CHATTER DETECTION IN MILLING WITH ACOUSTIC EMISSIONS AND DEEP LEARNING

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Motivation

- Milling is a highly crucial machining process in the modern industry. CNC machine tool companies have been trying to fulfill the demand towards high productivity, precision, efficiency and flexibility with its advances on cutting technology.

- In order to increase the efficienciecy of milling process, cutting parameters have been optimized for decades. However, there are still complications in milling process that is not possible to be solved easily.

- Chatter is a major limitation for the milling process. Occurence of chatter can cause poor surface quaility and waste of materials.

Motivation

- Detecting and suppressing chatter is very crucial for better surface qualities and tool life. For example, Renault has found that the extra cost of an 2.0 Dci engine due to chatter is approximately 0.35€[1].

Possible solutions of chatter caused problems;

- With the new trends of Industry 4.0, it is becoming more typical to implement Artificial Intelligence (AI) methods to increase the performance of milling processes.

- Chatter in milling process is a nonlinear problem. Since many AI methods are suitable for solving nonlinear problems. Using a neural network based model for chatter detection is higly beneficial.

[1]J.V. Le Lan, A. Marty, J.F. Debongnie, CIRP (Eds.), A stability diagram computation method for milling adapted to automotive industry, in: Proceedings of the CIRP Second International Conference on High Perfor- mance Cutting, 12–13 June 2006, Vancouver, British Columbia, Canada, 2006.

Contents

Slot milling process

- Milling technology is one of the advanced manufacturing technologies which is being applied in CNC machines until recently.
- Compare to turning process, milling operations have a more comples nature. Since the cutting tool has a discrete contact with work part, it is harder to investigate the occurance of chatter in milling processes.

Figure 1: 5 axis milling machine tool

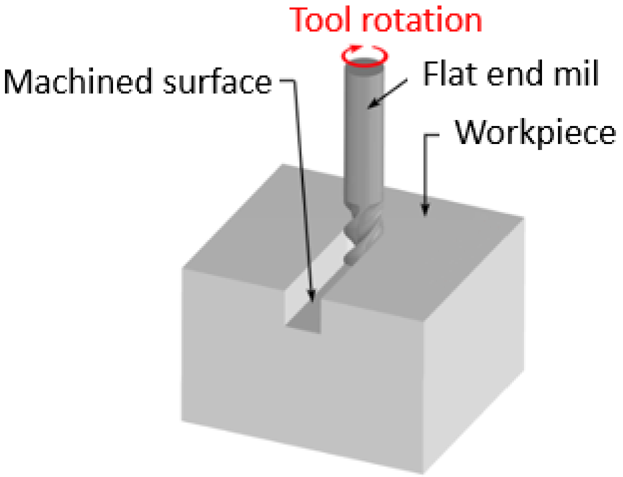

Figure 2: Slot milling

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Chatter

Chatter is a vibration that caused by the dynamic interaction of workpiece and cutting tool during machining operations [2].

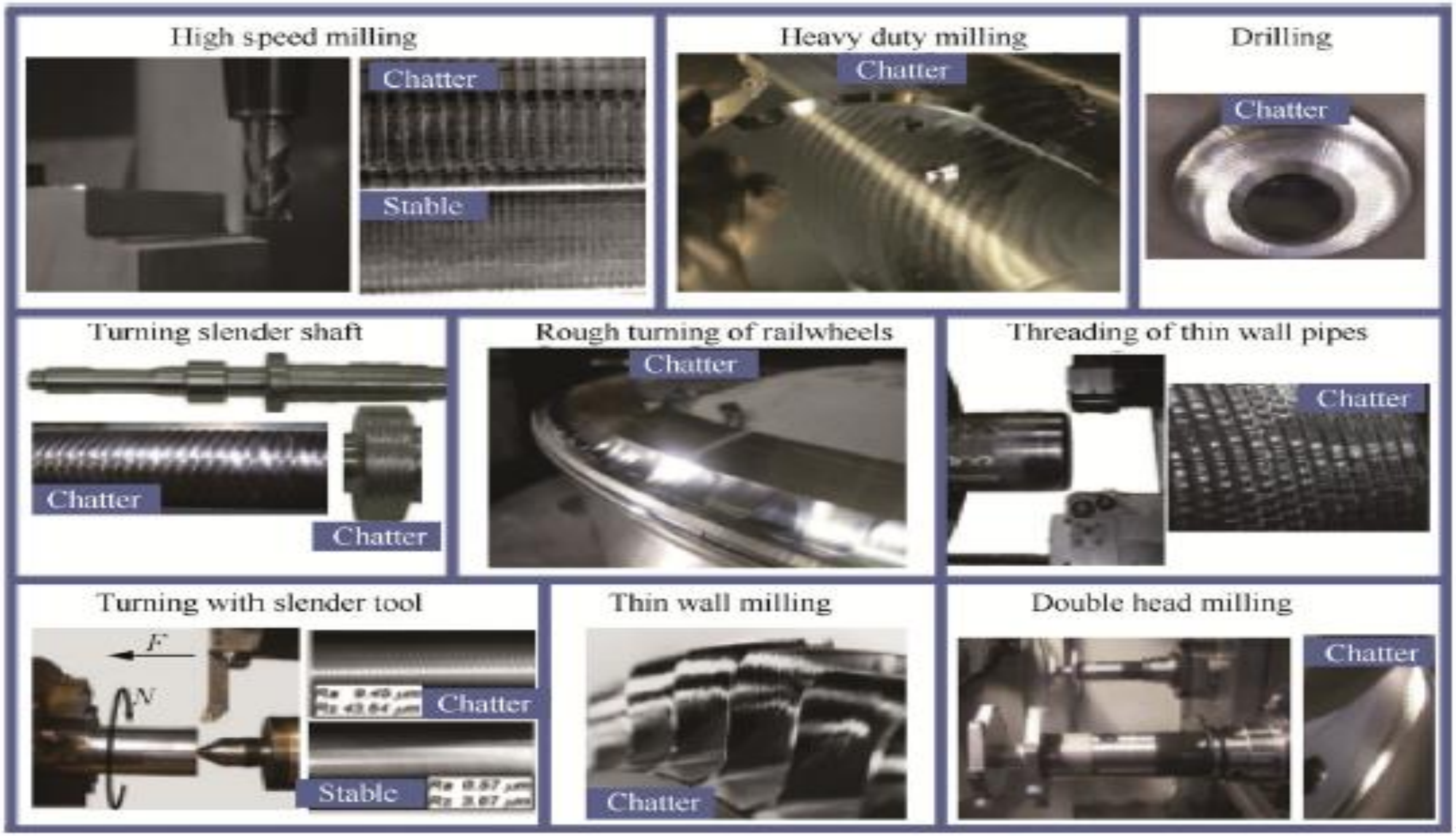


Figure 3: Challenging chatter problems in machining processes [3]

[2] Tekeli, Alper, and Erhan Budak. "Maximization of chatter-free material removal rate in end milling using analytical methods." Machining Science and Technology 9.2 (2005): 147-167.
[3] Caixu, Y. U. E., Haining, G. A. O., Xianli, L. I. U., Liang, S. Y., & Lihui, W. A. N. G. (2019). A review of chatter vibration research in milling. *Chinese Journal of Aeronautics*, *32*(2), 215-242.

Chatter Identification and Detection

- Chatter can occur in different types in a machinig process such as; frictional, thermo-mechanical, mode couplign and regenerative chatter.

