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A Convolutional Neural Network for CNC Milling Machines Processes Classification

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***Abstract*—In recent years, manufacturing processes have undergone many technological innovations. Such technological leverages are accelerated even more with the advent of Industry 4.0, resulting in embedding advanced techniques such as Artificial Intelligence (AI) and Machine Learning (ML) in almost every industrial system. AI and ML play a key role in the field of Fault Diagnosis and Prognosis (FDP), due to their capacity to predict failures in the system or to locate faults, reducing both the time needed for maintenance and its costs. The latter becomes more crucial in the field of Computer Numerical Control (CNC) machines as one of the most robust pillars of the production chain where achieving a reliable FDP becomes a challenging task. However, the variety of tool types and operations makes CNC machines the perfect training field for ML, ensuring a large amount of different data to learn. In this paper, a data-driven model, more specifically a Convolutional Neural Network (CNN), is developed to assert if the quality of the process remains acceptable or not, and so if the machine has to be maintained based on a vibration signal captured by a triaxial accelerometer installed on 4-axis horizontal Brownfield CNC milling machines. In addition, data are collected over a period of two years, we developed a second CNN model to classify processes based on the month and year, highlighting the presence of information regarding the aging of the machine during the whole period of evaluation. As the result shows, both time and frequency domain-based features reach an accuracy of about 100% for the first classification problem. Considering different machines and various working processes in addition to different time windows from February 2019 to August 2021, time domain-based features correctly predict more than 85% of all processes containing information about the aging of the machine.**

***Index Terms*—Machine Learning, Industry 4.0, Predictive maintenance, Smart Manufacturing, CNC machine, Short Time Fourier Transform, Industrial Dataset.**

I. Introduction

The advent of Industry 4.0 and 5.0 has heralded a transformative era in manufacturing, marked by the integration of cutting-edge technologies that have refined the production process. In this epochal shift, a primary role is played by sustainability and reliability, driving the need to address operational challenges. In this context, Fault Diagnosis and Prognosis (FDP) has emerged as a critical tool in the arsenal of industrial operations, facilitating proactive maintenance strategies to ensure smooth and efficient production workflows. The main objective of FDP is twofold: to identify anomalies within sensory data and to forecast potential failures base on predictive analytics, preempting potential disruption before they escalate into costly downtime or malfunctions. By leveraging advanced analytics, FDP enables stakeholders to anticipate and address issues before they compromise efficiency or pose safety risks. This proactive approach not only minimizes operational faults but also optimizes resource utilization, leading to significant cost savings in maintenance and repair activities. Artificial Intelligence (AI) and Machine Learning (ML) form the cornerstone of FDP, providing the computational power and analytical sophistication necessary to process vast amounts of sensor data in real time. Deep Learning (DL) techniques, in particular, excel at extracting intricate patterns and correlations from raw sensor data, enabling FDP systems to identify anomalies with a high degree of accuracy. By continuously learning from past data and adapting to changing conditions, AI and ML algorithms enhance the efficacy of FDP systems enabling them to evolve and improve over time. Within the domain of FDP, Computer Numerical Control (CNC) machining represents a fertile ground for innovation and optimization. CNC machines, equipped with precision controls and diverse tooling capabilities, generate rich streams of data that can be harnessed to drive predictive maintenance strategies. By integrating AI, ML, and FDP techniques, CNC machining facilities can enhance operational efficiency, minimize downtime, and extend the lifespan of critical equipment. In this work, we propose a data-driven method based on a Convolutional Neural Network (CNN) in order to address two different but connected problems: the classification of operations processed by a CNC machine based on their quality, and the classification of operations based on the time batch in which they are taken in order to highlight the presence of the aging of the machine that lowers the quality of the processes. The rest of this paper is organized as follows: Section II provides a description of the problem tackled in this paper, Section III explains the approach applied and the features, in Section IV the model training and the results obtained are shown and finally, in Section V we explain the final considerations on our work and provide suggestions for future works.

