool. The ranges were assigned according to manufacturer's specifications, and equalled $W < 0.2$ mm

for the “Good” drill, $0.2 \text{ mm} < W < 0.35 \text{ mm}$ for the “Worn” drill, and $W > 0.35 \text{ mm}$ for the “Requiring replacement” drill.

A total number of 610 profiles were scanned into a digital version for analysis and further processing with an image quality was 1200 [dpi]. A sample set of drilled holes (from random profiles) is presented in Figure 3.



Figure 2. Example of a scan of chipboard profile with drilled holes.

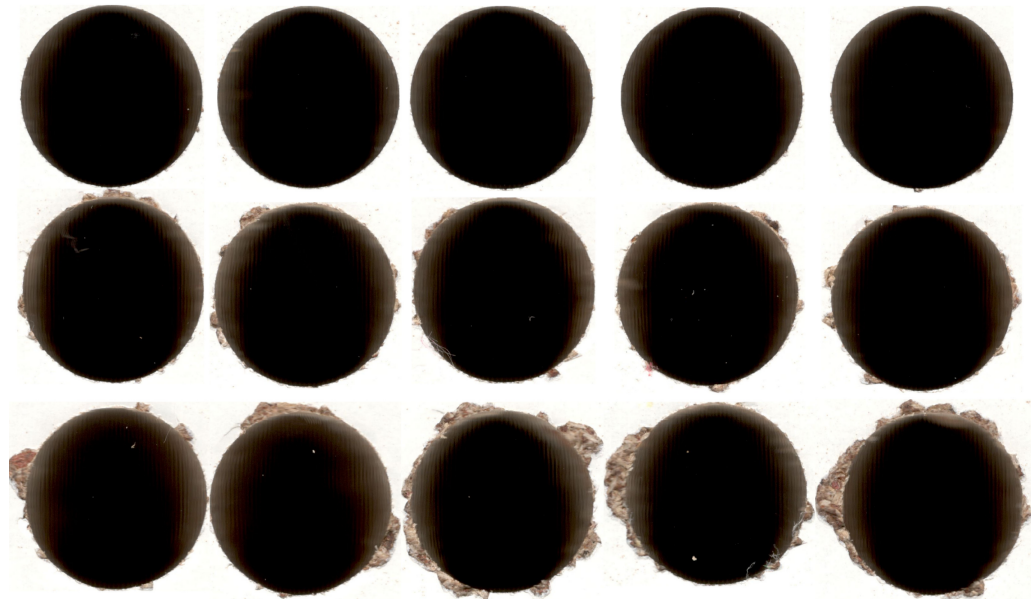


Figure 3. Examples of holes on different profile scans used for research analysis (“Green” on **top** row, “Yellow” in the **middle**, and “Red” on **bottom**).

2.2. Image Preparation

After scans of 610 chipboard profiles were obtained, images were then divided into separate files for each of the holes. Storing them in such a way allowed easier analysis of individual cases, as well as automation of the further image processing.

To ensure that a homogeneous dataset is used, a segmentation was performed (Figure 4), which included the following steps:

- Loading individual image from a file;
- Enhancing contrast;
- Conversion to black and white image (“bw”) with fixed threshold value;
- Conversion to black and white image (“bw2”) with adaptive threshold value;
- Summing up both thresholds (“bw”+“bw2”);
- Filling holes;
- Labelling;
- Removing artefacts;
- Saving the resulting image.

