Integration of process parameters and condition monitoring data through Deep Learning models for predictive maintenance

Gabellini M.*, Civolani L.*, Regattieri A.*, Calabrese F.*, Bortolini M.*

* Department of Industrial Engineering, University of Bologna, Viale Risorgimento 2, 40124 – Bologna – Italy (matteo.gabellini5@unibo.it, lorenzo.civolani@unibo.it, alberto.regattieri@unibo.it, francesca.calabrese9@unibo.it, marco.bortolini3@unibo.it)

Abstract: Manufacturers, particularly machine tool builders, are increasingly adopting servitization, transitioning from selling products to offering integrated product-service systems (PSS). Machine tool companies aim to create value-added processes by providing predictive maintenance services and ensuring machine users can minimize downtime through up-to-date machines. However, the health condition of machines is significantly influenced by process parameters and operating conditions, often overlooked during machine operation. This results in the accumulation of unlabeled condition monitoring data, posing challenges in constructing predictive models for health assessment and prediction. Although some of this data resides in Programmable Logic Controllers (PLC), obtaining information directly from users is challenging due to privacy concerns, as users perceive PLC data as sensitive and are hesitant to share it with manufacturers. Consequently, there is a need to develop a data collection platform capable of remotely gathering both condition monitoring and sensitive data. This study addresses the integration of process parameters and condition monitoring data to facilitate predictive maintenance servitization in the machine tool industry. To this aim, sequence classification, sequence-to-sequence classification and sequence regression approaches based on Convolutional Neural Network and Long Short-Term Memory are adopted. These lightweight algorithms efficiently predict the machining processes, the tool, and the depth of cut, automatically storing contextual information for each manufacturing process sequence. This model contributes to creating a comprehensive database that producers can utilize to develop maintenance plans for users. The proposed approach is validated through a case study involving a five-axes CNC machine, underscoring the importance of automatically collecting contextual information for real-time monitoring and enhancing PHM techniques. The findings contribute to the realization of predictive health monitoring methods, fostering large-scale interoperability and servitization in maintenance practices.

Keywords: Predictive Maintenance, Machine tool, Time series classification, Data collection

1.Introduction

Predictive Maintenance represents a great opportunity for manufacturing companies to improve productivity and profitability. The possibility to continuously monitor physical assets and predict their failures is particularly beneficial in the machine tool industry. In this context, the Industrial Internet of Things (IIoT), Edge and Cloud computing, and Deep Learning would enable smart machining processes that adjust process parameters in real-time to optimize performance and improve product quality (Zonta *et al.*, 2020). In addition, those technologies would allow machine producers to offer integrated solutions to clients and reduce investment risks (Greenough and Grubic, 2011). In other words, a maintenance servitization business model could be adopted to collect the data from machines spread worldwide and develop intelligent models for achieving high quality and availability performance (Lin *et al.*, 2019). The reference framework for adopting a predictive maintenance strategy is the so-called Prognostics and Health Management (PHM), which provides all necessary steps to predict the Remaining Useful Life (RUL) of components and systems from the collection of sensor signals from machineries. However, implementing the PHM framework in industrial environments is challenging and the need to adapt scientific research to practical use is emerging (Lei *et al.*, 2020). Indeed, while extensive studies exist on categorizing machine faults and predicting the RUL of components, industrial settings present unique challenges such as a lack of labeled data and historical failure information (Calabrese *et al.*, 2022), especially from the perspective of the machine producer.

Indeed, machine producers should collect massive data from both sensors installed on the machine and the PLCs. Sensors provide Condition Monitoring (CM) data from which relevant information on tools' wear can be extracted. The PLC provides process parameters which allow to understand the operating condition of the machine. Both types of data should be integrated in a unique dataset, which requires a time-consuming data pre-processing (Calabrese *et al.*, 2019). However, clients are unwilling to share sensitive data, like the parts geometry and materials, the manufacturing process steps, and the process parameters. In other words, CM data are not associated with any operating condition, resulting in unlabelled datasets.

