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TOOL WEAR PREDICTION BY DEEP LEARNING FROM AUGMENTABLE VISIBILITY GRAPH REPRESENTATION OF TIME SERIES DATA

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Abstract: *Tool wear prediction has a crucial role for improving manufacturing quality and reliability due to optimizing tool replacement schedules, reducing downtime, and improving overall production efficiency. Deep learning models, having the ability to analyze large and complex datasets, can extract relevant information, and make accurate predictions about the condition of cutting tools. We propose a smart detection methodology based on converting the available sensory data collected from a CNC milling machine into a visibility graph representation. Due to the high dimensionality of the data with 44 attributes related to machining, a multilayer visibility graph representation is achieved after this conversion procedure, resulting in a 44-layered 128x128 adjacency matrix formation. A novel data augmentation technique specifically applicable to graph representation is also employed to increase the data size originally composed of 18 experiments into 360, each one represented as a multilayer graph. Augmented graph representations are further input to a custom CNN deep learning architecture with a split of 70% train, 10% validation and 20% test instances. Results indicate that Augmented Graph-induced classification of CNC mill tool with custom CNN model (GA-CNN) yields full accuracy for detecting whether the tool is worn or not.*

Key words: *Tool wear prediction, time series classification, visibility graph, deep learning, data augmentation, smart manufacturing, Industry 4.0.*

1. PROBLEM DESCRIPTION

Time series analysis and classification play a pivotal role in various domains, encompassing medical recordings [1], financial series [2], sound waves [3, 4], cybersecurity [5], and industrial sensor data such as manufacturing processes [6]. The emergence of artificial intelligence has led to significant advancements in time series classification, yet the utilization of Deep Neural Networks (DNNs) for this task remains relatively limited [7]. One potential reason for this disparity is the inherent nature of time series data as sequential values, which does not conform to the conventional input format expected by deep architectures designed for image classification. Despite this, attention-based Long-Short Term Memory networks (LSTMs) [8], Recurrent Neural Networks (RNNs) [9], and Deep Neural Networks (DNNs) [7] have proven to be effective contenders among the deep architecture frameworks for time series classification.

While traditional approaches such as the nearest neighbor (NN) classifier coupled with a distance function [10], often enhanced by Dynamic Time Warping (DTW) distance when combined with an NN classifier [11], and various machine learning techniques and their combinations [7] are still considered robust baselines for TSC, recent research efforts have focused on developing ensemble methods that surpass the performance of existing machine learning-based TSC models. Notably, these studies commonly involve a data transformation procedure that maps the original time series data into a new feature space.

Graph-based representations of time series offer a promising approach for capturing the underlying patterns that characterize the series.

The process of converting the series into graphs can involve defining either the time points or the amplitude values as the vertices of the graph [12]. Both approaches require a sampling rate that is at least twice the highest frequency present in the signal, as dictated by the Nyquist theorem [13]. However, when the sampling rate greatly exceeds this requirement, downsampling becomes a viable method for reducing the dimensionality of the data [14]. The challenge then lies in determining which data points should be retained and which ones can be discarded during the downsampling procedure. This decision depends on the specific starting point chosen for the downsampling process and can result in multiple graph representations for a given signal, depending on the time intervals defined by the downsampling rate. Notably, this augmentation capability, corresponding to the downsampling rate, presents an opportunity, particularly when dealing with the need for large volumes of training data to effectively tune the numerous parameters within deep learning architectures.

Accurately predicting tool wear is essential for optimizing milling operations in diverse industries. Deep learning techniques have emerged as promising tools for precise and reliable mill wear prediction [15]. By harnessing the capabilities of deep neural networks, these models can effectively analyze large amounts of sensor data collected from milling machines. Deep learning algorithms automatically extract pertinent features and construct robust predictive models that can accurately estimate tool wear [16]. These models consider various factors such as rotational speed, feed rate, material properties, and environmental conditions to provide real-time wear predictions. Incorporating deep learning into tool wear prediction enhances overall productivity, facilitates proactive maintenance planning, and optimizes costs by enabling timely replacements and repairs [17].

Tool wear prediction is essential in industries like metalworking, machining, and manufacturing because it helps optimize tool replacement schedules, reduce downtime, and improve overall production efficiency [18]. The connection between deep learning procedures and tool wear prediction lies in the ability of these models to analyze large and complex datasets, extract relevant information, and make accurate predictions about the condition of cutting tools. This predictive maintenance approach can significantly reduce operational costs and improve the efficiency and reliability of manufacturing processes [17].