The first operation performed after loading the image was a simple contrast enhancement. The operation was meant to highlight the edge detail along the hole border, especially in case of any laminate imperfections. It also removed the value gradient resulting from uneven lighting, that could occur both in the hole and laminate areas, which should be universal in colour (black or white accordingly). This operation was performed according to Equation (2):

$$f(x) = \begin{cases} 0, & \text{value lower than } 0.5 \times 255. \\ 255, & \text{value higher than } 0.9 \times 255. \end{cases} \quad (2)$$

To further improve the input data, it was necessary to accordingly point out the actual edge of the hole, including any damaged fragments. The approach involved conversion to black and white image, where each pixel will only have one of the two values. At the same time accurate conversion with only single threshold was not possible. Therefore, all were subjected to two-stage image conversion (Figure 4). The first step was standard image conversion to black and white with a static threshold (“bw”), equal to 0.1. The second threshold (“bw2”) was the basis for unifying the hole using the adaptive method. This made it possible to obtain an exact outline of the hole (without its centre), while avoiding the loss of edges or imperfections constituting damage to the laminate. Edges are important from the point of view of quality assessment.

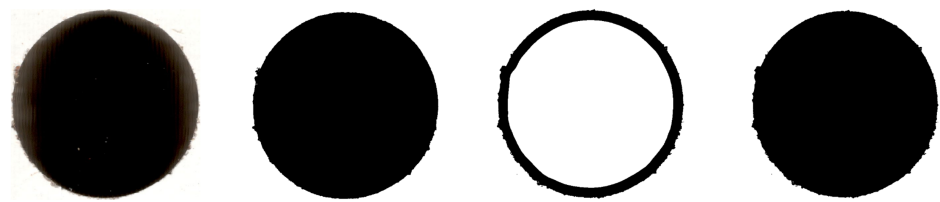


Figure 4. Steps of segmentation (left to right): input scan, “bw”, “bw2”, “bw” + “bw2”.

The same algorithm was used for the entire profiles (Figure 5). This operation was also able to remove traces of scratches, marker marks or dirt remaining on the profile. Removing redundant information from the image is an equally important aspect as accurately outlining the shape of the hole edges, since it is distorting the input data.

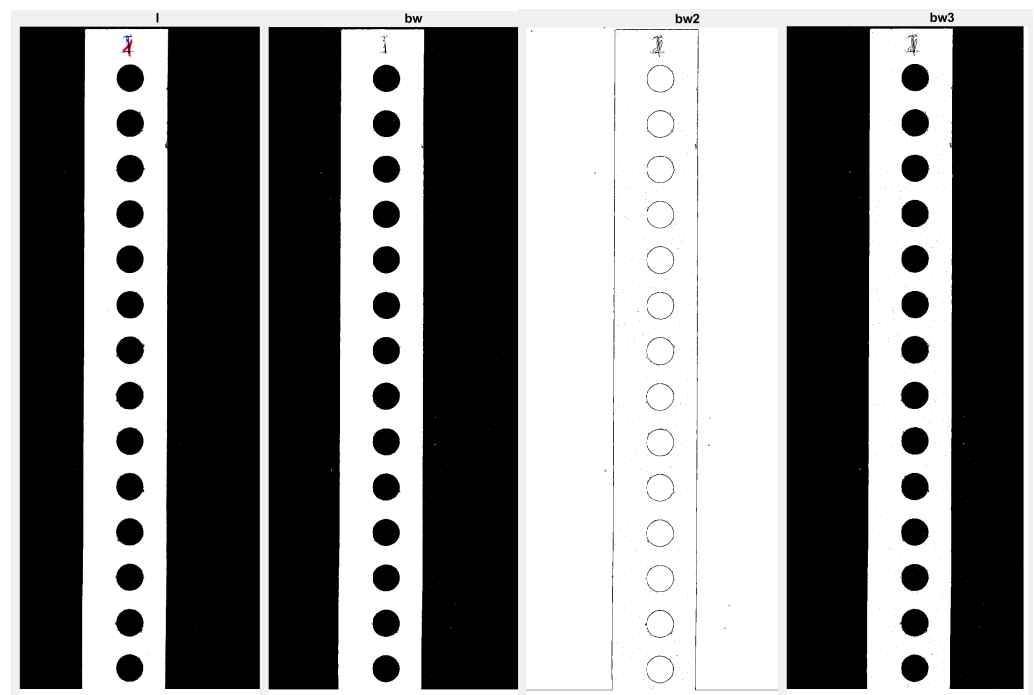


Figure 5. Steps of profile segmentation (left to right): input scan, “bw”, “bw2”, “bw” + “bw2”.