In the literature, the lack of the information of operating condition has been faced mainly through two approaches, i.e., unsupervised learning algorithms (Del Buono *et al.*, 2022) and transfer learning (Cheng *et al.*, 2022). In the first case, unsupervised models are used to group the data in several clusters, one for each operating condition. Then, a RUL prediction model is trained for each cluster. On the contrary, transfer learning aims to build a unique prediction model that could work in all operating conditions. Despite the high accuracy achievable by these models, they require a lot of training data in all possible conditions.

An alternative and appealing solution for obtaining labeled data and improving PHM performance may involve automatic data collection during manufacturing processes (Qiu *et al.*, 2023). Building upon the authors' prior work (Calabrese *et al.*, 2023), this paper presents a novel framework for automatically gathering contextual information determining the operating conditions alongside CM data, ensuring that the data shared by the client remain anonymous. Specifically, CM data collected via sensors can be leveraged to predict the operating condition using supervised learning models directly at the edge. Consequently, clients can anonymize the data and transmit a comprehensive dataset to the machine producer. This framework offers the following benefits:

- Data pre-processing and manual labelling are eliminated
- Contextual information can be used alongside CM data as input for RUL prediction models, enhancing their prediction accuracy
- The tool's history can be reconstructed effortlessly, facilitating its behavior monitoring, modeling, and prediction

Within this framework, the present paper proposes a methodology to obtain a complete dataset, including CM data and contextual information. In particular, the methodology aims to collect information usually recorded in the PLC, e.g., the specific machining process being executed, the corresponding tool, and the depth of cut, by applying three different Deep Learning models to CM data. Specifically, a sequence classification approach and a sequence-to-sequence classification approach based on One-Dimensional Convolutional Neural Networks (1D-CNNs) are employed to determine the machining process and tool; a sequence regression approach based on Long Short-Term Memory (LSTM) is utilized to determine the depth of cut. Overall, this lightweight algorithm is suitable for both training and real-time inference at the edge of machinery, facilitating data collection and monitoring alongside Condition Monitoring data.

The remaining of the paper is organized as follows. Section 2 describes the methodology and methods used to predict In Section 3, the proposed methodology is applied to a dataset collected from a 5-axes CNC machines including two different parts. In addition, a comparison between sequence classification and sequence-to-sequence approaches is made on data to validate the proposed methodology. Finally, section 4 summarizes the paper, highlighting the main results of the methodology, its potential applications as well as its limitations and future directions of the research.

2.Materials and methods

Classification and regression problems can be feature vector-based, sequence-based, or sequence-to-sequence-based. The feature vector-based learning approach assigns a class label to each point of the feature vector (Calabrese *et al.*, 2018). In contrast, in sequence classification/regression or sequence-to-sequence classification, the entire sequence is available to a classifier before classification (Xing, Pei and Keogh, 2010). The sequence classification problem is particularly suitable for time series data, in which correlations exist between space (variables) and time (variable values at different time steps). In addition, while the sequence classification approach assigns a single class to all points in the same sequence, thus generating a single label, the sequence-to-sequence approach assigns a class to all points in a sequence.

Shallow machine learning models, such as Decision Trees (DT) or Support Vector Machines (SVM), can only accept input data in the form of a feature vector. For this reason, this study utilizes a deep architecture to learn the relationships between collected signals and the manufacturing process. Time series data is typically classified using Recurrent Neural Networks (RNNs), such as LSTM, which can capture long-term input information. However, they may struggle to extract features from high-dimensional data and exhibit low generalization performance. Conversely, Convolutional Neural Networks (CNNs), while unable to capture dependencies in long-term data, excel at extracting spatial features from sequential data (Xu *et al.*, 2023).