The current study focuses on presenting a methodology for tool wear prediction by converting the multidimensional sensor data into visibility graph representations, also applying a novel time-hop data augmentation technique to improve the number of available instances to feed deep learning architectures. This technique depends on slight variations of graph representations of sensory data after time-hop slices extracted, without the need for synthetic data generation or data distortion techniques. By the way, a data transformation method that converts time series into a graph-based feature space with realistic augmentation is achieved. The resulting data structure is an adjacency matrix that can be readily input into deep architectures that are ideally suited for image-based inputs.

2. APLICATION FIELD

The proposed model for graph-representative prediction of tool wear with the aid of its highly augmentable nature is applicable to any kind of time series data, specifically to multidimensional sensory data thanks to its availability as a multilayer representation [19, 20]. Univariate time series data such as sound waves or financial series are also applicable fields with the limitation that sampling rates should be sufficiently high to facilitate the proposed augmentation methodology that employs downsampling at a rate equal to the augmentation rate. Multidimensional sensory data sampled at high frequency are the natural application field of the proposed method.

3. RESEARCH STAGES

Stages to investigate the efficiency of the proposed model and implementing it with a suitable CNC milling dataset includes following:

i. Problem definition: Tool wear prediction using multivariate sensory data is the core of the study, requiring a suitable time series recording from CNC milling machine.
ii. Literature review: Evaluating how the problem is handled by the researchers, and the availability of visibility graph approach within this scope.
iii. Data retrieval: Finding a dataset which includes labels as worn and unworn cutting pieces, also being in time series format composed of attributes such as feed rate, clamping pressure, positioning of the part, etc.
iv. Data processing: Implementation of the visibility graph conversion for the available time series data.
v. Data augmentation: Development and implementation of the time-hop augmentation strategy for the graph-formatted data.
vi. Model selection: Designating a moderately structured deep learning model to classify the augmented and graph-formatted data.
vii. Evaluating the results in comparison with the recent studies carried out with the same dataset.

4. METHODS USED

4.1. Dataset

This study focuses on time-hop augmentation of graph representations of time series related to manufacturing process, applicable for both univariate and multivariate series. Therefore, we need a time series data to demonstrate the graph-converted output of the series and its augmented versions. In this regard, we use a multivariate sensory dataset labeled as CNC Mill Tool Wear, a series of machining experiments run on a CNC milling machine in the System-level Manufacturing and Automation Research Testbed (SMART), performed in the University of Michigan. The extraction of the data in time series format have been performed using the Rockwell Cloud Collector Agent Elastic software [21]. Collection of the machining data was performed on a CNC machine recording the variations of tool condition, feed rate, and clamping pressure. The purpose of each experiment was producing a finished wax part with an "S" shape as presented in Fig. 1. The dataset is composed of 18 files in csv format, each one recorded for a separate experiment performed with a worn or unworn tool. Records include various attributes forming the multivariate nature of the series, such as the experiment number, material (wax), feed rate, and clamp pressure. Additionally, output of each experiment (file) is also given in a separate file (train.csv) including the necessary metadata for each experiment such as tool condition (worn or unworn) and qualifying condition after visual inspection (yes or no).

Fig.1. The shape aimed to be produced in the CNC milling experiments, sourcing the dataset in Ref [21]

Each file of the dataset (experiments 01 to 18) has measurements from the 4 available motors in the CNC, listed as X, Y, Z axes and spindle (S), recorded with a sampling rate of 100 ms. All available data from these parameters result in a collection of 48 attributes (44 of them available as sensory data) provided for each csv file. These attributes are available as the dimensions of a multivariate time series. The dataset can be primarily used for tool wear detection or inadequate clamping detection.

4.2. Method

This study; (i) applies visibility graph method to a time series sensory data of machining experiments run on a CNC milling machine (ii) proposes a graph-level augmentation technique by handling the data in signal level and introduces the augmentation methodology into the graph conversion strategy. By the way, a graph-specific augmentation technique is proposed that is applicable to univariate or multivariate time series format.

Data augmentation is a crucial part of deep learning tasks due to the demand on high volume of data which determines the quality of the learning process of deep architectures. The main reason for this demand is the necessity of optimizing a huge number of hyperparameters introduced by the deep architecture that most of the concurrent deep learning models are featuring [22]. Availability of big data also avoids overfitting, a phenomenon referring that a model perfectly fits the training data but may fail to propagate this for unseen data. Data augmentation techniques propose data-space solutions to overcome the problem of limited data by various techniques to increase the number of available data instances. These techniques include variations of geometric transformations, color space augmentations, kernel filters, image mixing, random erasing, augmentation of feature space, adversarial training, generative adversarial networks (GANs), neural style transfer, and meta-learning [23].