After the completion of this process, set of individual, clean images was obtained, accurately outlining actual hole shape for each of the experiments. The images were stored in the sequence they were made, to check the window required to accurately describe the drill state.

2.3. Diagnostic Features

In order to perform the classification process, each processed image was using a set of diagnostic features. After the initial evaluation, the following set of features were chosen, as they contained most information related to the drill state:

1. Radius of the smallest circumscribed circle of the hole;
2. Radius of the largest circle inscribed in the hole;
3. Difference of hole radii;
4. Area of holes;
5. Convex surface area;
6. Circumference;
7. The major axis of the ellipse described in the image;
8. Minor axis of the ellipse described in the image;
9. Massiveness (surface area/convex area).

Each image was assigned a single vector containing all features. Data for all images formed a feature matrix, which was normalized along each column, by dividing the values by the maximum value in each set. This results in all feature values to be placed in (0–1) range, which is important for classifier training process. Since the data in selected features are similar in nature, there was no risk of introducing a scaling error.

The main part of the presented approach is based on Feature (3), which is the difference between the radius of circle inscribed in the hole, and the circumscribed one. It was noted by the manufacturer that the main problem with the production process comes not from the small chipping, but large and long splinter. In the first case, the jagged edge will still be covered by the masking elements. In the second case, while the overall surface of the damage might be small, it will still be visible on the final product. It was then decided to base the evaluation on the difference radius of those two circles (see Figure 6), to more accurately point out the unacceptable drillings.

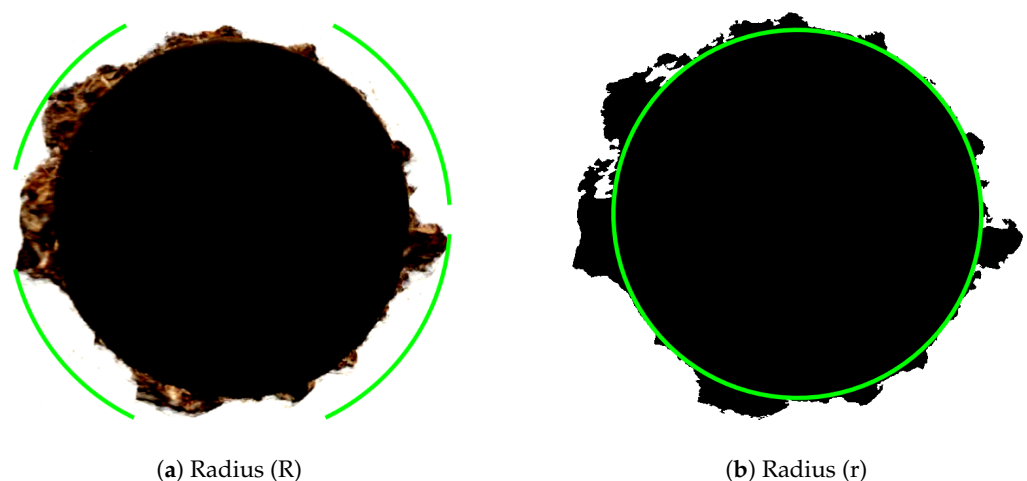


Figure 6. Comparison of hole radius—circumscribed (a) and inscribed (b) radius.

After incorporating the initial assumptions about main focus of the classification process, the features were then evaluated, using classical form of Fisher's measure. The diagnostic value of the k -th feature in recognition of two classes (i -th and j -th) is defined by Equation (3):

$$W_k(i, j) = \left| \frac{\mu_k(j) - \mu_k(i)}{\sigma_k(j) + \sigma_k(i)} \right| \quad (3)$$

This analysis produced a sorted value list for the used features. Effectiveness of individual features is shown in Figure 7.