(Bai, Kolter and Koltun, 2018) demonstrated that a new architecture called Temporal Convolutional Network (TCN) achieves higher accuracies than traditional LSTM. A general Temporal Convolutional Network (TCN) architecture comprises multiple residual blocks containing two sets of dilated causal convolution layers followed by normalization, ReLU activation, and spatial dropout layers. The primary component of the TCN is the dilated causal convolution layer, which operates across the time steps of each sequence, giving the network the ability to learn long-term relationships. In the 1-D convolutional layer, filters move along the input, computing the dot product of the weights and the input, and then adding a bias term. Dilated convolution expands the input area that the model can observe without increasing the number of parameters. The spatial dropout layer randomly sets inputs to zero to alter the network architecture between iterations and prevent overfitting. Finally, the ReLU layer is an activation layer that sets a threshold equal to zero for all negative inputs, applying a nonlinear activation function.

2.1.The proposed methodology

Since manufacturing processes consist of sequences of different operations, interspersed with idle times, and each operation is carried out with different tools and characterized by different process parameters, sequence or sequence-to-sequence approaches are preferred over feature-vector-based algorithms. The difference between sequence classification and sequence-to-sequence classification is illustrated in Figure 1. In sequence classification, the training set contains several sequences for each class (label). In contrast, in sequence-to-sequence classification, the training set contains several sequences, each containing sub-sequences belonging to different classes. From a learning perspective, the difference lies in the consideration of past observations. While sequence classification does not consider the order of sequences belonging to different classes, the sequence-to-sequence approach considers the order in which different classes appear in the entire sequence, as they can affect each other.

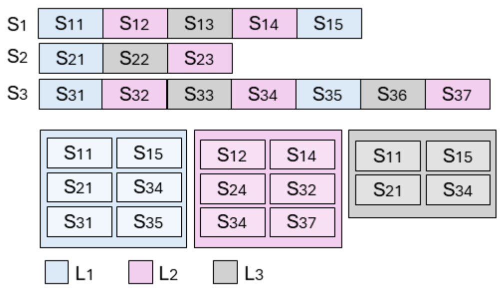

Figure 1 Sequence to sequence classification vs. Sequence classification

The proposed methodology, depicted in Figure 2, aims to gather three types of information: the tool used during machining, the specific process executed by that tool, and the depth of cut of the process. Since the tool and the process are categorical data, classification approaches are chosen, while regression approaches are used to predict the depth of cut, which is a numeric value.

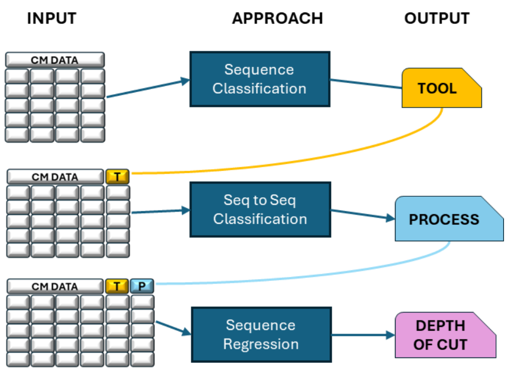

Figure 2 The proposed methodology

The methodology composes of three steps. First, the sequence classification approach is applied to predict the tool. In this scenario, the CM data is grouped into sequences based on the tool used at those timestamps. Sequence classification is used for this purpose because the tool used in a specific process does not depend on the tool used in the preceding process.

In contrast, a sequence-to-sequence classification approach is employed to determine the process, as the current process may be influenced by previous processes. This constitutes the second step of the methodology, utilizing both the CM data and the tool predicted in the initial step. The input sequences encompass all available manufacturing processes and includes different labelled sub-sequences.

Finally, the third step focuses on gathering information related to the depth of cut. For this purpose, an LSTM is chosen since the output is numerical. The model takes into account both the CM data and the tool and process determined in steps 1 and 2. In this case, the CM data are organized into sequences based on the tool used at those timestamps and the specific machining process performed.

Ultimately, the methodology yields a comprehensive dataset, comprising CM data, machining processes, tools, and depth of cut for each observation.