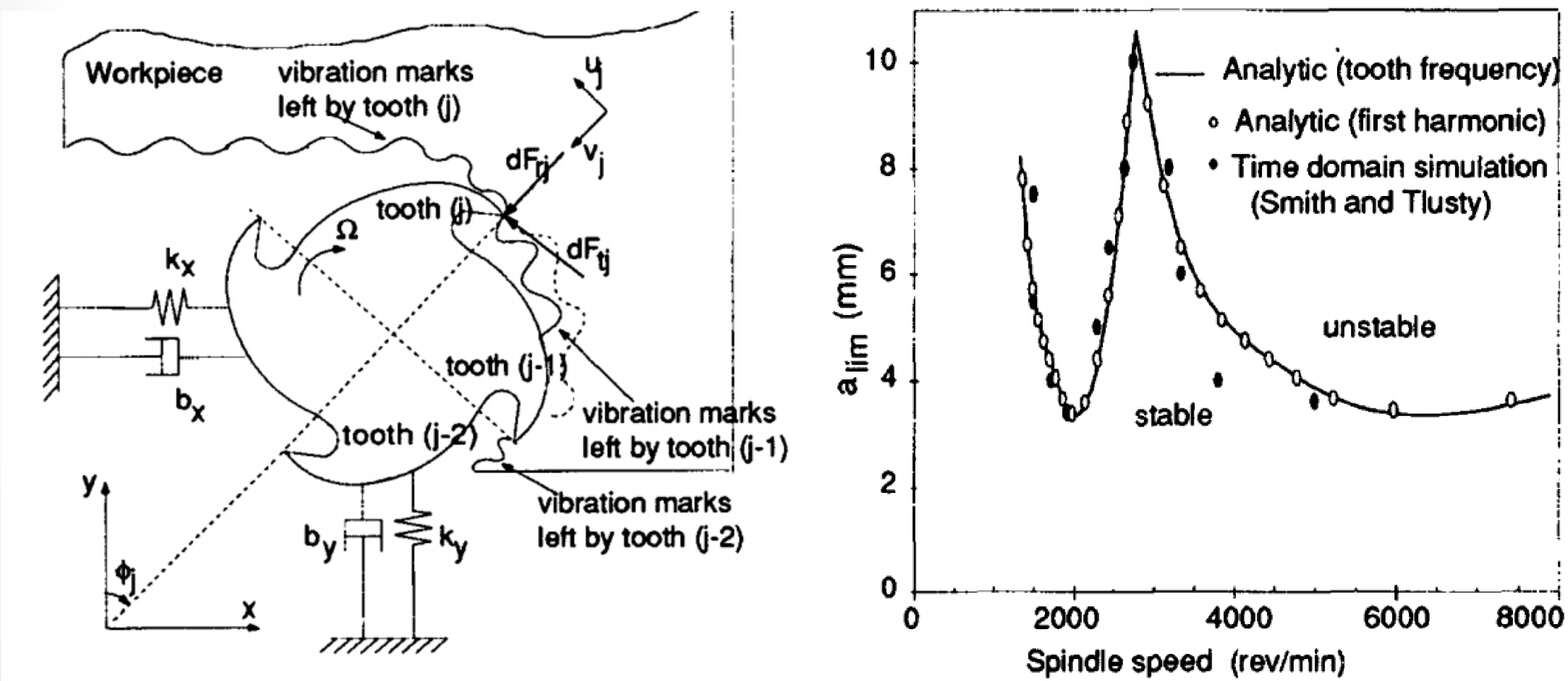


Figure 4: Dynamic model of milling and stability lobes[4]

[4] Altintaş, Y., & Budak, E. (1995). Analytical prediction of stability lobes in milling. CIRP annals, 44(1), 357-362.

Chatter Detection

- Prosess monitoring of milling operations generally conducted by following the same steps and harware.
- Different types of sensors can be used for data acquisition. Typical types of sensors and their arangements can be seen in Fig 5.

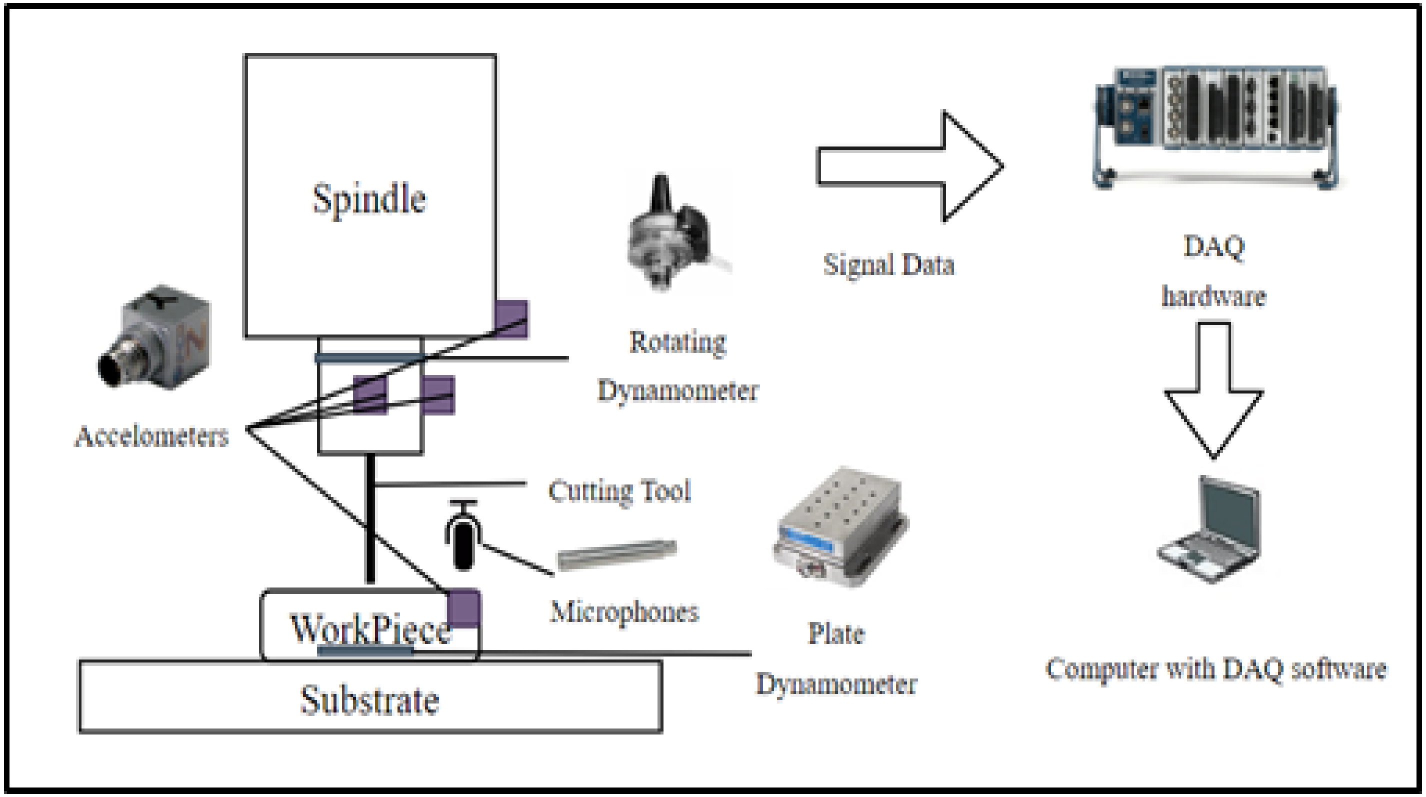
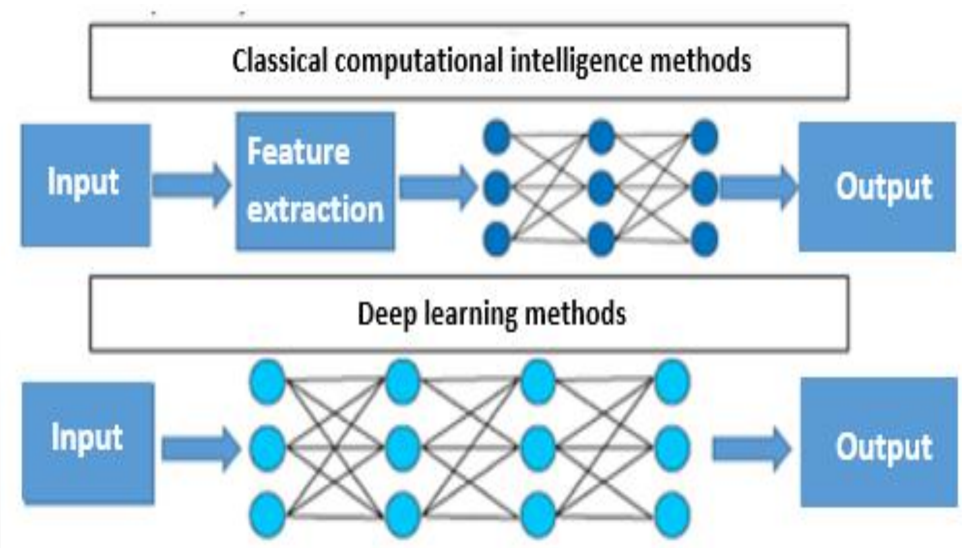


Figure 5: Typical sensor types and locations in milling process monitoring for chatter detection

Contents

Artificial Intelligence

- Artificial intelligence (AI) is a broad term that covers fuzzy logic, regression methods and all computational intelligence applications.
- The use of sensors has recently increased in many areas including self-driving cars, UAV's and robotics, these sensors can be used for training AI algorithms.
- As a type of machine learning methods, deep learning methods that uses sensory data as inputs have a great potential of solving complex problems.