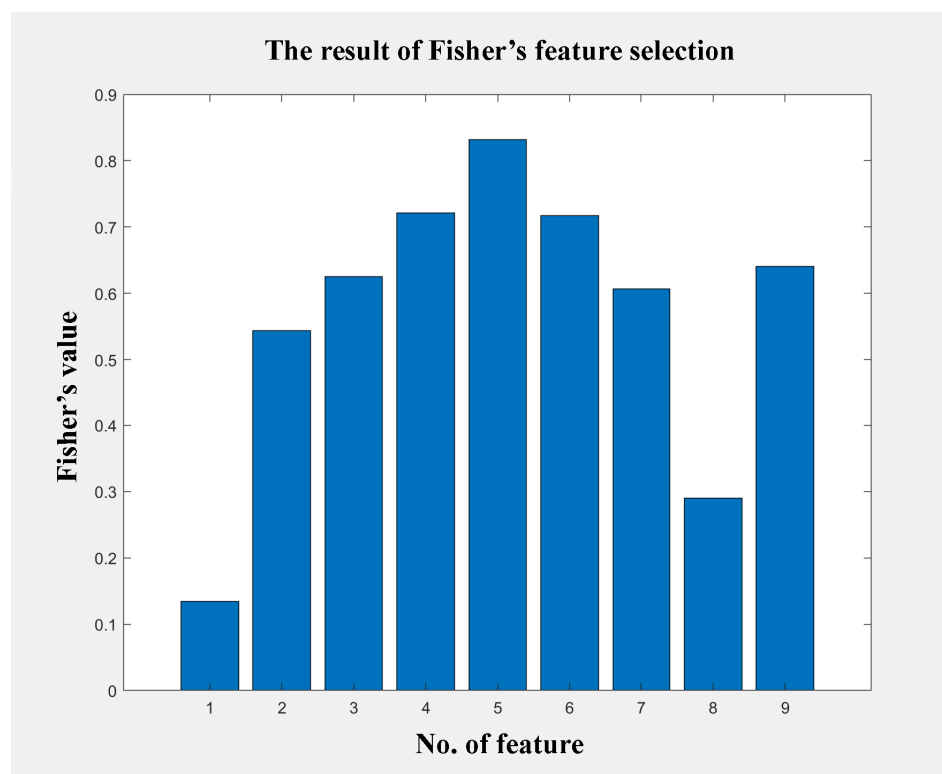


Figure 7. The result of features selection using Fisher's measure.

2.4. Classifiers

After obtaining and evaluating the initial feature set, it was then necessary to test them using different classifiers. A total of 5 state-of-the-art algorithms were chosen and adopted to the presented problem. The used classifiers were: support vector machine (SVM), K-nearest neighbours (KNN), Random Forest (RF), radial basis function (RBF), and multi-layer perceptron (MLP). The classifiers were used, since they perform well in various classification-based approaches, and consist of good baseline for feature evaluation. At the same time results obtained should allow for accurate classification.

2.4.1. Support Vector Machine (SVM)

First of the selected algorithms is a well-known method, used to find a hyperplane in n -dimensional space, where n is the number of features describing single data point. In theory, there are many different hyperplanes that can separate different class data. The main objective is to find one, that has a maximal margin—distance between closest data points of two separated classes. The broader the separation, the better the confidence of further classification would be.

The method consists of two main steps: data mapping into a multidimensional space and applying a function to separate data into decision classes. The name SVM comes from support vectors—data points close to the hyperplane separating classes, influencing its position. New classified data can be used to predict the group to which the new value should belong [38].

2.4.2. K-Nearest Neighbours (KNN)

Second chosen classifier is a grouping method, used to find data clusters in multidimensional sets. It is one of the simplest supervised ML algorithms, but it tends to give good results even in complex cases. The goal of the algorithm is to find similarities between different clusters of data, finding the best categories for each point. This is also a non-parametric algorithm, so additional advantage here is that it does not make any assumptions about data structure [39]. Additionally, since the classification is based on

closeness of a point to a specific data cluster, after the training process it can be easily used to assign new data points to the existing sets.