3.Case Study

The methodology presented in the previous section has been validated through a case study conducted on a 5-axis numerical control machine, consisting of 3 linear and 2 rotational axes, installed within a pilot plant representing a small-scale simulation of the so-called future digital factory. The machine is equipped with various sensors; therefore, in addition to general information such as operational status, name, status, and program execution time, machine alarms, and name and dimensions of the tool loaded on the spindle, it is possible to collect several signals of interest for both the spindle and the motion axes. Specifically, regarding the spindle, temperature, set and actual rotation speed, and load evaluated as a percentage of the maximum are recorded. For each of the 5 axes, instead, the following are recorded: status (an indicator to distinguish positive and negative direction advancements and reached position), set and actual position, tracking error, current, set and actual power, set and actual feed rate, set and actual torque, and motor load. For data acquisition and transfer, the machining center is equipped with an OPC/UA (Open Platform Communication Unified Architecture) server. This server streamlines the exchange of information among programmable logic controllers (PLCs), human-machine interface (HMI), and other machinery for the purpose of interconnectivity.

The signals and parameters used in this case study, along with their sources, are reported in Table 1. As it can be seen, the depth of cut of each process has been manually collected from the field during machining processes, since this information was not available in the PLC.

Table 1: Available Data

Group	Data	Source
Spindle	Temperature [°C * 100], Speed, [rpm],	Sensors

Axes	Driveload [% current] Feed Rate [mm/min] – [deg], Actual Current [A], Actual Power [W]	Sensors
Tool	Name, dimension	PLC
Part	Program name	PLC
Process	Depth of cut	Field

In order to test the methodology and demonstrate its potential benefits, two different machining processes were considered: one to produce an aluminum sensor cover (Figure 3a), and another to manufacture a steel cubic support (Figure 3b). The sensor covers, starting from an aluminum cube, undergo the following sequence of machining operations: facing of the top face (roughing and finishing), circular internal roughing with a 16 Ø mill, circular external roughing with a 16 Ø mill, circular internal roughing with a 10 Ø mill, circular external finishing with a 16 Ø mill, circular internal finishing with a 10 Ø mill, roughing of the external side pocket, finishing of the external side pocket, drilling for the creation of two holes, deburring of sharp edges. For the machining of the top face of the cubic support, the following operations are performed: facing of the face (roughing and finishing), external contour roughing, internal contour finishing, drilling with a 4 Ø bit to create six holes, drilling with a 10.3 Ø bit to create one hole, creation of a rectangular pocket with an 8 Ø mill (roughing and finishing). For the machining on the bottom face of the cube, the following operations are performed: facing of the face (roughing and finishing), external contour roughing, drilling with a 10.3 Ø bit to create one hole, creation of a rectangular pocket with a 10 Ø mill (roughing and finishing), creation of a circular pocket with a 10 Ø mill (roughing and finishing), deburring of sharp edges.

Figure 4 Workpieces geometry

Figure 4 shows the trend of the feed rate of axis X during the manufacturing process of the sensor cover. As it can be seen, As seen in the second graph of Figure 4, the tools have been grouped into 4 classes: solid milling cutter, insert milling cutter, drilling bit, and center drill, plus one additional class labeled "idle," indicating that no tool is in use at that moment. Similarly, the machining processes have been grouped into 5 classes: roughing, finishing, drilling, deburring, and smoothing, plus one class labeled "idle," indicating that the machine is idle at that moment. Note that smoothing is not depicted in the figure but is included among the classes since it's not a machining operation in the sensor cover process but only in the cubic support process.

In total, 5 sensor covers and 4 cubic supports were realized. Given the wide range of products that a company can manufacture, dividing model training by parts would mean building a customized methodology that needs to be reworked every time the system undergoes a change. Instead, in this study, the decision was made to include the machining processes of both parts in the same input dataset, in order to make the methodology more generalizable and flexible. For this reason, in the following presentation of the methodology results, no distinction will be made between the sensor covers and the cubic supports. Instead, the results will be presented in the next subsection following the various steps of the methodology, describing for each of them the input data and their format, the approach followed, and the model performances in terms of accuracy or prediction error, both on the training set and the test set.