Flowchart of classical intelligence method versus deep learning

- Since the deep learning methods are more suitable for bigger datasets, it can be preferable to use deep learning for in-process chatter detection strategies

Deep Learning

- Deep learning, which is the newest and one of the most advanced machine learning methods, was applied to image recognition, sentiment analysis, and natural language processing in its early days of emergence.
- In addition, in the area of manufacturing, it has a great potential in chatter detection which requires a significant number of data.

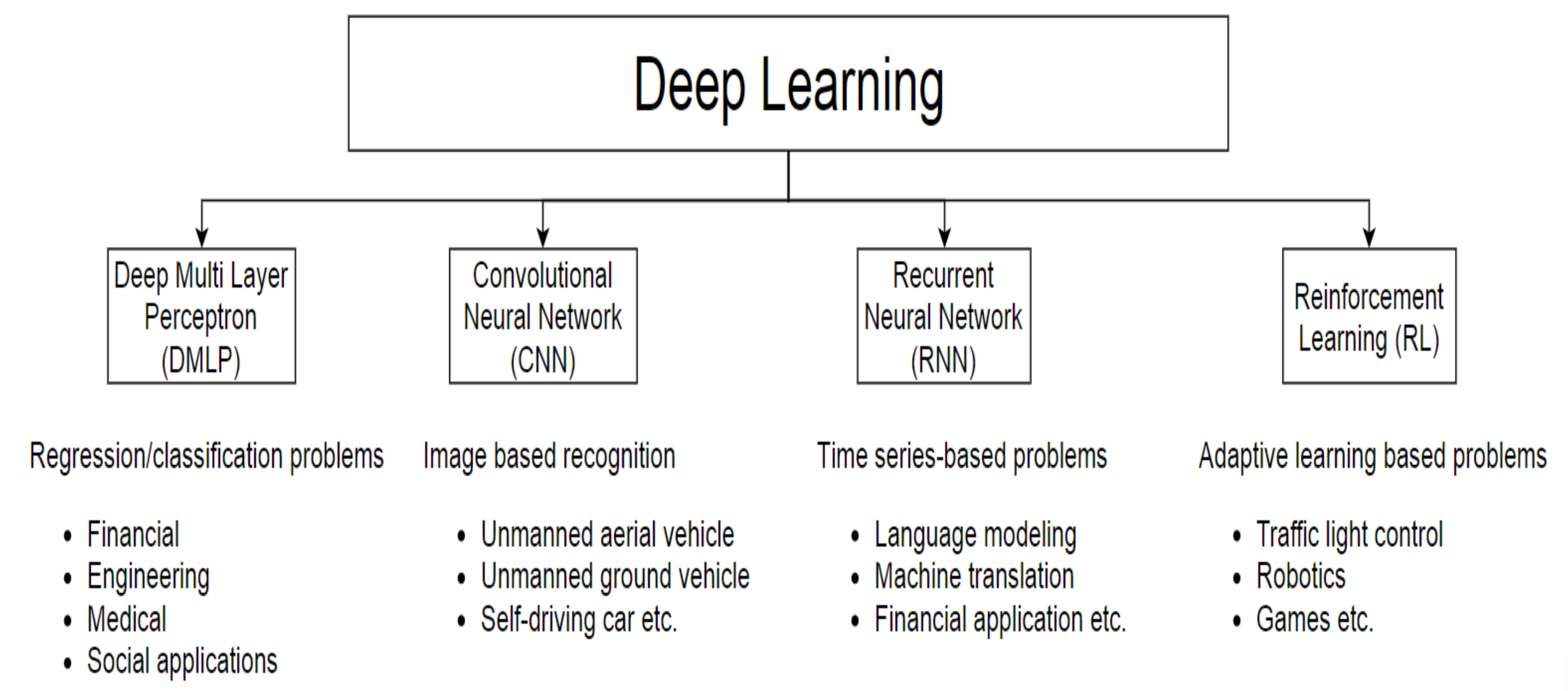


Figure 6: Deep learning categories and applications

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Convolutional Neural Network

- In a CNN model, an image is usually used as the input. For this reason, the CNN method, which is a type of advanced deep learning method, has been proven in the fields of image classification & recognition .
- In this work, *spectrograms* used as input images.

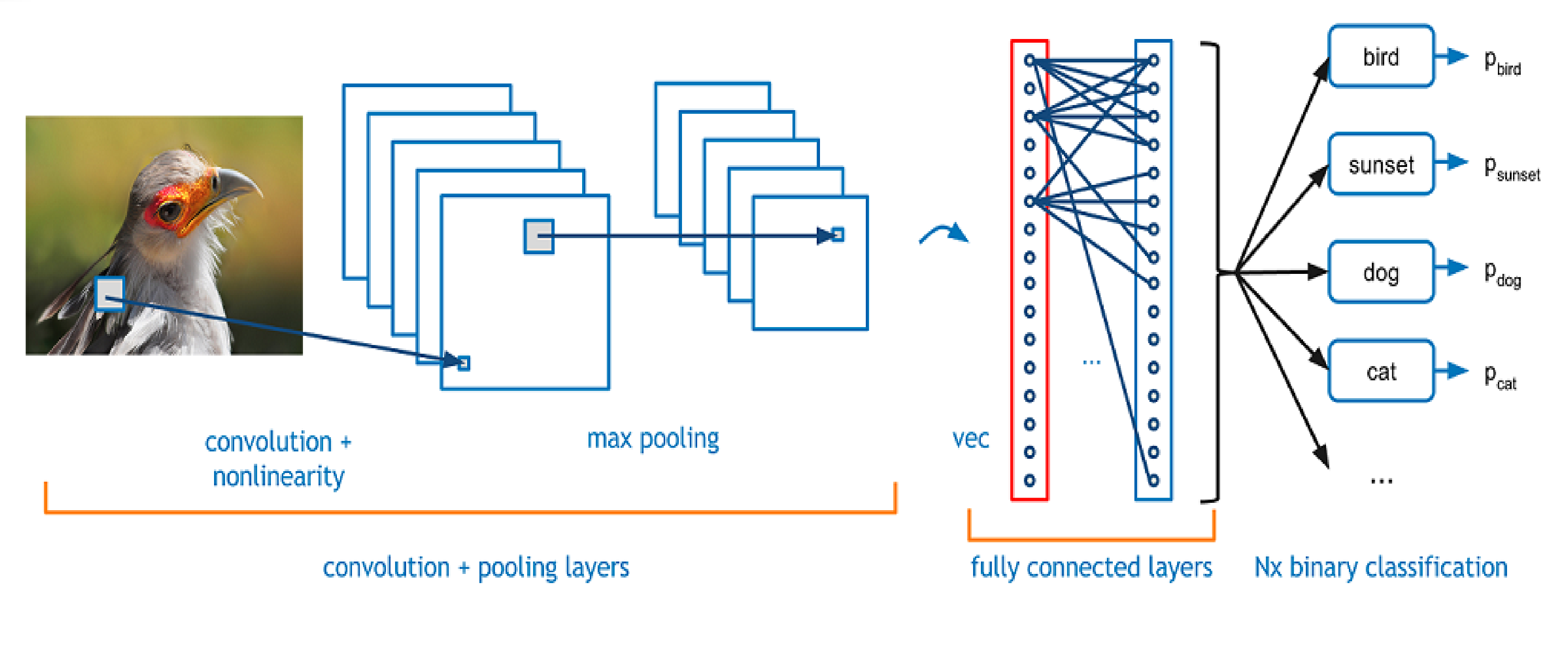

Figure 7: An example of CNN process

Convolutional Neural Network

- In image processing, a **kernel**, **convolution matrix**, or **mask** is a small matrix. It is used for blurring, sharpening, embossing, edge detection, and more. This is accomplished by doing a convolution between a kernel and an image.