One disadvantage of the algorithm is that it requires a predefined number of labels, so in case of datasets with an unknown number of classes, finding the optimal number can pose additional problems. In the case of research presented in this paper, the number of classes is known, hence the choice of this method as one of the used classifiers [40].

2.4.3. Random Forest (RF)

Third classifier is Random Forest. This classifier consists of set of random decision trees, operating as an ensemble. Each decision tree works separately, providing a classification according to its structure. Final output of the RF classifier is then chosen by the majority vote of all the decision trees composing it.

The main advantage of this classifier is that it uses a large number of mostly uncorrelated models. Even if one trees sometimes return incorrect results, the general outcome should still be accurate, since the ensemble is not so prone to individual bias. The method's effectiveness is much greater than that of a single tree because the advantage of classifying the entire forest determines the final result for different decision paths [41].

2.4.4. Radial Basis Function (RBF)

The third used configuration assigns radial basis function as a kernel for SVM network. The RBF values are determined by calculating the distance from the origin or centre point. In order to do so, absolute values are incorporated. The distance is then calculated accordingly.

This function was used, since it performs well in cases, when data require classification in a non-linear way, which is the case for the presented problem. The radial function is primarily intended to find the optimal distance from a given point. They are effective in prediction, which can positively affect the performance of neural algorithms [42,43].

2.4.5. Multi-Layer Perceptron (MLP)

Final method is one of the most popular ones when it comes to artificial neural networks. This solution was formed as an extension to the binary classification models based on perceptrons, addressing the fact that an initial solution could not be used to classify non-linear data. In the case of MLP, the mapping between inputs and outputs is non-linear. In general, apart from the input and output layers, the MLP will have at least one hidden layer. In the perceptron each neuron needs to have an activation function enforcing a threshold. In case of MLP an arbitrary activation function can be used.

The underlying functions are regressive (for linear methodologies) or classification (for non-linear methodologies). The method uses feed-forward algorithm, meaning that inputs are combined with weights and subjected to the activation function. Each linear combination is then propagated to the next layer. This process is repeated through each hidden layer to the output layer. Additionally, the method uses back-propagation, interactively adjusting weights in network, with the goal to maximize the cost function. After calculating the weighted sums and forwarding them through all layers, the gradient of mean square error is calculated between input and output pairs. Weights are then propagated back to the NN starting point. This gives the opportunity to correct learning based on the results achieved and the knowledge of the correctness of the previous iteration [44].

3. Results and Discussion

The basic operations carried out in analysing the prepared images of holes allowed for creating a set of features. The effectiveness of a given feature in the general classification was selected based on the possibility of an unambiguous interpretation based on the measured values. For the set of features (Figure 7), the authoritative features were obtained in the following order: 5, 4, 6, 9, 3, 7, 2, 8, 1.

Out of all 10 accepted diagnostic features, only 3 achieved a level of effectiveness above 70%. For these 3 most authoritative features, a graph of the classification of a given feature in relation to its affiliation was created (Figure 8).