II. Problem Description

During their operational life, CNC machines, much like any other heavy-duty industrial equipment, undergo wear and tear over time. This gradual degradation can lead to a decline in the quality of the production output, and in the worst cases to a machine failure. To address this challenge, it is crucial to monitor the quality of the processes in real-time using data gathered from sensors embedded within the machines that capture meaningful information, such as acceleration data. By adopting a proactive maintenance approach, potential issues that could cause significant disruptions can be preemptively addressed. The analysis of the information obtained through the sensors poses a unique challenge, as it involves dealing with data that evolves over time, making it a problem linked with time series, especially, a time series classification problem. To tackle this task, in the last years researchers have turned their attention on Machine Learning (ML) and Deep Learning (DL) techniques. Such methods have been extensively explored in recent scientific literature [1], and among them, Convolutional Neural Networks (CNNs) stood out as one of the main tool for processing sequential data [2]. Focusing on CNC machine processes classification, many different methodologies have been proposed in the last decade. These techniques range from traditional ML algorithms such as Random Forest and Light Gradient Boosting Machine, both based on decision trees, to more sophisticated DL approaches such as Artificial Neural Networks (ANNs) and CNNs [3]–[5]. A comprehensive review of these techniques has been conducted in [6], providing valuable insights into the current landscape of solutions within this domain. The notable advancements in recent years underscore the ongoing endeavors to enhance the maintenance and performance of CNC machines through intelligent, data-driven methodologies. By harnessing the power of ML and DL techniques, researchers and industry practitioners are paving the way for more efficient and reliable CNC machining processes. Real-time monitoring and predictive maintenance strategies enabled by these approaches not only optimize production quality but also minimize costly downtime and repair expenses. As we continue to delve deeper into the realm of intelligent data analysis, the future holds immense promise for the further advancement of CNC machining technology.

III. Contributions

To classify vibrational data coming from CNC machine operations based on their goodness or the time batch in which they are acquired, we developed two Convolutional Neural Networks (CNNs) in this paper. CNNs are highly effective in time series classification due to their ability to identify local patterns, regardless of their temporal position. This makes them very resilient to shifts in data. CNNs learn hierarchical representations, where lower layers identify simple patterns while higher layers learn more complex features. Sharing parameters allows them to efficiently learn shared temporal patterns across data segments, which facilitates generalization. Moreover, CNNs can handle high-dimensional data, such as multivariate time series, without extensive feature engineering, making them a powerful choice for such tasks. Both proposed models have a similar structure:

- **Input layer:** the model receives as input a window of tunable size [*window_size, n_features*], where *window_size* is the length of the window considered and *n_features* is the number of features used.
- **Convolutional layers**: the target of these layers is to reduce the dimensionality of the data, encoding it, but at the same time ensuring that the information won't be lost.
- **Dense and Output layers:** data are then passed through a series of Dense layers in order to achieve the dimension of the desired output which is [*num_classes*].

The final shape of the output can vary depending on the aim of the model. In the first case, num_classes is equal to 2, i.e. good or bad, instead, in the second case the number of classes is equal to the number of time batches, which is 6. In Figure 1, we can see a representation of the model used for the quality classification task. The loss function applied during the training of the model is Categorical Cross-Entropy, also called Softmax Loss, obtained from the formulas:

$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}}$$

$$CE = -\sum_i^C t_i \log(f(s)_i)$$

where s is the score vector produced by the NN, $f(s)_i$ is the Softmax calculated at time i, and CE is the Cross Entropy obtained. Categorical Cross-Entropy is used for multi-class classification to train a CNN to output a probability over the C classes for each input.

The model inputs are derived from time-domain signals and frequency spectra of vibrations, which are measured along the x, y, and z axes by sensors affixed to the machine.

Both proposed models are deployed to address a supervised classification task. The primary objective of the first model is to effectively categorize the quality of machine processes as either "good" or "bad," leveraging nominal labels specified within the dataset.

Instead, the second model is designed with a distinct aim: to accurately forecast the time batch during which operations were executed. This predictive capability aids in discerning the machine's "aging" process, wherein data collection occurs across discrete time intervals, resulting in distinct feature sets.

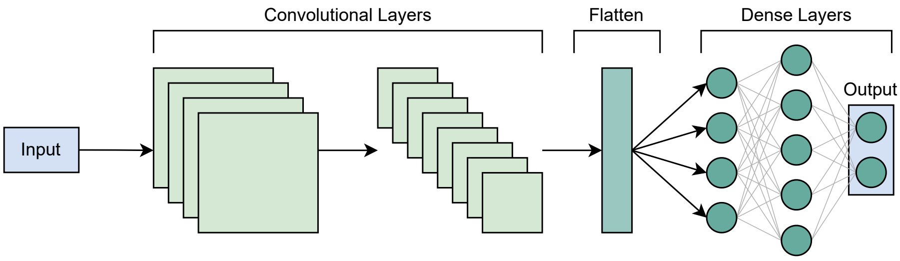


Fig. 1: The CNN used to classify the quality of CNC processes. The last dense layer is composed by 2 units, i.e. the number of output classes