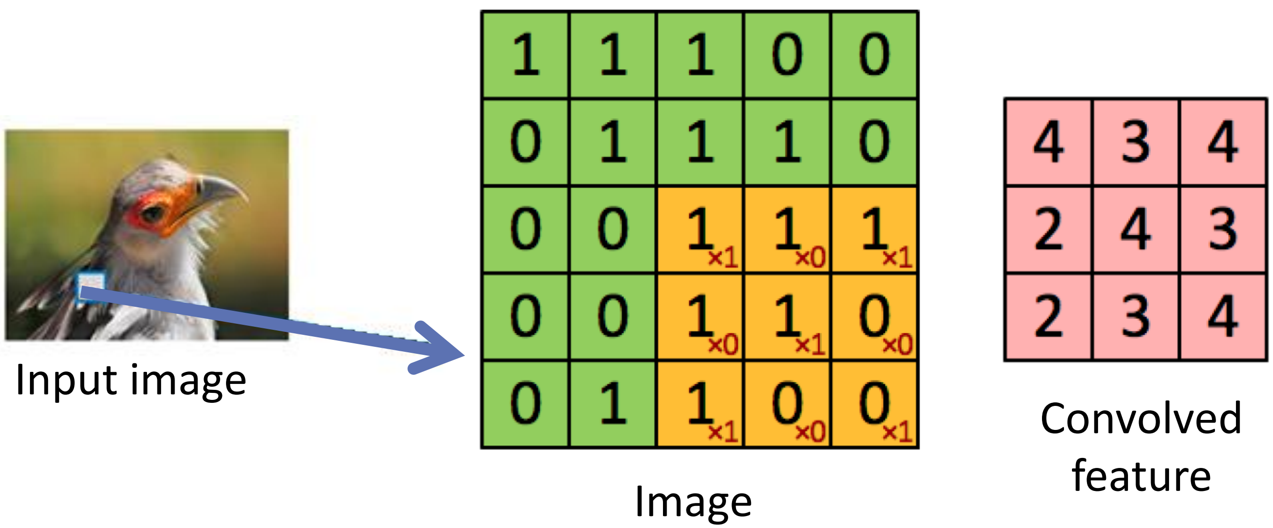

Figure 8: Kernel filter and convolution example

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Literature Review

- Acoustic emission (AE) sensors, accelerometers and dynamometers are widely used in chatter detection for obtaining time domain data.
- Delio et al. (1992) used acceleration, displacement, and AE sensor in order to detect chatter. They compared the performance of these sensor types in the monitoring of the chatter formation. The result of their study shows that acoustic emission signals are more efficient to detect chatter.
- Time domain signals generally convert to frequecny domain signals for chatter detection.

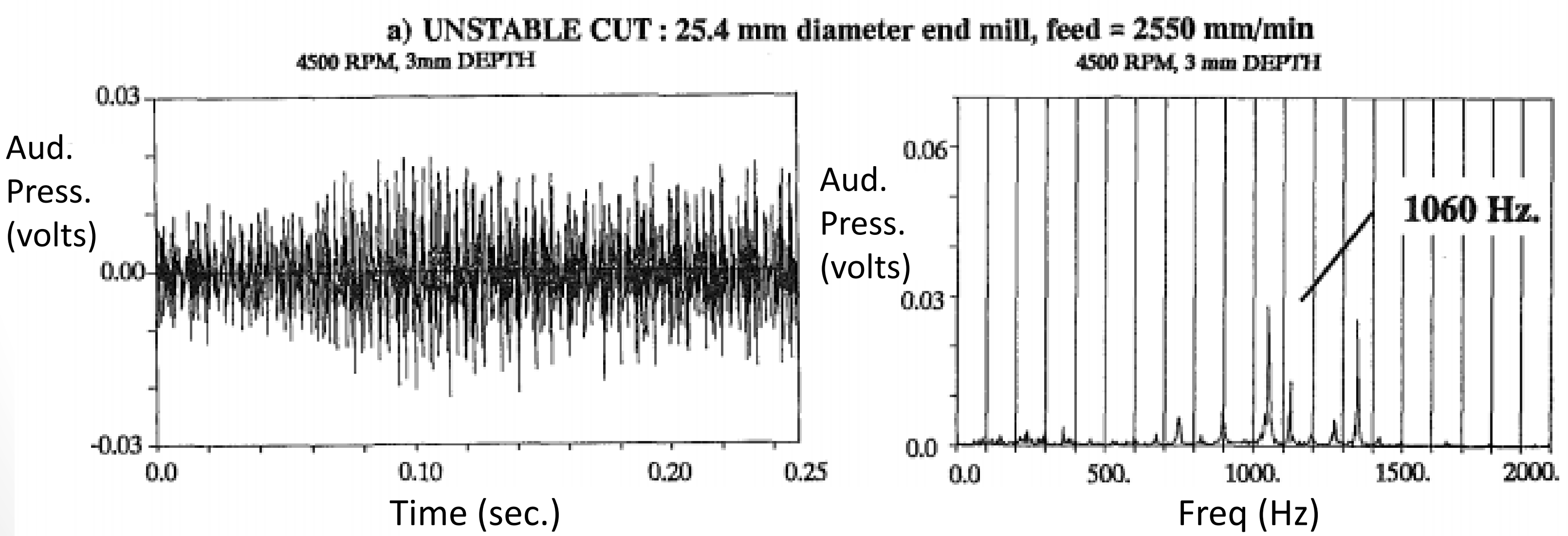

Figure 9: An example of AE sensor data in time and frequency domain [5]

[5] Delio T (1992) Use of Audio Signals for Chatter Detection and Control. J Manuf Sci Eng. doi: 10.1115/1.2899767

Literature Review

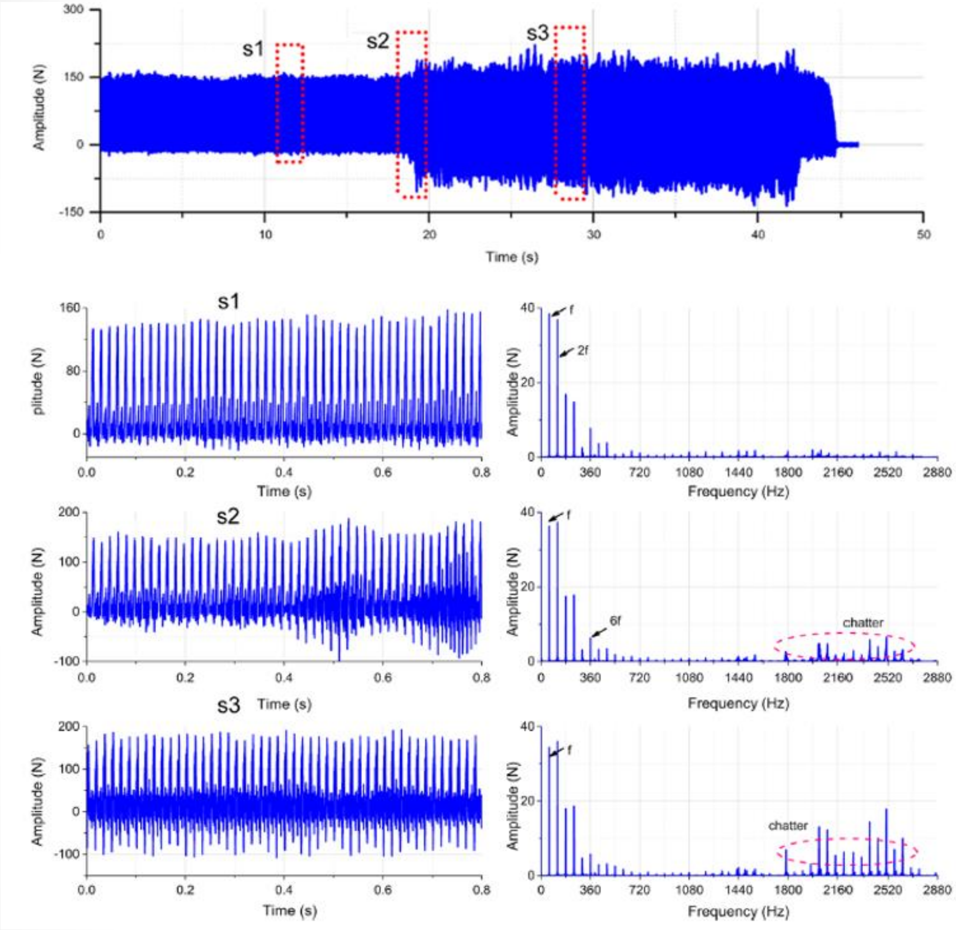

Figure 10: Stationary and non-stationary conditions [6]