3.1.Results

The first step of the methodology involves applying the sequence classification approach to the data collected from

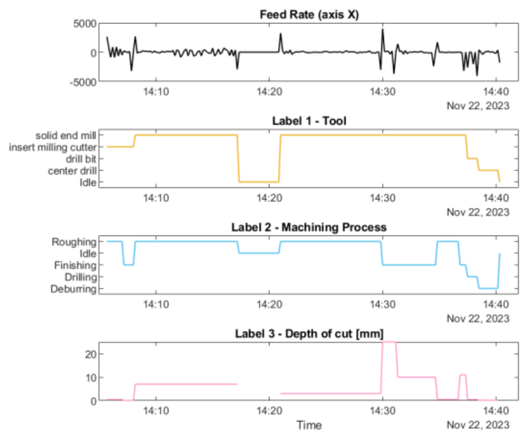

Figure 3 Feed rate of axis X during the manufacturing process of the sensor housing

sensors to predict the tool used during each phase of the process. The different input sequences were identified by grouping observations by tool. Therefore, a total of 96 sequences were obtained, divided among the different tool classes as follows: 44 for no tool (idle), 8 for the insert milling cutter, 31 for the solid milling cutter, 7 for the center drill, and 6 for the drilling bit. These sequences were divided into three sets: training, validation, and test, including 80%, 10%, and 10% of sequences, respectively, as suggested in the literature. Then, the TCN architecture has been trained on the training and the validation set and tested on the test set, and its performance are reported in Table 2.

Table 2: Performance of step 1

	Training	Validation	Test
N seq	76	9	11
Mean Accuracy (%)	100	100	81.82

In particular, the confusion matrix shown in Figure 5 displays the prediction accuracy on the test set for each tool. As can be observed, all sequences labeled as "idle" and those made with the insert milling cutter and the center drill were correctly classified. However, only 50% of the operations carried out with the solid milling cutter were classified correctly. The remaining 50% are incorrectly classified as being performed with the insert milling cutter. In addition, since the drill bit was not used in any of the test sequence, the accuracy of prediction for that tool cannot be computed.

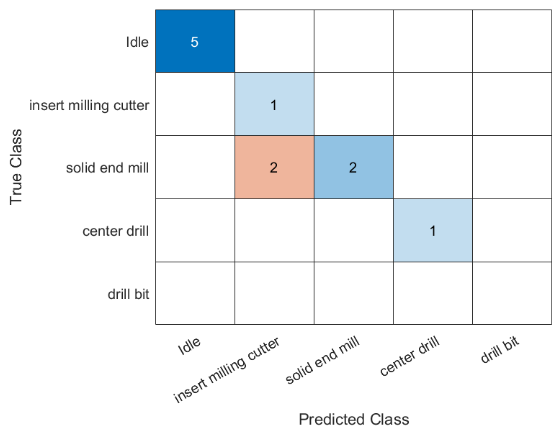

Figure 6 Confusion Matrix of Step 1

The second step of the methodology involves applying the sequence-to-sequence classification approach to the data collected from the sensors, along with the information on the tool obtained from the previous step, to predict the specific machining process. In this case, the input sequences correspond to the 9 machining processes carried out, with 6 used for training and 3 for testing. Results are shown in Table 3.

Table 3: Performance of step 2

	Training	Test
N seq	6	3
Mean Accuracy	100	87.20

Figure 6 displays the true classes and those predicted by the model for the three test sequences. Since the sequence-to-sequence approach assigns a label to each point in the sequence and not a unique label to the sequence, the prediction accuracy is computed comparing single observation predictions. Specifically, observations labeled as "idle" are classified correctly in 97.85% of cases, those labeled as "roughing" in 96.26% of cases, "smoothing" in 0% of cases, "deburring" in 17% of cases, "drilling" in 50% of cases, and "finishing" in 46.93% of cases. As can be seen, for more frequently executed machining processes, such as "idle" and "roughing," a higher accuracy is achieved. However, a higher prediction error is observed for the third machining sequence, corresponding to the production process of the cubic support.

