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Machine Learning-Driven Force Analysis for Tool Wear Prediction Systems

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Abstract

A system designed to forecast tool wear by utilizing a force sensor to monitor the wear of the tool's flank and applying a Convolutional Neural Network (CNN) for forecasting purposes. The methodology is demonstrated through experiments in milling, utilizing dry machining with a ball endmill on a stainless-steel component. The flank wear of the tool is directly assessed using a digital microscope throughout the operation. The forecasts produced by the system's machine learning model are based on a database filled with data from past experiments. Future versions of the system will be enhanced with an adaptive control (AC) system, which will continuously interact with the machine learning model to fine-tune feed rate and spindle speed, thereby optimizing flank wear management and extending tool lifespan. The adjustments by the AC system will be guided by the forecasts from the machine learning model and the force sensor readings, which can detect alterations in cutting forces indicative of tool flank wear. The primary objective of this study is to demonstrate the machine learning model, especially through CNNs, capability in predicting tool wear with an anticipated accuracy of 90%. Further experiments will be conducted to validate these results and to expand the measurement scope to enhance the system's accuracy.

Keywords: Flank wear, Adaptive control, ML, convolutional neural network, force sensor

INTRODUCTION

Milling, an essential industrial process that shapes metal by removing material, is expected to continue playing a significant role in the future. However, it encounters several challenges, especially concerning the deterioration of tools and their eventual breakdown, which can affect both the process's efficiency and its economic feasibility. Consequently, there's been a growing focus on monitoring the condition of tools in automated manufacturing processes [1, 2]. The deterioration of tools alters the texture of the parts being machined, leading to unforeseen errors in their shape, which can reduce the tool's lifespan and increase the cost of production. From a technical and financial standpoint, it's crucial to develop an intelligent system that can track the condition of tools throughout the milling process [3–5]. Such a system would allow for the early detection and replacement of tools, improving the precision of the cutting operation and ensuring that the parts produced meet the required technical standards [6, 7]. The deterioration of tools often impacts the clearance face (flank wear) and the rake face (crater wear). Among these, flank wear (VB) is typically used as the main indicator for determining when a tool needs to be replaced. Studies have indicated that when the flank wear land width (VBb) exceeds a certain limit, it negatively affects the quality of the surface finish,

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the accuracy of dimensions, and the stability of the milling process [8, 9]. Therefore, tool failure due to flank wear can be evaluated by the maximum value of VBb, and its progression can be forecasted over time. This paper will concentrate on the progression of flank wear. The significance of monitoring tool condition has been extensively explored, with primary goals including improving sustainability, advancing automation in the cutting process, ensuring the quality of the surface finish and dimensions, and decreasing the need for tool replacements, which in turn saves a considerable amount of production time.

Different TCM systems have been suggested, using various kinds of sensors like acoustic emission (AE), force, acceleration, and resistance between the tool and the material being worked on [11]. However, most of the current techniques that use machine learning (ML) models are not available online. The uniqueness of this approach is in combining self-learning and self-adaptive elements to create a smart system for detecting and predicting tool wear during the machining process [12, 13]. The self-learning part enables the system to gather, recognize, and forecast tool flank wear using Convolutional Neural Networks (CNNs). The self-adaptive part combines this forecast with data from force sensors to decide the best adjustments for the machining job, thereby increasing the tool's durability [14, 15]. Figure 1 shows the system's structure. This approach emphasizes creating algorithms that can learn from data and make predictions based on that data, rather than following fixed programming rules. These algorithms rely on making predictions based on data by creating models from sensor data [16-17]. Moreover, this approach sets the stage for an autonomous control system that can operate on its own, achieving a level of self-awareness. The system uses a force sensor to keep an eye on tool flank wear and employs a CNN for predictive modeling [18]. The effectiveness of this method is demonstrated through tests on a milling machine for dry machining with a non-coated ball endmill on stainless steel, where flank wear is monitored in real-time with a digital microscope, and the predictions from the ML model are enhanced by an experience database that includes data from past experiments.