- In the stable state which consists of stationary signals, the rotation frequency was dominant on frequency-domain data as shown in Fig 10. Nevertheless, the energy of the milling operation is dominated gradually by chatter frequency when a non-stationary condition is observed.
- This approach can be integrated with CNN algorithms since CNN uses images as inputs.

[6] Zhang Z, Li H, Meng G, Tu X, Cheng C (2016) Chatter detection in milling process based on the energy entropy of VMD and WPD. Int J Mach Tools Manuf 108:106–112 . doi: 10.1016/j.ijmachtools.2016.06.002

Literature Review

Tablo 1: Existing works of chatter detection using AI algorithms

Reference	Title	Method
Zahra and Lange, 2002	Tool chatter monitoring in Turning Opearations using wavelet analysis of ultrasound waves	MLP and ANN
Rahman et al., 1995	On-line Cutting State Recognition in Turning Using a Neural Network	Neural network
Yao et al., 2010	On-line chatter detection and identification based on wavelet and support vector machine	SVM
Chen et al., 2019	Intelligent chatter detection using image features and support vector machine	SVM

- Existing implementations of AI algorithms to chatter detections generally use traditional methods.
- On the other hand CNN methods provide better solutions for big datasets.

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- Methodology
- Chatter Detection with CNN
- Results & Verification
- Conclusion & Futureworks

Methodology

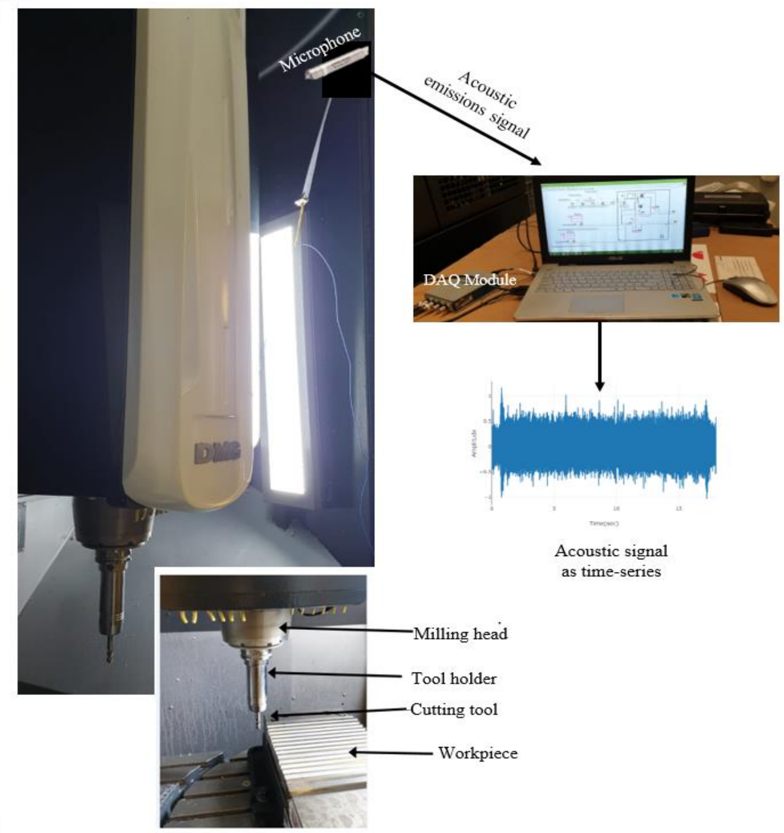

Figure 11: The machine tool and data acquisition setup

- The experiments were conducted on a DMG-MORI® 5 axis milling machine which is able to operate up to 12000 rpm in order to machine slots on an aluminum 7075 workpiece as shown in Fig 4.

- The microphone is attached inside the working cabin, it is able to collect AE up to 20000Hz

[6] Zhang Z, Li H, Meng G, Tu X, Cheng C (2016) Chatter detection in milling process based on the energy entropy of VMD and WPD. Int J Mach Tools Manuf 108:106–112 . doi: 10.1016/j.ijmachtools.2016.06.002

Methodology

Tablo 1: Process parameters

Test No:	Depth of cut (mm)	Spindle speed (rpm)
1	2	3150
2	2	3430
3	2	3760
4	3	3760
5	8	3760
6	3	4200
7	8	4730
8	3	4730
9	3	5400
10	8	5400
11	3	6300
12	8	6300
13	3	7500
14	8	7500
15	3	9500
16	6	9500
17	8	9500
18	10	11000
19	6	11000
20	1	11000
21	1	9500
22	1	7500
23	1	5400
24	1	4730
25	1	3760
26	1	6300

- A three-flute tungsten-carbide cutting tool with a diameter of 10 mm and length of 72 mm was used for the slot milling operations and 0.08 mm/tooth were used as feed parameter.
- Acoustic data is sampled at 12800 Hz and all samples were used without any down-sampling operation in order to maintain a high-resolution sampling. No filtering is used during acquisition to keep the raw data for future processing.

[6] Zhang Z, Li H, Meng G, Tu X, Cheng C (2016) Chatter detection in milling process based on the energy entropy of VMD and WPD. Int J Mach Tools Manuf 108:106–112 . doi: 10.1016/j.ijmachtools.2016.06.002

Methodology

- The collected AE data is the form of time-series. For cleaning and converting to another form requires preprocessing operations.
- A python script was created to process the raw data captured via LabVIEW.
- The time domain data is split into one-second intervals to increase the number of samples and to correctly identify chatter.