The third step of the methodology involves applying the

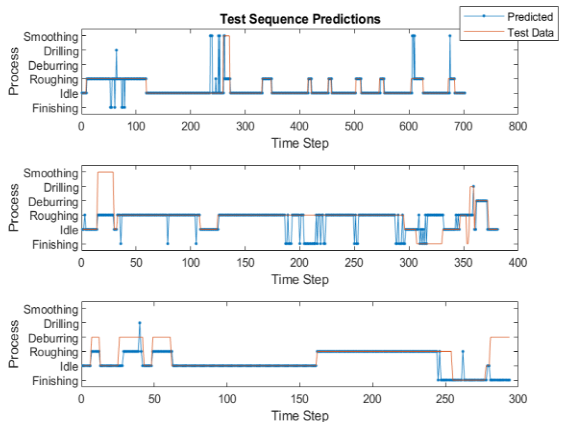

Figure 5 Test sequence prediction step 2

sequence classification approach to the data collected from the sensors, along with the information on the tool and the machining process obtained from the previous steps, to predict the depth of cut. The different input sequences were identified by grouping observations by tool and process. In addition, sequences containing less than 10 points (100 seconds) were excluded. Therefore, a total of 48 sequences were obtained, divided into three sets as described in Table 4.

Table 4: Performance of step 3

	Training	Validation	Test
N seq	38	4	6
Mean RMSE	0	2.4	6.4

3.2. Experiments

To justify the adoption of either the sequence classification or sequence-to-sequence classification approach and to demonstrate the benefits of applying the present methodology, three experiments were conducted to address the following questions:

1. Does the sequence of tool usage play a significant role when predicting the tool for each phase of the manufacturing process of a part?
2. Does the tool information contribute to better classification of different machining processes?
3. Does the tool and process information contribute to better prediction of the process depth of cut?

To address question 1, a sequence-to-sequence classification approach has been applied to the 9 manufacturing processes to predict the tools used in each phase. Figure 7 shows the test sequence predictions against the test sequence actual labels. When the machine is idle and no tool is used, the 90.12% of points are classified correctly; similarly, when the solid end mill is used, the accuracy of prediction is equal to 88.77%, and when the insert milling cutter is used, the accuracy is equal to 86.67%. On the contrary, only 12.90% of observations are correctly classified in the case of center dirll, and the 25% in the case of drill bit. Comparing these results with the results of step 1, it can be seen that both the mean accuracy and the number of the correct predictions is lower in this case. In general, using a sequence classification can increase the mean prediction accuracy by almost 20%.

To address question 2, a sequence to sequence classification approach has been applied to the input data to predict the machining process without the information on the used tool. In this case, the input sequences are identified only according to the machining processes, since it is assumed that the information on the tool is not available. The mean accuracy on the test set is equal to 80.53%, while prediction accuracies for specific processes are the following: observations labeled as "idle" are classified correctly in 80.68% of cases, those labeled as "roughing" in 94.77% of cases, "smoothing" in 0% of cases, "deburring" in 17.74% of cases, "drilling" in 50% of cases, and "finishing" in 36.73% of cases. Comparing these results with the test accuracy of step 2, it can be seen that considering the tool can increase the mean prediction accuracy by almost 6%.