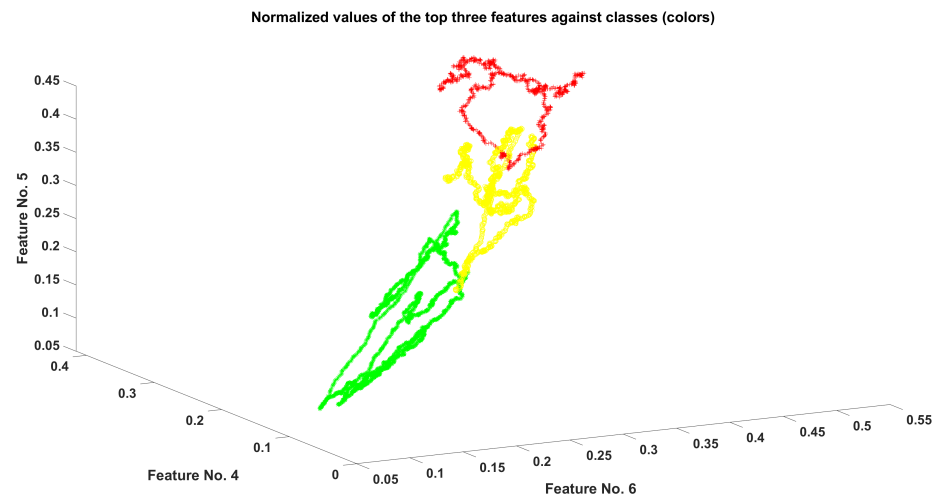


Figure 8. Normalized values of the top three features against classes (colours: green, yellow, and red).

Based on the classification algorithms, a cross-validation method was used based on the entire dataset, containing 8540 images of holes. For each degree of drill wear (Good, Worn, Requiring replacement), the Pareto rule 80/20 was applied—80% of the data were used for training, and the results were tested on the remaining 20% of examples.

Each classifier model was evaluated for different values of two chosen parameters— i and j . The main loop operated for the step length parameter in the regression correction cycle for i -previous images in the range 1 to 200. The second loop operated for the number of used features, from the selected set, ranging from 1 to 9 (parameter j). The features were added in the order of increasing effectiveness, starting with best performing features.

Because classification based on one feature has, inherently, low efficiency, an analysis method was adopted in terms of an incremental set of best features added sequentially based on the results presented in Figures 9–11. Three graphs were prepared to show the discrepancies between the same classification methodology and the accuracy of successively added features. The most stable in the study (k-NN), the best in the study (RF) and the most readable in terms of time (SVM) were presented.

In Figure 9, showing the k-NN classifier, the resulting lines can be grouped into two main sets representing accuracy. For one (5) and two (5,4) features, the accuracy does not exceed 75–80%, regardless of the used window. After the third most important feature is added to the set (5,4,6) the accuracy grows close to 95% for the remaining sets. The k-NN classifier is a fairly accurate solution, but, above all, it is stable with the appropriate selection of parameters. The groups of features [5,4,6], [5,4,6,9], and [5,4,6,9,3] achieved the best accuracy in this case. The k-NN Classifier is often used as a baseline in many considerations because of its stability, as well as the fact that it does not require as many hyperparameters as other algorithms, while being fairly resistant to overtraining.