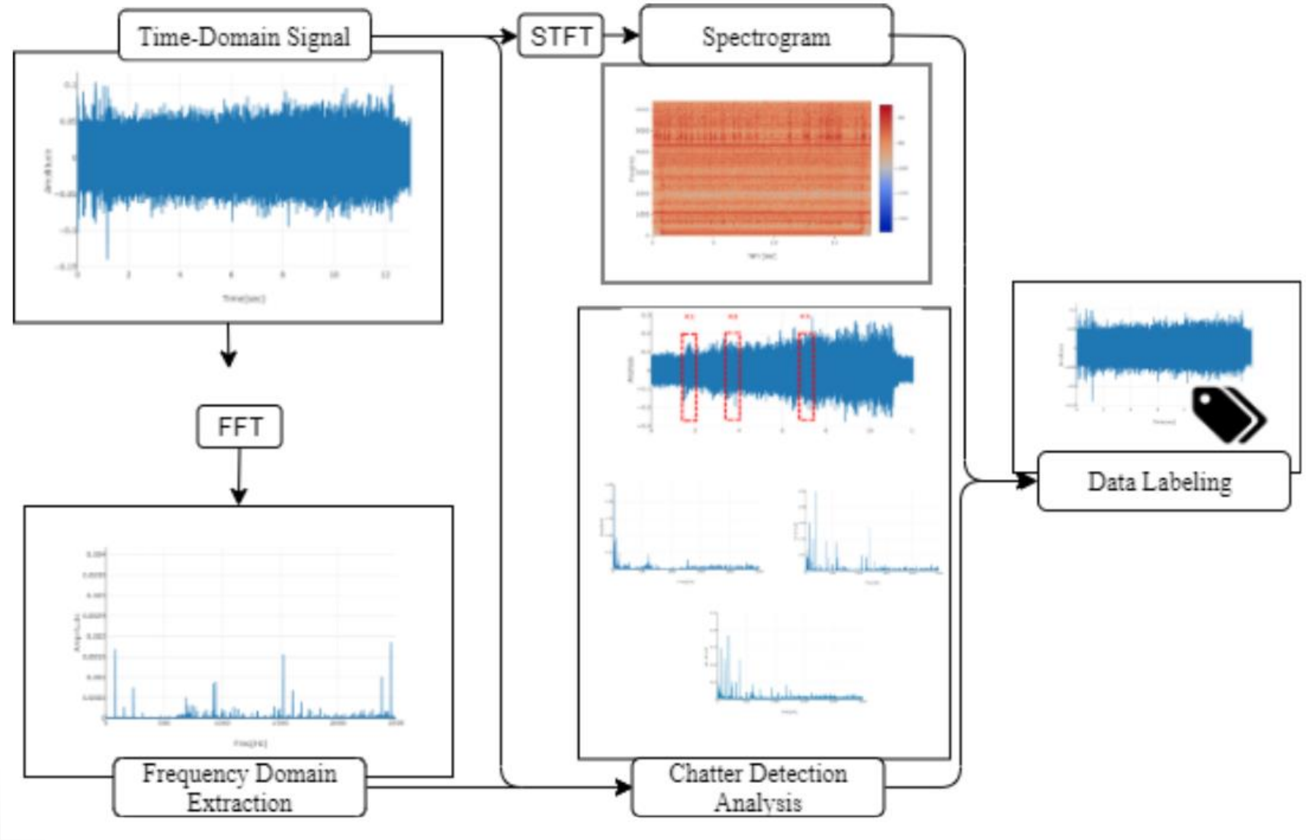

Figure 12: Overall chatter detection and labeling process

Methodology

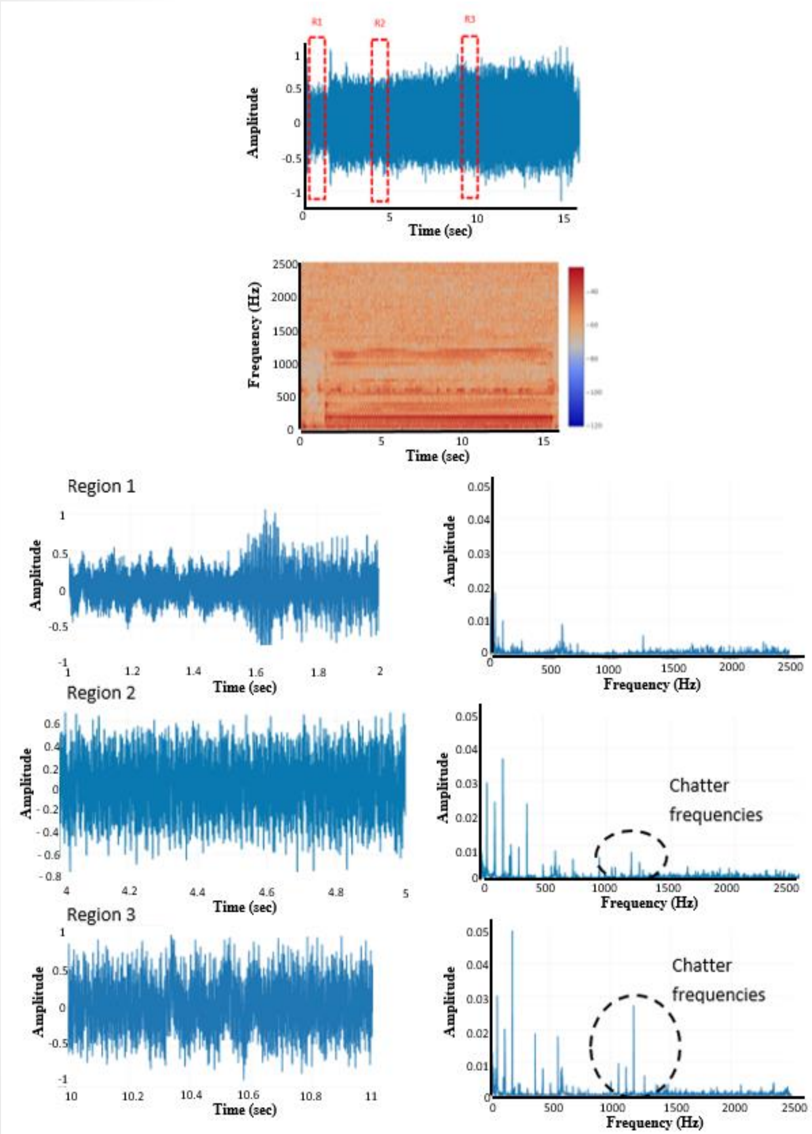

Figure 13: Unstable cutting AE signals (spindle speed 3760 rpm, feed rate 902.4 mm/min, doc 3 mm)

- For each slot, 3 different regions with 1 second lengths are choosen.
- These one second regions are extracted in both time and frequency domain.
- Each frequency domain data is inspected.

In the unstable slot milling process, it is observed that the chatter frequency gradually dominates over the data in the frequency domain as shown in Fig 13.

Methodology

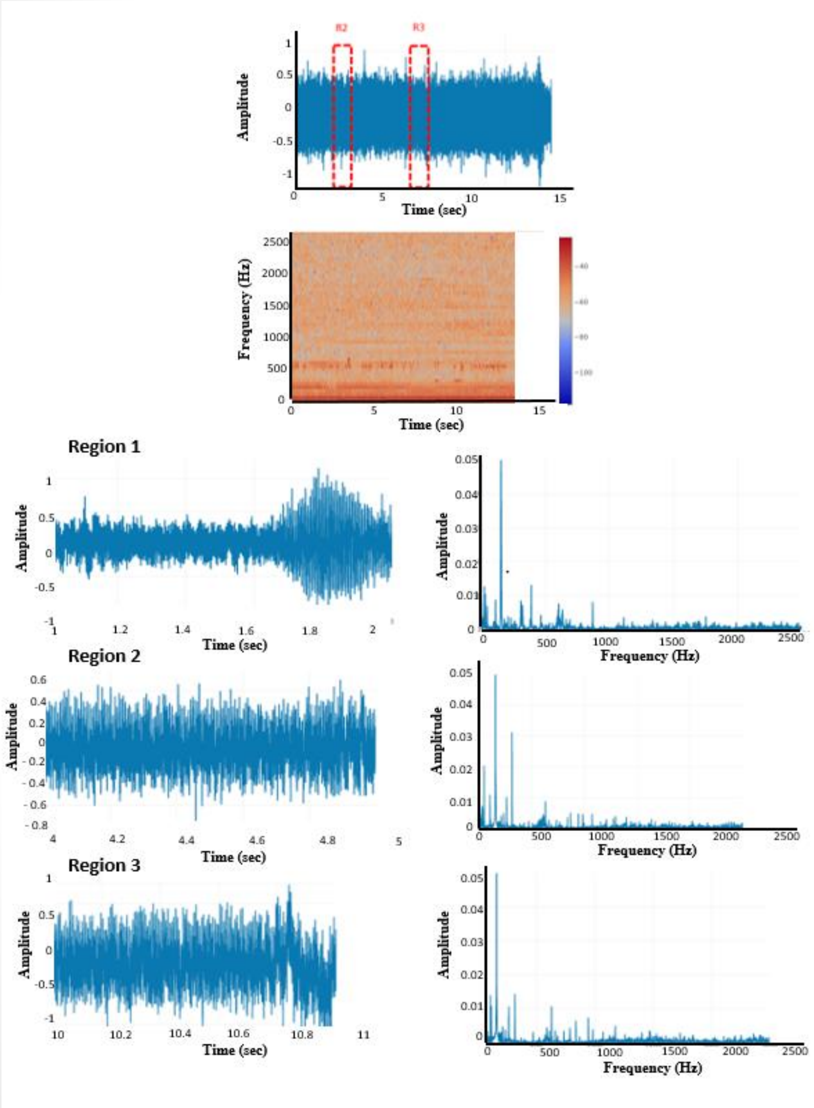

Figure 14: Stable cutting AE signals (spindle speed 3150 rpm, feed rate 750 mm/min, doc 2 mm)

- When it is a stable slot milling process, chatter frequencies are not observed, and the rotation frequency continues to dominate as shown in Fig 14.