Graph representative learning deals with smart conversion strategies of unstructured data into graphs, those are available as adjacency matrices. These matrices have two dimensions of equal size, easily evaluated as grayscale images of square format. Therefore, some of the data augmentation techniques expressed above, especially proposed as image conversion techniques, are applicable for graph representations as well. However, augmentation techniques specific for graph representations are not sufficiently studied by the researchers. The current study converts the time series data collected from machining experiments run on a CNC milling machine, employing the visibility graph intension.

4.2.1. Conversion strategy from time series to visibility graph

The visibility graph strategy is a computational technique used in the field of computational geometry. It involves constructing a graph representation of the visibility between a set of points in a given geometric space. In this approach, each point is treated as a node in the graph, and edges are added between nodes if there is a direct line of sight or "visibility" between them, as illustrated in Fig. 2. By connecting all visible points, the visibility graph provides a comprehensive view of the accessible paths within the space, enabling efficient path-finding algorithms to be applied. This strategy proves particularly useful in various applications, such as time series classification, robot motion planning, and network optimization, where determining the visibility relationships between points is crucial for making informed decisions.

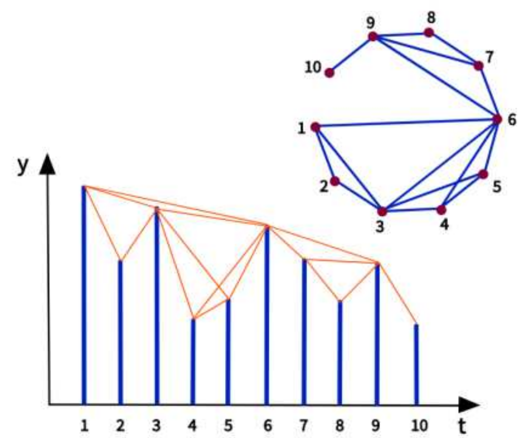


Fig.2. Conversion of a time series into graph using visibility graph method [24]

The visibility graph strategy can be leveraged in the classification of manufacturing data to uncover valuable insights and facilitate effective decision-making processes. In this context, the visibility graph represents the relationships and connectivity between different data points in the time series dataset related to manufacturing. By constructing a visibility graph, the connections between consecutive data points in time become apparent, enabling the identification of distinct patterns within the series. This approach allows for the creation of a comprehensive representation of the data's underlying structure, making it easier to discern patterns, anomalies, and trends. With the visibility graph, classification algorithms can be applied to assign appropriate labels or categories to data points based on their proximity and connectivity in the graph, specifically for tool wear prediction in the current study. By employing the visibility graph strategy, manufacturers can gain a deeper understanding of their data and make informed decisions to optimize processes, improve quality control, and enhance overall productivity.

The visibility graph methodology follows the connection criteria between data points in series format such as: (t_a,y_a) and (t_b,y_b) will have visibility, and correspondingly will become two connected nodes of the related graph, if any other data point (t_c,y_c) placed between them satisfies the condition in Eq. 1.

Time series data points are expressed as pairs (t,y) in Eq. 1, where t denotes time and y denotes amplitude values. The amplitudes of two data points that are being checked for a connection are represented by the values of y_a and y_b, while y_c indicates the amplitude of a third point that is located between these two points. A direct line drawn between the values of y_a and y_b cannot connect the places a and b if the y_c value forms an obstacle between the others. This approach is proven to inherit some specific properties of the relevant time series and produces a graph that depicts the visibility patterns across time. By the way, random series are transformed into random graphs, while periodic series are transformed into regular graphs and so on [25].

The dataset converted into an adjacency matrix format, demonstrates the graph representation of sensory data from CNC milling machine. Since each experiment consists of 44 available dimensions, each dimension (column)

$$y_c < y_b + (y_a - y_b)\frac{t_b - t_c}{t_b - t_a} \tag{1}$$

can be converted into a separate graph, resulting in a 44-layer graph representation (illustrated in Fig.3 for 3 dimensions). As a result, this section of the study generates 18 multilayer graph representations for 18 available experiments, each one consisting of 44 layers, which can be treated as a visual input to deep learning architectures.