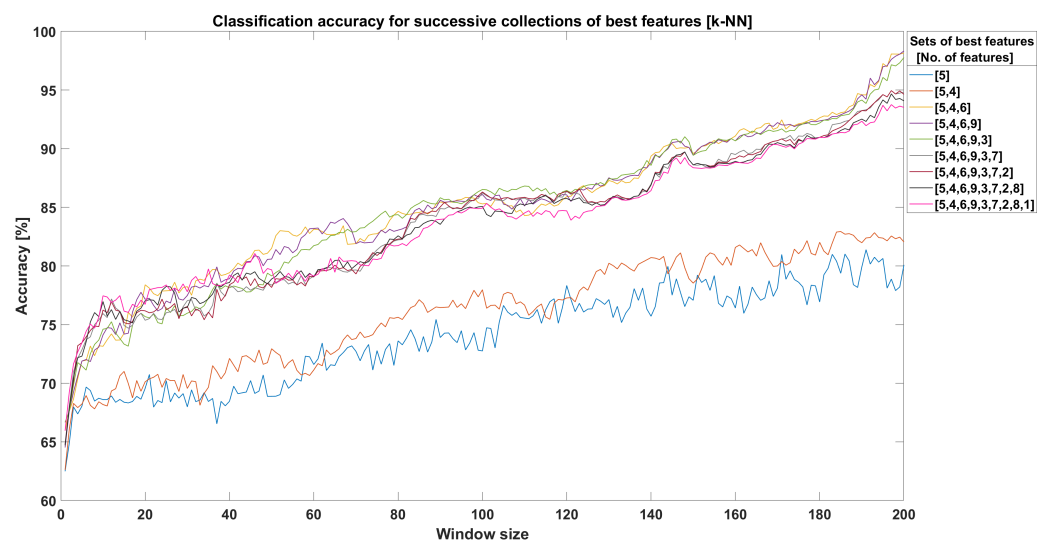


Figure 9. Classification accuracy for successive collections of best features [k-NN].

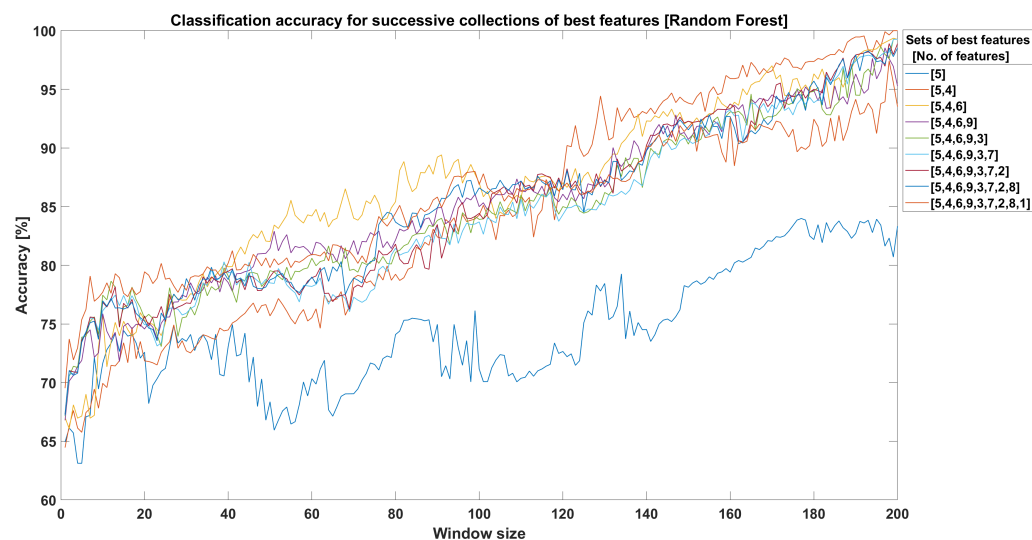


Figure 10. Classification accuracy for successive collections of best features [Random Forest].