In forthcoming updates, the system will be upgraded with an adaptive control (AC) system, specifically engineered to constantly engage with the machine learning (ML) model. This system will fine-tune the feed rate and spindle speed to more effectively control flank wear and prolong the life of the tools [19-20]. The adjustments made by the AC system will be guided by predictions from the ML model and the feedback from the force sensor, which gauges the changes in cutting forces that indicate shifts in flank wear. This research highlights the ML model's, especially the convolutional neural networks (CNNs), ability to precisely predict tool wear, reaching an accuracy of around 90%. Further studies will be conducted to confirm these findings and to broaden the range of measurements to improve the system's accuracy [21–23]. The proposed system for detecting tool wear in real-time utilizes a force sensor to monitor the degradation of the tool's flank and machine learning, in particular CNNs, to predict this degradation. This method is demonstrated through experiments with a milling machine for dry machining using a non-coated ball endmill on stainless steel. In-situ assessments of flank wear are carried out using a digital microscope [24, 25]. The predictions from the ML model are based on an experience database that includes data from previous experiments.

This approach also lays the groundwork for a self-operating control system capable of functioning independently without the need for human input, thereby attaining a degree of self-awareness. This approach delves into the creation of algorithms capable of learning from data and making forecasts [26, 27]. These algorithms, rather than adhering strictly to set instructions, utilize data to forecast outcomes by constructing models from sensor data. In upcoming iterations, the system will be upgraded with an adaptive control (AC) system that will constantly engage with the machine learning model to fine-tune feed rate and spindle speed, thereby enhancing flank wear management and prolonging the life of tools [28–30]. The adjustments implemented by the AC system will be informed by forecasts from the machine learning model and data from a force sensor, which measures alterations in cutting forces linked to flank wear. This study underscores the machine learning model's ability, through Convolutional Neural Networks (CNNs), to evaluate tool wear, achieving an accuracy

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rate of 90%. Additional research will be undertaken to verify the consistency of these findings and to broaden the scope of measurements to improve the system's precision [31-32]. The incorporation of self-learning and self-adaptive capabilities into the Tool Control Module (TCM) system marks a significant breakthrough in machining technology, offering a promising strategy for enhancing tool wear detection and prediction, which in turn leads to more effective and accurate manufacturing processes [33, 61]. This paper presents a tool wear detection system integrated into the machining process that employs a force sensor to monitor the progression of tool flank wear and uses a Convolutional Neural Network (CNN) for predictive modeling. The methodology is demonstrated through experimental milling tests conducted under dry machining conditions with a non-coated ball endmill on a stainless-steel workpiece [34, 35]. Flank wear measurements are performed in real-time using a digital microscope. The forecasts provided by the machine learning model are based on an experience database that gathers data from past experiments.

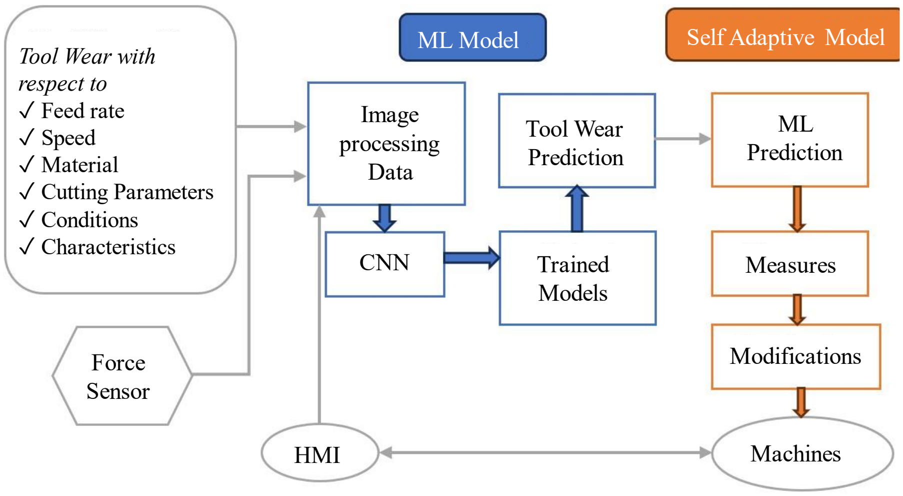

Figure 1. Tool wear prediction model Methodology.

METHODOLOGY

Real-time Wear Forecasting Mechanism

The system for detecting tool wear during production processes depends on a knowledge base to instruct the Convolutional Neural Network (CNN) in identifying the relationship between the tool and the material being processed by assessing the forces involved. Once trained, the CNN can accurately predict when the tool needs to be replaced. The control mechanism then utilizes the data from the CNN to adjust the feed rate and the rotational speed of the spindle to achieve the desired force. This strategy is aimed at achieving two main goals:

1. *Self-learning:* Accurately predict tool wear by learning from previous machining operations.
2. *Self-adaptive:* Maintain the force level as determined by the CNN to extend the tool's lifespan and enhance the quality of the work surface.