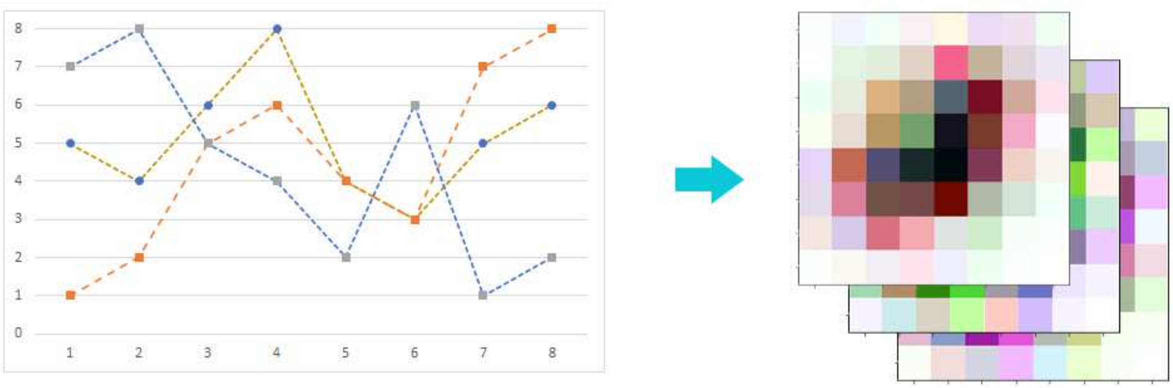


Fig.3. Conversion from multivariate time series to multilayer visibility graph

4.2.2. Graph-based augmentation strategy

Data augmentation plays a crucial role in deep learning by addressing the challenge of limited labeled training data. Deep learning models typically require large amounts of labeled data to achieve high performance and generalization. However, obtaining such extensive and diverse labeled datasets can be impractical or expensive. Data augmentation offers a solution to this problem by artificially expanding the training dataset through various transformations and modifications. By applying techniques like rotation, scaling, cropping, flipping, or adding noise to the existing data, data augmentation creates new instances that retain the original label information. This augmented dataset introduces greater variability, enabling the deep learning model to learn robust and generalized representations. Data augmentation helps prevent overfitting by exposing the model to a wider range of scenarios and variations it might encounter during inference. It also enhances the model's ability to handle diverse data sources, lighting conditions, orientations, and other real-world factors. Therefore, data augmentation is a vital technique in deep learning that effectively leverages existing labeled data to improve model performance, increase generalization, and ultimately, enhance the model's ability to handle real-world challenges.

In this regard, the data available for the current study, having 18 experiments needs a high rate of augmentation to feed a deep learning architecture. Since the above-mentioned augmentation strategies have a limited capacity to increase the number of instances, a more structural and robust augmentation technique is highly needed. Consequently, we propose a novel time-hop data augmentation technique to improve the number of available instances to feed deep learning architectures. This technique depends on slight variations of graph representations of sensory data after time-hop slices extracted, without the need for synthetic data generation or data distortion techniques. By the way, a data transformation method that converts time series into a graph-based feature space with realistic augmentation is achieved.

The proposed augmentation technique is specific for an available graph conversion strategy, having the only limitation of sampling rate that should be sufficiently greater than the Nyquist rate for the given signal. Assuming that a downsampling rate of D times preserves the main characteristics of the given series, an augmentation rate of D times will potentially generate D slightly different graph representations of the original signal. Each version of augmented signals is generated after a one time-hop is applied to the original series and starting from this shifted *(s)* point, a downsampling rate of D is applied to pick a slice from the original series. Visibility graph conversion is later applied to this extracted (down sampled) data slice to achieve a graph representation. Since the time-hop procedure is applied to all available (44) columns, the resulting multilayer graph representation satisfies the condition to be at least slightly different from the sibling augmented graphs from the same original signal, for all available layers (generated from separate columns). The proposed methodology is illustrated in Fig. 4.