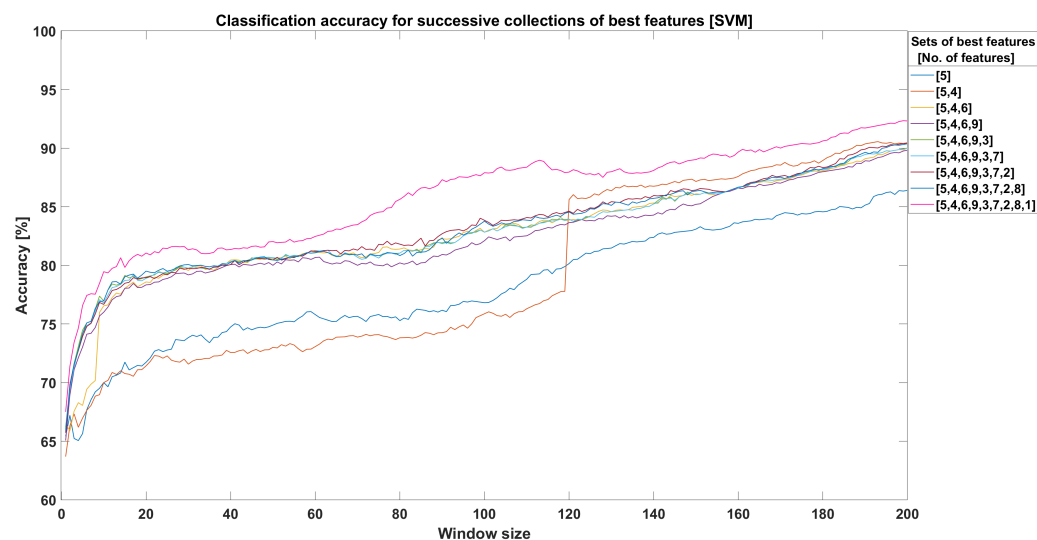


Figure 11. Classification accuracy for successive collections of best features [SVM].

Figure 10 outlines results for the Random Forest classifier. Similarly as with k-NN, two sets can be chosen, with the first one containing only the approach with a single feature (5). The accuracy here does not exceed 85%, despite increasing the window size. For the remaining feature sets, the accuracy steadily increases, reaching values close to 100%. During the training process large fluctuations are present along each line, but it is caused by the nature of the algorithm. Random Forest uses a random subspace method which relies on reduction in the correlation between estimators in an ensemble by training them on random samples of features instead of the entire feature set.

The third classifier is an SVM, presented in Figure 11. It can be noted, that this approach gives the best accuracy in maximum of window range for all provided features but the overall accuracy do not exceed 90%. This graph also shows a tendency for a natural increase in accuracy in proportion to the number of features used. The results are the best for this classifier when all nine of them are used. This can be due to the fact that the SVM classifier is strongly dependent from many hyperparameters. The selection of optimal ones is an extremely difficult and laborious process with a large impact on classifier generalization abilities.

From the original classifier set the MLP and RBF algorithms did not achieve the assigned, minimal threshold of 80% accuracy. Out of the remaining classifiers, the SVM performed worse, only slightly exceeding the 90% accuracy threshold, with a maximal number of features. The K-NN algorithm was second in that aspect, achieving higher results, starting with three best features. The RF classifier performed best, achieving almost the 100% accuracy threshold.

What is important to note is that all algorithms required a significant number of prior images to accurately classify drill wear state. In accordance with initial assumptions, prior data about state of created holes and changes in them is an important factor, increasing the overall algorithm accuracy. Additionally, for the best performing algorithm, the differences between the three best features, and sets containing more of them was not substantial, and acceptable results were produced. The best features in terms of initial set were: feature 5 (convex surface area), feature 4 (area of holes), and feature 6 (circumference).

4. Conclusions

In this work, a method for drill-condition monitoring, based on image analysis was shown. The presented solution uses photos of drilled holes. For the correct analysis, methods were used that emphasize features, such as the outline and damage around the perimeter. The collected physical features and image information was calculated and used to further train the ML classifiers. The presented work evaluates classifier performance, influence the number of used features has over the training process and size of image window required to accurately assign wear class.

Total of three classes were considered: good, worn, and requiring replacement. Best performing classifier was able to accurately assign drill wear state, even with three best features (major axis of the ellipse circumscribed on the hole (7), circumference (6), and area (4)). It was also confirmed, that all classifiers required large image windows (containing sets presenting subsequent drillings), to achieve high accuracy (close to 100%).

The drilling operation most often occurs during furniture production, especially cabinet furniture, which is often produced from laminated chipboard with MDF. The study data are a pilot dataset and, due to limited resources, were obtained in laboratory conditions, using sample scanning. However, in industrial conditions, we assume the installation of photo cameras that monitor the condition of the opening edge on an ongoing basis and transmit the signal to the computer, where it will be analysed.

The presented approach is easy to use in the production environment, since after the training process all that is required to classify the drill wear is the current image of drilled set of holes. At the same time, there are some possible areas for improvement—i.e., testing different features and classification methods.

Overall, the presented approach achieved satisfactory results, and can be a good basis for further analysis.

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