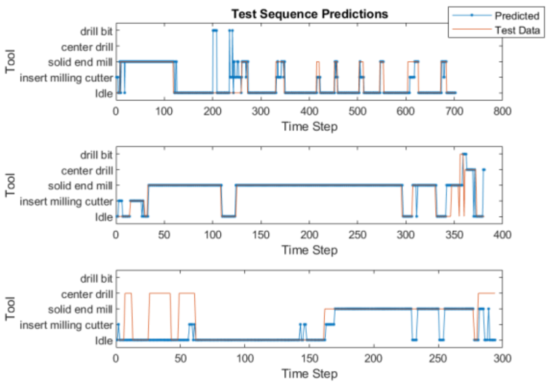

Figure 7 Test sequence prediction (step 1) using sequence-to-sequence approach

Finally, to address question 3, the sequence regression is applied to the CM data without any information on the tool and the process. In this case, the sequences for training are identified only according to the value of the depth of cut. For this reason, the number of sequences is higher (two different processes with different tools can have the same depth of cut). Results are summarized in Table 9.

Table 5: Performance of step 3 - Benchmark

	Training	Validation	Test
N seq	44	5	6
Mean RMSE	0	10.32	13.44

3.3.Discussion

In general, the results emerging from the case study are promising.

First, it is evident that for those classes with many sequences in the training set, errors on the test set are very low, demonstrating the high generalization ability of the TCN. Indeed, looking at the first step and considering the "idle" class, both in the case of sequence classification and in the case of sequence-to-sequence classification, the number of correctly classified sequences is 100% in the former and over 90% in the latter. Similarly, looking at the second step and considering the "idle" and "roughing" classes, with the sequence-to-sequence approach, over 96% of sequences are correctly classified.

Secondly, the comparison between the sequence classification and sequence-to-sequence classification approaches highlights two fundamental aspects related to the choice of these approaches, particularly sequence classification. Indeed, the approximately 20% reduction in prediction accuracy observed in the first experiment indicates, on one hand, that the sequence-to-sequence approach is not suitable for predicting the tool, as the order in which different tools are used is not important for this purpose. This result is consistent with the decision to consider the production processes of different parts. On the other hand, this result justifies the preference for sequence classification over feature-based classification, as point-by-point classification is not suitable. This finding is consistent with the hypothesis that it is the temporal relationship between points within the same phase of the process that determines the process itself and the tool used.

Finally, from the second and third experiments, it is evident that the prediction accuracy and generalizability of the model increase as contextual information is included. Specifically, by including information about the tool, the prediction accuracy of the manufacturing process increases by approximately 6%; by including information about both the tool and the manufacturing process, the error in predicting the depth of cut decreases by approximately 200%.

4.Conclusions

Predictive Maintenance and its servitization can bring significant benefits in terms of productivity and profitability. On one hand, continuous machine monitoring and the RUL prediction of its components can reduce defect rates, wear, and the number of breakdowns, thereby increasing quality, productivity, and availability. On the other hand, thanks to the support offered by new technologies for data collection, exchange, and analysis, remote monitoring is enabled, allowing machine manufacturers to offer integrated product-service solutions and reduce investment risks. This paper fits into this scenario by proposing a data-driven methodology for the automatic collection of information regarding the operational conditions in which machines operate while keeping sensitive information that customers are unwilling to share confidential. In particular, the case of a CNC machine is examined, from which weak signals from sensors related to the spindle and tool are collected. The objective is to train lightweight models on the machine edge to provide the manufacturer with a complete dataset that can be anonymized. To this end, three models for classification and regression are used, taking sequences of points as input rather than feature vectors. The first two models, based on a TCN architecture, aim to determine the tool used and the specific phase of the machining process. The last model, based on an LSTM, predicts the depth of cut.

The application of the methodology to 9 manufacturing processes of two different parts and its validation through 3 different experiments has led three main outcomes. Firstly, high generalization ability is demonstrated, particularly evident for classes with ample training data, showcasing low errors on the test set. Notably, both sequence classification and sequence-to-sequence classification achieve high accuracy. Secondly, the comparison between these approaches underscores the importance of sequence classification, as it outperforms sequence-to-sequence classification in predicting tools, which does not rely on tool order. Moreover, it justifies the preference for sequence classification over feature-based methods, aligning with the hypothesis that temporal relationships within process phases determine tool and process. Lastly, including contextual information enhances prediction accuracy and model generalizability.