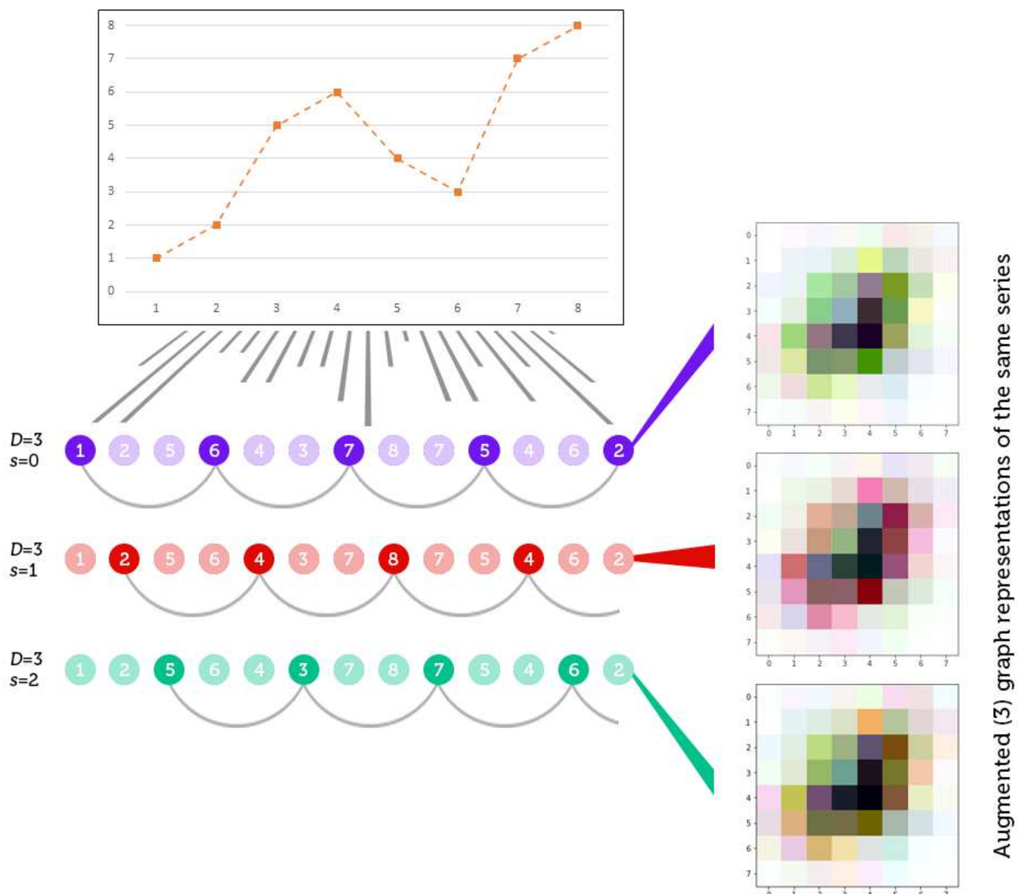


Fig.4. Time-hop augmentation strategy for the visibility graph conversion for time series data

4.2.3. Deep learning model

Since the converted data is in graph format represented with adjacency square-matrices, a moderately structured CNN model should successfully classify the instances. We customized a CNN model, summary given in Table 1. In combination with the visibility graph conversion and the applied augmentation technique, this new approach is labeled as Graph-Augmented CNN (GA-CNN) classifier by the authors.

Table 1.

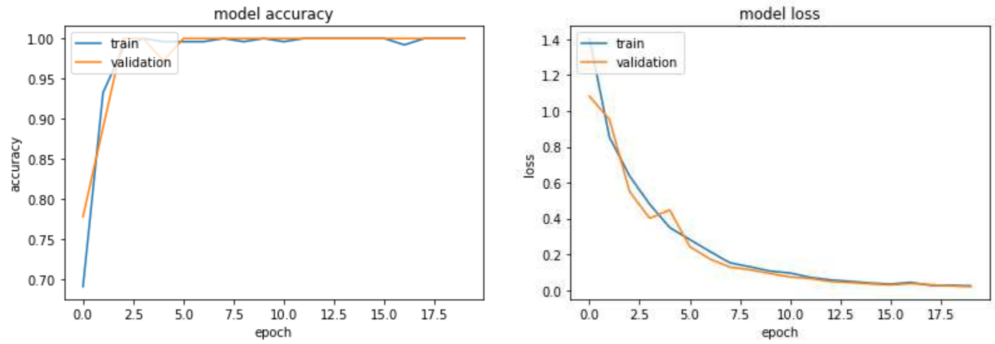
The architecture of the GA-CNN model used for tool wear classification of graph-converted time-series data.