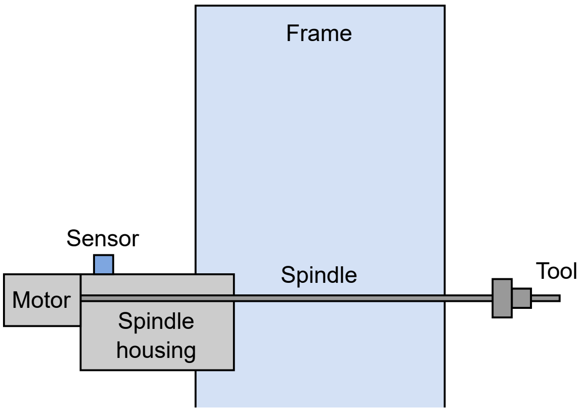


Fig. 2: Setup of the experiment conducted in [7].

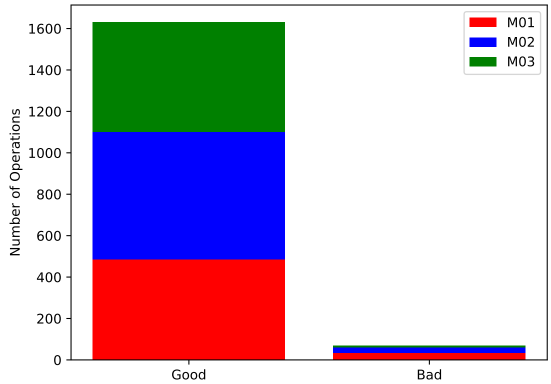


Fig. 3: Number of good and bad operations in the dataset

IV. Results

A. Dataset

To address these real-world conditions a new CNC research dataset from a real production environment collected over a different period including different machines and operations has been published in [7]. The vibration signal is collected from different 4-axis horizontal CNC machining centers during production using a triaxial accelerometer mounted on the rear bearing, as can be seen in Figure 2.

The data are collected in a production plant and belong to 3 different brownfield milling machines (M01, M02, M03) on a regular basis in the time interval from October 2018 to August 2021. For each process, the time frame is tagged as "Month_Year" and represents the 6-months interval before the label, for example, "Feb_2019" refers to the period between October 2018 and February 2019. Furthermore, since the machines performs a sequence of different operations using various tools on aluminium parts, the dataset is composed of data from 15 different operations. The number of good and bad operations can be seen in Figure 3, only the 4,28% of the dataset is made of bad operations.

For each process, we have features referred to:

- **Time**: month and year when the data have been measured.
- **Machine and Process**: name of the machine and process to which the data refers.
- **Acceleration**: data about the acceleration captured on all axes x, y, and z.
- **Label**: "good" or "bad".

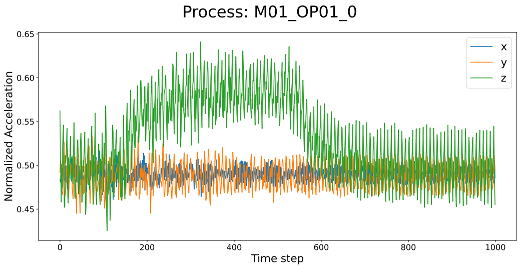
Examples of a good and a bad process can be found respectively in Figures 4a and 4b. The data in these figures have already been normalized in order to be in the interval $[0, 1]$.

In addition to time-domain, spectrum analysis provides a clear picture of the vibration signature. This is important because the aging of the machine could be represented in the captured data as noise at specific frequencies. While, such spectral components will not be presented when the machine is in good condition.

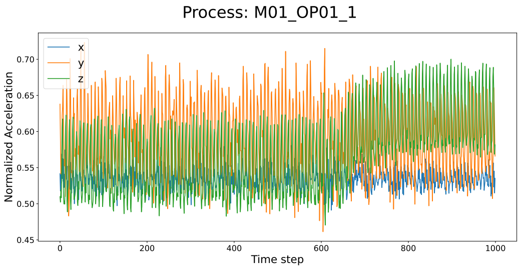
By obtaining both time and frequency domain data, we can test our models with different approaches, using them individually, or at the same time.