- These observations were used to assign a label to each sample. Before introducing the spectrograms to the CNN, by using STFT method, each sample is converted into spectrogram which is a time versus frequency representation of the time-series signal.

Contents

Chatter Detection with CNN

- Each input consists a spectrogram with 1 second length and labeled as chatter or no chatter

- In total, 147 spectrogram data were passed to the CNN model.
- First layer consists of 10 convolutional filters with kernel size of 5.
- These 10 filters have passed through a max-pooling layer with kernel size 4 and Rectified Linear Unit (ReLU).

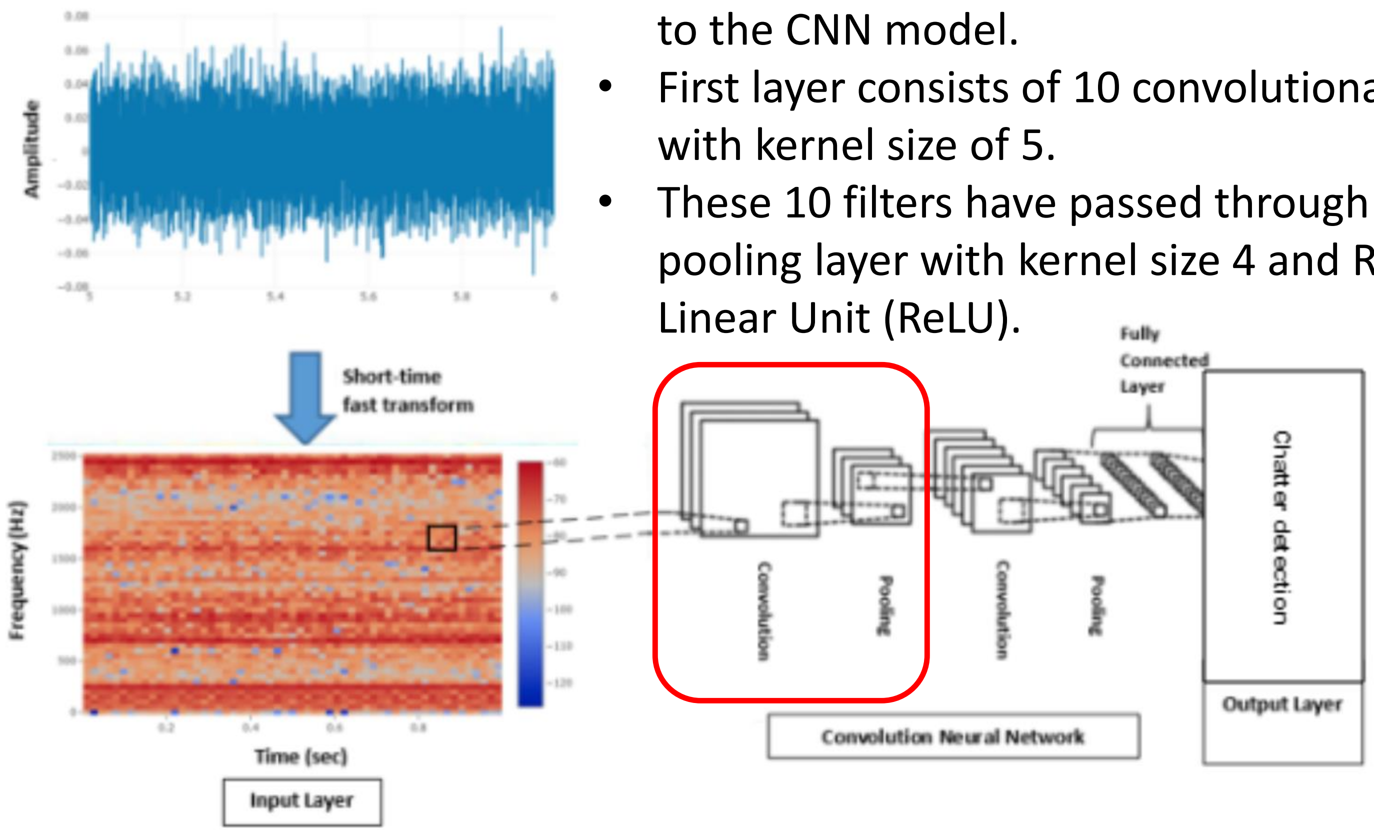

Figure 15: Process of tool wear prediction using CNN

Chatter Detection with CNN

- The second layer has the same configuration as the first layer. These two layers are added in successive order to act as a feature extractor.

- These automated feature extracting properties of deep learning models form the main difference between classical machine learning and deep learning.

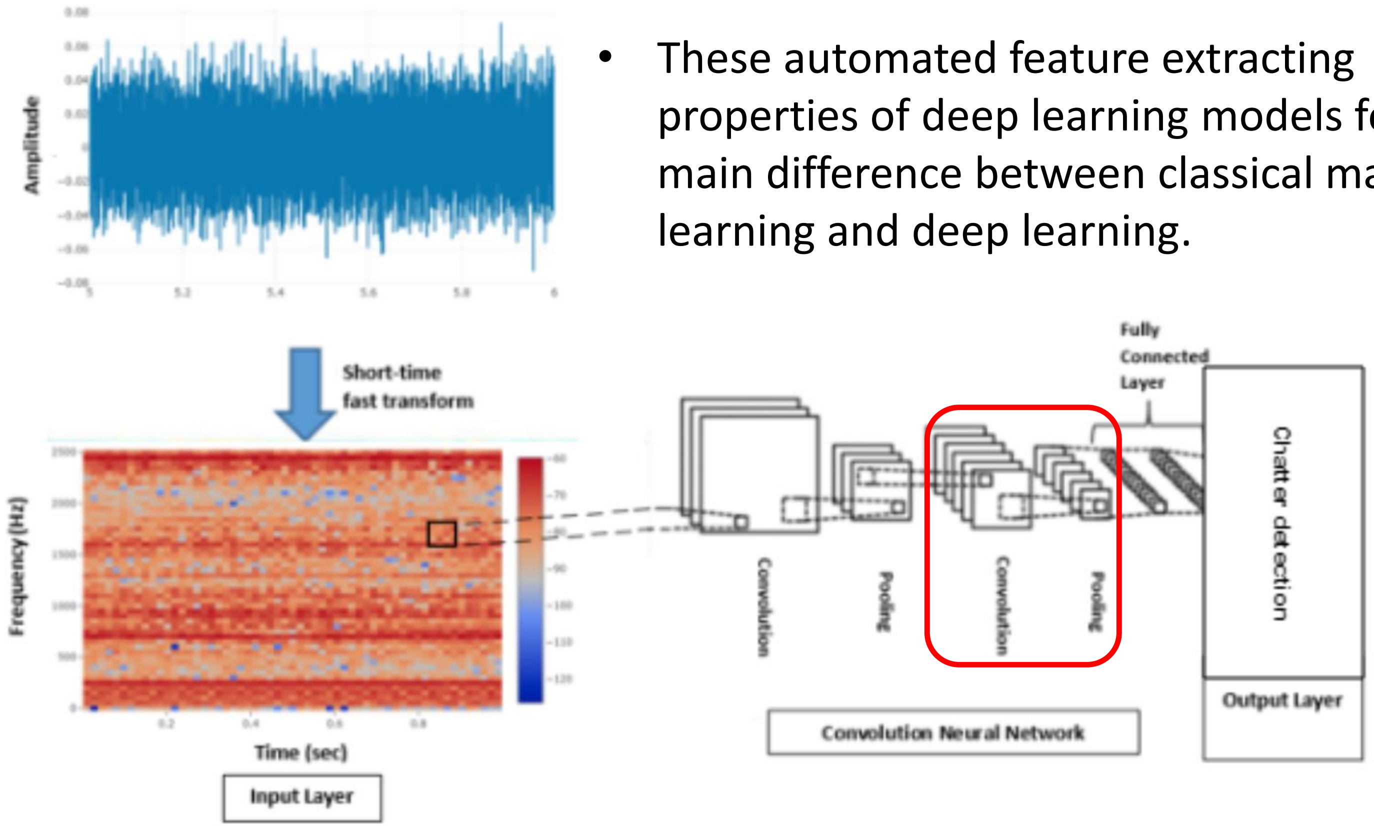

Figure 16: Process of tool wear prediction using CNN

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Results and Verification

- Several CNN architectures were investigated to find the optimal structure. In addition, several hyper parameter settings are applied. Selected architecture design and hyper parameters setup play crucial role because of the lack of data.