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 128, 128, 64)	640
activation_6 (Activation)	(None, 128, 128, 64)	0
conv2d_5 (Conv2D)	(None, 126, 126, 64)	36928
activation_7 (Activation)	(None, 126, 126, 64)	0
max_pooling2d_2 (MaxPooling2	(None, 63, 63, 64)	0
dropout_3 (Dropout)	(None, 63, 63, 64)	0
conv2d_6 (Conv2D)	(None, 61, 61, 64)	36928
activation_8 (Activation)	(None, 61, 61, 64)	0
conv2d_7 (Conv2D)	(None, 59, 59, 64)	36928
activation_9 (Activation)	(None, 59, 59, 64)	0
max_pooling2d_3 (MaxPooling2	(None, 29, 29, 64)	0
dropout_4 (Dropout)	(None, 29, 29, 64)	0
flatten_1 (Flatten)	(None, 53824)	0
dense_2 (Dense)	(None, 128)	6889600
activation_10 (Activation)	(None, 128)	0
dropout_5 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 2)	258
activation_11 (Activation)	(None, 2)	0

Total params: 7,001,282
Trainable params: 7,001,282
Non-trainable params: 0

5. RESULTS

We applied an aggressive augmentation rate as *D*=20 for the 18 available experiments, each having 44 dimensions. No additional augmentation strategy such as rotation, zoom, distortion etc. are applied, in order to observe the success of the proposed augmentation method. With the augmented size of 20x18=360, a split of 70% train, 10% validation and 20% test is applied with a batch size of 8 and 20 epochs.



(a) (b)

Fig.5. Model accuracy and loss for tool wear prediction performed by the custom CNN model

Table 2.

Comparison of the results with the recent studies handling the same dataset.

Ref	**Year**	**Model**	**Accuracy**
[26]	2021	Logistic Regression	72%
[27]	2021	Ensemble (XGBoost, Random Forest, and AdaBoost)	99.52%
[28]	2021	Random Forest J48 Multilayer Perceptron	99.7% 99.2% 96.9%
[29]	2022	CNN AE-LSTM (AutoEncoder-LSTM) k-NN	92% 77% 85%
[30]	2022	BCNN (Bayesian CNN)	99%
Our method	2023	GA-CNN	**100%**

Experimental results indicate that full accuracy (100%) is swiftly achieved in the initial epochs, with the learning curves given in Fig. 5. No overfitting is observed in the learning and error curves those are very consistent for train and validation data.

The proposed GA-CNN model overperforms the recently proposed classifiers as given in Table 2. This is an indicator that the proposed augmentation technique has a potential to increase the data amount even in aggressive rates.

6. FURTHER RESEARCH

The proposed graph-augmentation model is successful for the tool wear prediction task performed with a multidimensional sensor data, which encourages its adoption for other time series classification tasks in multidimensional nature with limited instances. Therefore, classification of Electroencephalograms (EEGs), Electrocardiograms (ECGs), Human Activity Recognition tasks (HAR) etc. are the potential application fields for the proposed model.

Specific to industrial applications, the proposed model presents a flexible framework especially for the time series data for high sampling rates, potentially applicable to automated event/fault detection from process monitoring data. Predictive maintenance applications generally rely on features from principal component analysis, which require a moderate level of preprocessing. The proposed framework can replace these steps as a whole, facilitating detection of potential events from streaming multidimensional time series data.

7. CONCLUSIONS

The current study handles the data collected from a CNC milling machine in an innovative way to facilitate accurate tool wear detection. Instead of handling the raw data as it is, it constructs graph representations from the series from each sensor separately, resulting in a multilayer graph representation for each experiment. Moreover, due to the need for high number of instances in deep learning tasks, a graph-induced augmentation technique is proposed. By the way, tool wear prediction for a CNC milling task is facilitated by the proposed augmentable deep learning framework.

Results indicating full accuracy show the potential of the approach, that deserves application to other time series classification tasks, especially with multivariate and limited data scenarios. The proposed GA-CNN model also shows the potential of graph representative learning for industrial applications, capturing the higher order patterns in the multidimensional signal activity.

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Predicția uzurii sculei prin reprezentarea graficului multistrat

Predicția uzurii sculei are un rol crucial pentru îmbunătățirea calității și fiabilității procesului de fabricație. Propunem o metodologie de detectare inteligentă bazată pe conversia datelor senzoriale disponibile colectate de la o mașină de frezat CNC într-o reprezentare grafică multistrat. După preluarea datelor experimentale din timpul procesului de fabricație se realizează o reprezentare grafică de vizibilitate multistrat, rezultând o matrice de adiacență de 44 de straturi 128x128. O nouă tehnică de creștere a datelor aplicabilă în mod specific reprezentării grafice este, de asemenea, utilizată pentru a crește mărimea datelor prelucrate de la 18 la 360, cu o repartizare 70% testare, 10% validare și 20% simulare. Rezultatele indică faptul că metodologia propusă oferă o acuratețe deplină pentru a detecta dacă scula este uzată sau nu.

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