By reaching these goals, the system establishes a self-reliant control system that can operate efficiently even in unexpected situations.

Force and Flank Wear Assessment Technique

The significance of the cutting force in milling operations cannot be overstated, as it directly influences the design of the tool. It's crucial to keep an eye on the cutting force to determine the starting wear levels and to choose the right cutting parameters and tools. In this research, the examination of tool wear is carried out through force analysis with a Kistler piezoelectric dynamometer, model 9255C, which measures the perpendicular force components (Fx, Fy, Fz) during dry milling at a 60 kHz frequency per channel. The force signals from the milling process are then processed and amplified to match the sensitivity of the piezoelectric sensors, which can measure the force or mass applied. These signals are then sent to the data acquisition system cDAQ 9191 through the NI 9215 module, operated by NI Signal Express, and are recorded in a knowledge database for the creation of a Convolutional Neural Network (CNN) model. Every experiment involves making horizontal cuts along the y-axis using a down milling technique, with the cutter being pulled back to its starting positions for the next cuts until the entire surface is milled. The milling conditions used were a spindle rotation speed of 12,000 RPM, a feed rate of 1,600 mm/min, and cutting depths of 0.205 mm in the Y direction (DOCy) and 3 mm in the Z direction (DOCz). A 7 mm uncoated ball endmill constructed from tungsten carbide was employed, and the wear on the cutter's flank was evaluated after each milling operation using a digital microscope.

Approaches to Tool Wear Prediction Using

There are various methods for forecasting the deterioration of machinery, like Artificial Neural Networks (ANN) [36] and Support Vector Machines (SVM) [37], that depend on extracting features from the data before analysis because these methods have difficulty dealing with raw, unprocessed data directly. On the other hand, the algorithm being examined uses deep learning, which is skilled at discovering detailed patterns in large datasets without the necessity for manually designed features. Deep learning has achieved considerable advancements across different fields, such as image and speech recognition [38-40], and natural language processing [41, 42], among others [43]. A well-known deep learning framework, the Convolutional Neural Network (CNN) [44, 5], originally designed for classifying images, has been adapted to manage time series data [46, 47]. In this research, the CNN framework is expanded beyond its original uses by converting multivariate time series data from sensors into 3-channel images, which are then utilized as training data for the CNN. This conversion guarantees that the original time series information is retained in the image representation. By converting time series features into images, the CNN allows machines to visually recognize, classify, and learn detailed patterns and structures, thereby capturing the temporal aspects of the data [48–50]. The training of the CNN is specifically designed to identify natural patterns in the time series data that reflect the deterioration of the tool. While conventional machine learning techniques depend on manually engineered features, the CNN-based strategy presented here provides a more direct approach to understanding and leveraging complex data patterns, thereby improving the precision and efficiency of systems for predicting tool deterioration.

Structural Design of Convolutional Neural Networks

A common basic structure for a Convolutional Neural Network (CNN) starts with a convolutional layer that spreads multiple filters over the input image. This is then followed by a ReLU (Rectified Linear Unit) layer, which adds non-linearity and helps speed up the learning process. After that, a pooling layer is used to decrease the complexity of the output from the previous convolutional layer. Finally, a multilayer perceptron links to the last convolutional or pooling layer for the job of classification. This basic three-layer design can be modified as necessary to handle more complex data. In this setup, the design is inspired by the Tensorflow model created for the task of classifying the CIFAR-10 dataset, which has been effective in sorting images in the RGB color space [51–53]. The CNN model features two consecutive convolutional layers, each with 64 filters, along with ReLU and pooling layers. This configuration is designed to efficiently handle multi-channel image data for the task of classification.

RESULT & DISCUSSION

This part was created simultaneously with the complex machining research framework that was previously talked about. Initially, the Convolutional Neural Network (CNN) was trained and assessed using a data set from the 2010 PHM Data Challenge [54–56]. This particular data set was selected because it closely matched the kind of information that could be collected from the specific machining setup. It includes seven different signal channels, such as cutting force and vibration data in three dimensions, as well as details on acoustic emission from six 6 mm ball nose tungsten carbide cutters. The data gathering process occurred in real-time during 315 cutting tests conducted on a 3-axis high-speed CNC machine for each cutter. Since the machining setup was designed to measure cutting forces (Fx, Fy, and Fz), these forces were chosen from the PHM dataset for the CNN's training. The primary goal at this stage was to demonstrate the effectiveness of the learning module. In particular, with the real-time force measurements in three dimensions, the CNN was tasked with predicting the condition of the cutting tool.