In conclusion, the main advantage of the proposed methodology is the opportunity it provides to machine manufacturers to gather structured and comprehensive datasets, facilitating the construction of a tool failure behavior model and, concurrently, aiding in the prediction models of its remaining useful life.

Given the limitations of the current work, which stem from the limited availability of manufacturing processes, future research will focus on collecting more data and employing multi-label approaches. These approaches enable the prediction of multiple classes simultaneously, such as tool and manufacturing process, addressing the need for comprehensive analysis and prediction in industrial settings.

References

Bai, S., Kolter, J. Z. and Koltun, V. (2018) 'An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling'. Available at: http://arxiv.org/abs/1803.01271.

Del Buono, F. *et al.* (2022) 'Data-driven predictive maintenance in evolving environ- ments: a comparison between machine learning and deep learning for novelty detection', in Springer (ed.) *Smart Innovation, Systems and Technologies*, pp. 109–119.

Calabrese, F. *et al.* (2018) 'Components monitoring and intelligent diagnosis tools for Prognostic Health Management approach', in *Proceedings of the Summer School Francesco Turco*, pp. 142–148.

Calabrese, F. *et al.* (2019) 'Prognostic Health Management of Production Systems. New Proposed Approach and Experimental Evidences', *Procedia Manufacturing*, 39, pp. 260–269. doi: 10.1016/j.promfg.2020.01.333.

Calabrese, F. *et al.* (2022) 'Fault Diagnosis in Industries: How to Improve the Health Assessment of Rotating Machinery', in Scholz S.G., R.J., H., and R., S. (eds) *Sustainable Design and Manufacturing. KES-SDM 2021. Smart Innovation, Systems and Technologies*. Singapore, pp. 257–266.

Calabrese, F. *et al.* (2023) 'Condition Monitoring of CNC machines: machining process classification through Temporal Convolutional Networks', in *28th ISSAT International Conference on Reliability and Quality in Design, RQD 2023*, pp. 51–55.

Cheng, H. *et al.* (2022) 'The two-stage RUL prediction across operation conditions using deep transfer learning and insufficient degradation data', *Reliability Engineering and System Safety*. Elsevier Ltd, 225(May), p. 108581.

Greenough, R. M. and Grubic, T. (2011) 'Modelling condition-based maintenance to deliver a service to machine tool users', *International Journal of Advanced Manufacturing Technology*, 52(9–12), pp. 1117–1132. doi: 10.1007/s00170-010-2760-x.

Lei, Y. *et al.* (2020) 'Applications of machine learning to machine fault diagnosis: A review and roadmap', *Mechanical Systems and Signal Processing*. Elsevier Ltd, 138, p. 106587.

Lin, C. Y. *et al.* (2019) 'Edge-Based RNN Anomaly Detection Platform in Machine Tools', *Smart Science*. Taylor & Francis, 7(2), pp. 139–146.

Qiu, C. *et al.* (2023) 'A novel method for signal labeling and precise location in a variable parameter milling process based on the stacked-BiLSTM-CRF and FLOSS', *Advanced Engineering Informatics*. Elsevier Ltd, 55(August 2022), p. 101850.

Xing, Z., Pei, J. and Keogh, E. (2010) 'A brief survey on sequence classification', *ACM SIGKDD Explorations Newsletter*, 12(1), pp. 40–48.

Xu, D. *et al.* (2023) 'Spatio-temporal degradation modeling and remaining useful life prediction under multiple operating conditions based on attention mechanism and deep learning', *Reliability Engineering and System Safety*. Elsevier Ltd, 229(September 2022), p. 108886.

Zonta, T. *et al.* (2020) 'Predictive maintenance in the Industry 4.0: A systematic literature review', *Computers and Industrial Engineering*. Elsevier Ltd, 150(August), p. 106889.