B. Model testing

In order to develop our model we divide the original dataset using 80% of it for the training phase and the remaining 20% for the final testing phase, guaranteeing homogeneity between the training and test set. At first, from each process, we extract a window of length 1000 from the middle of the original time series in order to obtain new series all of the same length to be used as input to the model. Data are finally normalized to be in the interval $[0, 1]$ to obtain better results. For both classification



(a)



(b)

Fig. 4: Examples of process number 0 captured on Machine 1. The one in Figure (a) is labeled as "good" and the one in Figure (b) as "bad"

problems, we propose three approaches that differ in the input features given to the model:

- **Time domain:** input features are only the time series obtained on axes x, y, and z.
- **Frequency domain:** input feature is the spectrum obtained from data on axes y and z. Mainly to increase the sensitivity by removing axial forces during machining [8].
- **Time and Frequency domains:** input features are the time data from axes x and the spectrum from axes y and z.

In Table I, we can see the results obtained by all three approaches on the first problem, the one referred to the quality of the process. The models reached an accuracy of 100% when time data are in the input features, but also when using only frequency domain data the accuracy reaches 98%, showing that there is a clear difference between "good" and "bad" processes. These results are notable also considering the unbalance of the dataset where there are only 70 "bad" processes among 1702 total processes.

Machine	T_D	F_D	T+F_D
All	**1**	0.98	**1**

TABLE I: Process quality classification accuracy.

For what concerns the second problem, the time batch classification, we can see the results in Table II. In this case, results are clearly different when using the time or the frequency domain data. Models using only time domain information or using it combined with the spectrum data reach an average accuracy of 83% and 76% respectively, with peaks of 91% and 86% on the single datasets. The model using only frequency domain data obtained an accuracy of only 56% on the three datasets. Finally, in Figures 5 and 6 we can see the confusion matrixes for the best approaches in both classification problems.

Machine	T_D	F_D	T+F_D
M01	**0.91**	0.69	0.82
M02	**0.89**	0.61	0.86
M03	**0.81**	0.64	0.76
All	**0.83**	0.56	0.76

TABLE II: Time batch classification accuracy.

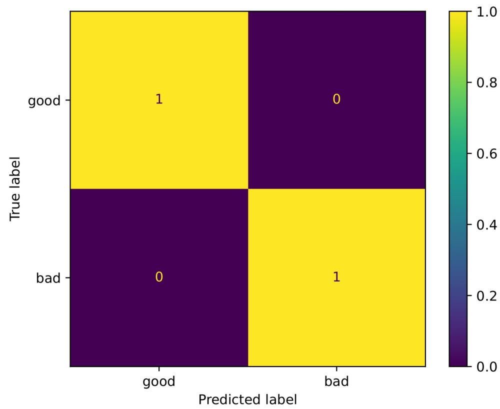


Fig. 5: Confusion matrix for the classification of good and bad operations.