In the PHM dataset, we focused on a specific cutter, cutter 6, identified in the challenge. This dataset detailed the wear in millimeters at each layer removed during the cutting process, categorized into three types: quick initial wear, consistent wear, and failure. Typically, the areas of a cutter experiencing wear would be identified using a wear progression curve, as illustrated in Figure 2. However, it's crucial to mention that different cutters could exhibit various wear patterns even when cut under identical conditions. To ensure the proof of concept's effectiveness across various scenarios, we opted to define the wear regions in a more general manner. The wear region definitions in Figure 2 represent the most extreme examples for the learning model. This approach underscores the initial steps in integrating CNN-based learning with actual machining data, showcasing its capability to correlate force measurements in real-time with the condition of the cutting tool. By training the CNN on this dataset, it was able to identify patterns between cutting forces and different stages of tool wear, paving the way for more precise predictive models in machining.

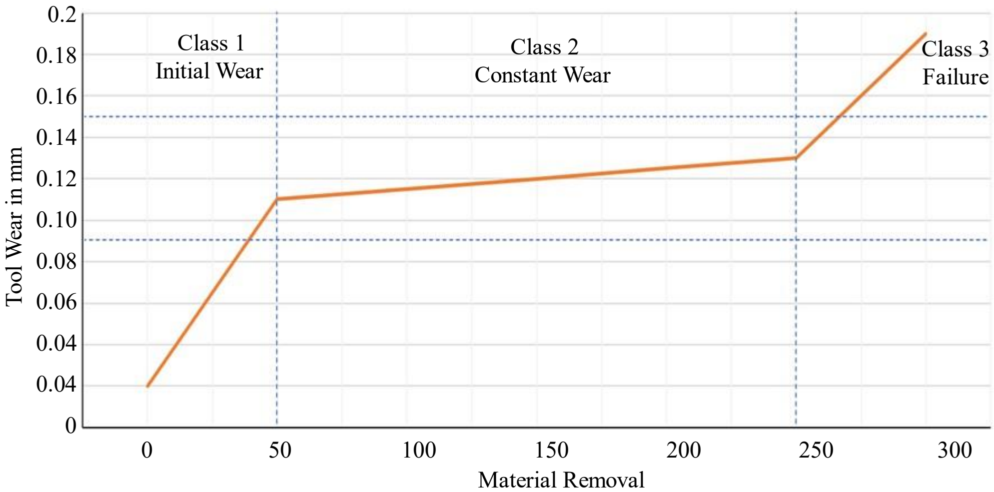

Figure 2. Evolution of Flank Wear with Cutting Operations and Wear Categories.

To handle the vast array of time series data linked to each layer, a representative group was chosen by picking a series of 2,000 measurements from the core area of the layer. This group acts as a manageable alternative for training and testing the Convolutional Neural Network (CNN). Each time series of cutting forces (Fx, Fy, and Fz) connected to a removed layer was then converted into three separate images using the Gramian Angular Summation Fields (GASF) technique detailed in [57-60]. The GASF method, as illustrated in Figure 3, involves two main steps for converting the time series data into a visual format suitable for CNN processing. First, the time series is normalized and transformed into a polar coordinate system. Then, the technique employs angular perspectives to detect temporal relationships by calculating trigonometric differences among each data point, resulting in an n×n matrix representation where n is the length of the original vector. Given the large amount of time series data, a Piecewise Aggregation Approximation (PAA) technique was used to simplify the data and smooth the time series while keeping important trends. This simplification ensures that the resulting images retain crucial temporal information while making the computation more efficient.

After generating distinct images for the forces Fx, Fy, and Fz for each layer, these images were scaled down from their original 2k by 2k dimensions to a more compact 512 by 512 pixels through PAA. Following this, these smaller images were merged into a single 3-channel image, which is now ready for use in the CNN model. Each of these 3-channel images was linked to a wear class, determined by the wear value recorded when the layer was removed during machining. This connection between visual representations and wear classifications allows the CNN to learn and predict the wear condition of the cutting tool by examining the features extracted from the transformed images. Essentially, this approach simplifies the representation of complex time series data, optimizing the use of CNN's capabilities. By converting raw sensor data into visual representations, the CNN can identify and learn patterns related to various stages of tool wear, improving the predictive model's accuracy and usefulness in machining operations.