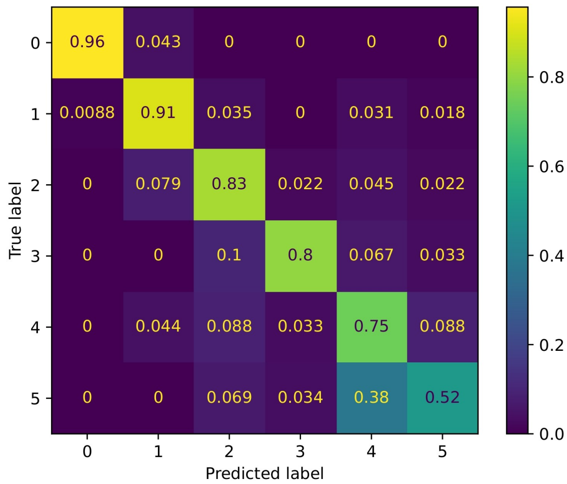
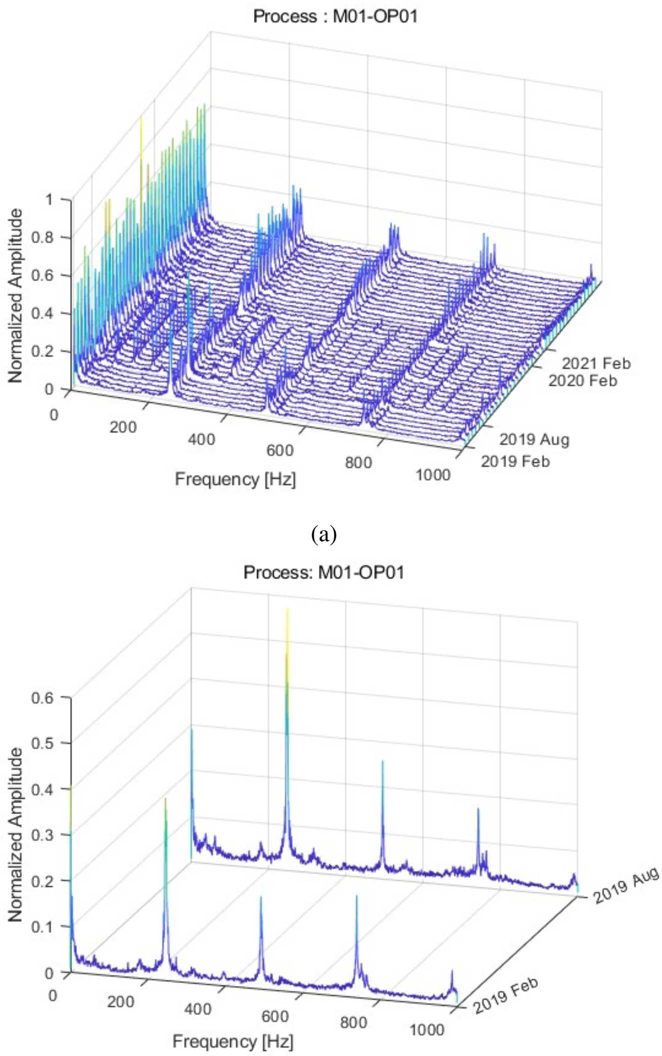


Fig. 6: Confusion matrix for the time period classification. Classes from 0 to 5 represent the six time intervals.

Higher prediction error over time as presented in 6, in principle, constructs a blind health index for evaluating the degradation process while applying a suitable maintenance decision plan. This may result in taking further steps to analyze how the critical component degrades over time. Therefore, the time-frequency analysis or vibration signature, in this case, can provide valuable insights towards prescribing mitigation solutions for optimum results. To address this let us consider the modulus of two orthogonal directions (y and z) as mentioned earlier. For the sack of simplicity, a step drill, with a speed of 250 Hz and, a feed rate of 100 mm/s (OP01) is considered a test operation. The time signal is segmented where each window's length is equal to 2.048 s considering 4096 samples and the Discrete Fourier Transform (DFT) of each piece is analyzed. Finally, the spectrograms for labeled processes as ”good” and ”bad” are shown in 7a and 7b respectively. As shown in this figure, although the quality of the piece/process is labeled as good, growing peaks and harmonics are evident. It is also worth mentioning about growing side lobes around the fundamental frequency as shown in 7b. Although a comprehensive study is required to have a clear view of all machines and performed operations while addressing temporal dependency, such details or patterns can be used to develop a sustainable prescriptive maintenance plan.



(a)

(b)

Fig. 7: Vibration spectrum signature: (a) processes are labeled as ”good” (b) processes are labeled as ”bad”.

V. Conclusions

Quality control for the produced pieces in both additive and subtractive processes, while a silent anomaly is developing, is a challenging task. It became more complex in case of dealing with real-world conditions and not relying only on laboratory limited-time experiments. The proposed method is applied to the benchmark dataset providing valuable insights for assessing operational quality through a detailed examination of both frequency and time domain data. As shown in figure 4, the contrast between satisfactory and deficient data is often significant, highlighting the effectiveness of our methodology. Furthermore, different and deeper tests can be developed on the first model shown in this work, such as splitting the dataset differently between the training and test set, focusing on the information obtained by the frequency data, in order to better assert the quality of the proposed approach.

It is crucial to note that our study places great importance on the exploration of our second model, which is centered on time batch classification. As results show, by utilizing time domain information, we can accurately classify processes within their respective time frames, achieving an impressive accuracy rate of over 80%. These outcomes suggest potential correlations between data distribution and machine aging or maintenance activities. Our study lays the foundation for future investigations that aim to monitor the health of machines during their operational lifespan by analyzing sensor data. Possible avenues for further exploration could include using autoencoders for semi-supervised learning to reconstruct time series data and detect anomalies, or modifying the models presented in this study to enable regression analysis. This would provide insights not only into the classification of outputs but also into their quality.

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