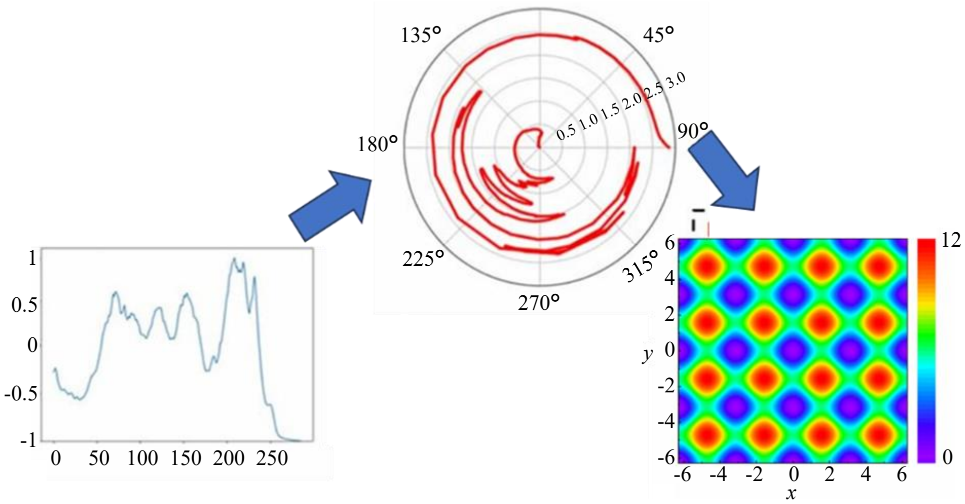

Figure 3. Time series Imaging.

The imaging technique produced 315 3-channel pictures that visually monitor the tool's movement across different stages of wear, showing a shift towards more circular forms as wear progresses. These pictures were divided into 80% for training and 40% for evaluation of the Convolutional Neural Convolutional Neural Network (CNN). The CNN underwent 1,000 rounds of training with softmax regression, employing learning rates of 0.2 and 0.02, and a decay rate of 0.2. Following the training period, the model underwent evaluation with the test dataset. Table 1 displays the confusion matrix, which details the outcomes obtained.

Table 1. Matrix showing results on the test.

N=90	**Rapid Wear in Actual**	**Uniform Wear in Actual**	**Failure Region**	
Initial Wear Predicted	15	3	0	18
Uniform wear Predicted	4	63	4	71
Failure wear Predicted	0	3	10	13
	19	69	14	

In the evaluation group, the model achieved a near-90% accuracy rate. Table 1 shows that the Convolutional Neural Network (CNN) accurately identified most of the "Uniform wear" cases (68 out of 66 real cases). However, there were a few misclassifications in the "Rapid initial wear" and "Failure wear" categories, suggesting that additional data from these wear stages might be necessary. This was expected, given that the model was developed and evaluated with data from just one cutter (315 images), leading to a small number of cases from these wear stages, which are represented by narrower sections in the wear curve. Identifying the second phase of wear patterns is crucial for creating a dependable online Tool Condition Monitoring (TCM) system, as it enhances the tool's performance. It's important to increase the diversity of cases in these wear stages to achieve a more consistent accuracy across all categories and to ensure the predictions are reliable when incorporated into the Adaptive Model. Despite these obstacles, the preliminary outcomes are encouraging, especially since no specific features were chosen for the analysis. This case demonstrates the CNN's capability to recognize the basic patterns in sensor data, establishing a solid groundwork for future progress in predicting and monitoring tool wear.

CONCLUSIONS

This research presents an advanced deep learning method for forecasting the deterioration of tools during machining operations. The results of the experiments show that the Convolutional Neural Network (CNN) successfully recognizes the connection between the forces applied during cutting and the wear on the tool's flank, without requiring the selection of features or the filtering of signals. This approach is adaptable to different materials and tools, as long as there is sufficient data that accurately represents their distinct characteristics. Although the sensors used in this research elevate the total expense, they enable the CNN to accurately track changes in force as the tool wears, offering several benefits such as simplicity of implementation and reliable predictions. Future research will expand on these findings by conducting wider experiments with different tools and incorporating additional sensors like vibrations and acoustic emissions. This expansion will necessitate enlarging the datasets for both training and testing to enhance the model's robustness and utility. Moreover, future studies will explore different CNN architectures to further refine their performance. A key objective for future research is to integrate a self-adjusting component into the system, which would enhance real-time monitoring and adaptive control of machining operations based on the anticipated tool wear condition. These developments are expected to enhance the efficiency and reliability of manufacturing processes in a range of industrial environments.

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