- Specifically, dropout rates on fully-connected layers affect the performances. Experiments shows that lower dropout rates make the model performs unsatisfactorily.

CNN Hyper parameters;

- Dropout :0.9
- Number of Epochs: 670
- Batch Size: 20
- Learning Rate: 1e-4
- Train-Test Ratio: 0.75 which splits all samples into 110 training, 37 test samples.

Results and Verification

- The learning curve of the prediction model is shown in Fig. 17. In early epoch (0-120) CNN predicts all test samples as 0 or 1. Therefore, test accuracy is alternating between the mean of 0-labeled and mean of 1-labeled samples.

- After that, training loss starts to decrease and alternation between label mean stops. At the end of the training process (670th epoch), 0.95 accuracy for training samples and 0.92 accuracy for test samples are obtained.

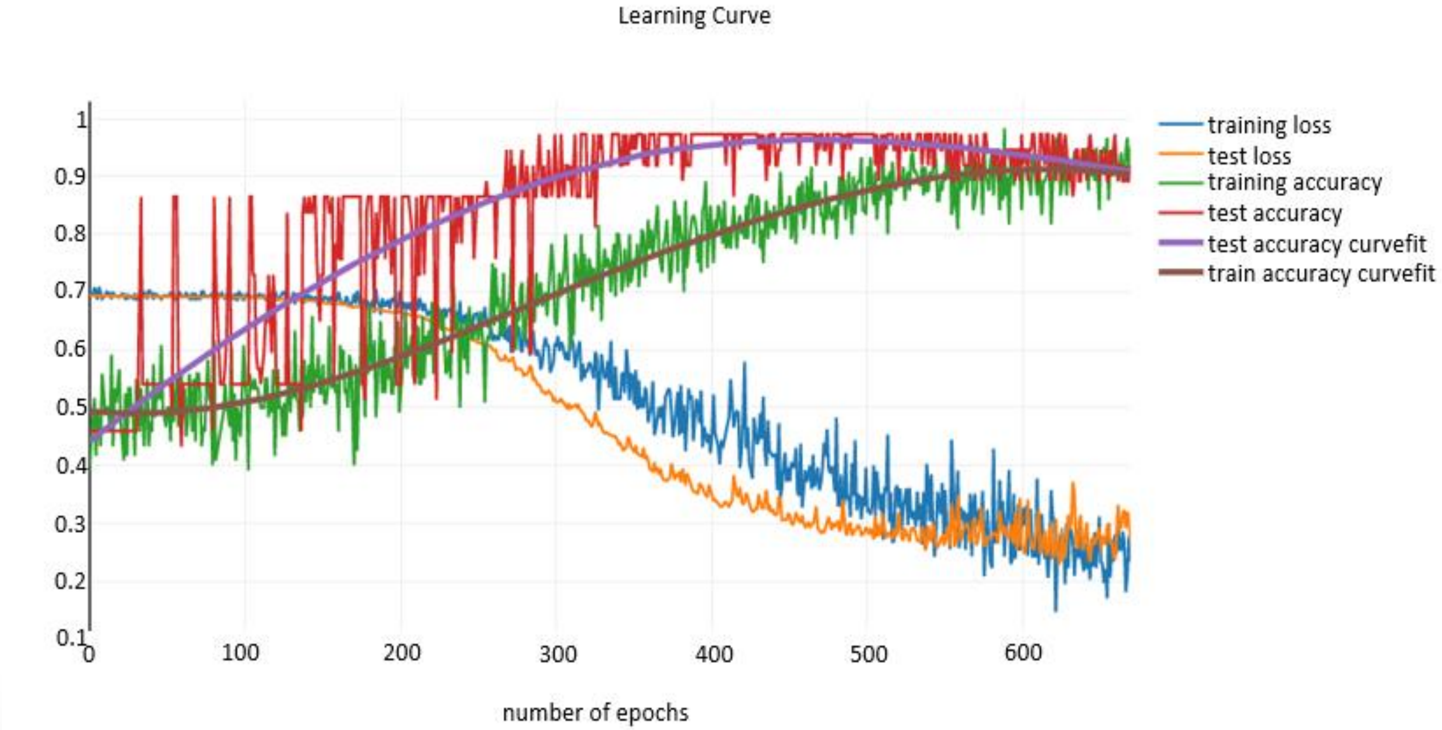


Figure 17: The learning curve of the prediction model

Results and Verification

- Confusion matrix for the developed chatter detection model is shown in Fig. 18. These matrices show true-positives (TP), false-negatives (FN), false-positives (FP) and true-negatives (TN) separately

- In training dataset; 50 samples are predicted as stable out of 51 stable samples and 54 samples are predicted as unstable out of 59 unstable samples.

- In test dataset; 14 samples are predicted as stable out of 17 stable samples and all unstable samples are predicted correctly.

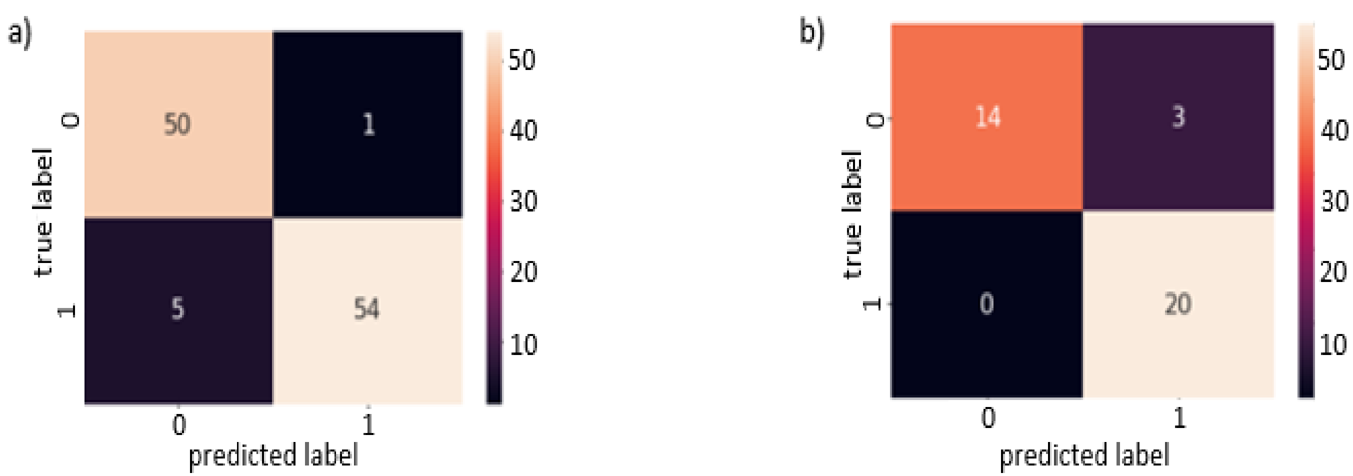


Figure 18: Confusion matrix a) Training predictions b) Test predictions

Results and Verification

- Receiver Operating Characteristic Area Under Curve (ROC-AUC) is shown in Fig. 19.

- Area under the curve is obtained as 0.98 which has a maximum value of 1.0.

- This ROC-AUC indicates that separation of probability distributions of the predictions is nearly ideal which means that predictions are perfectly distinguishable between stable and unstable.

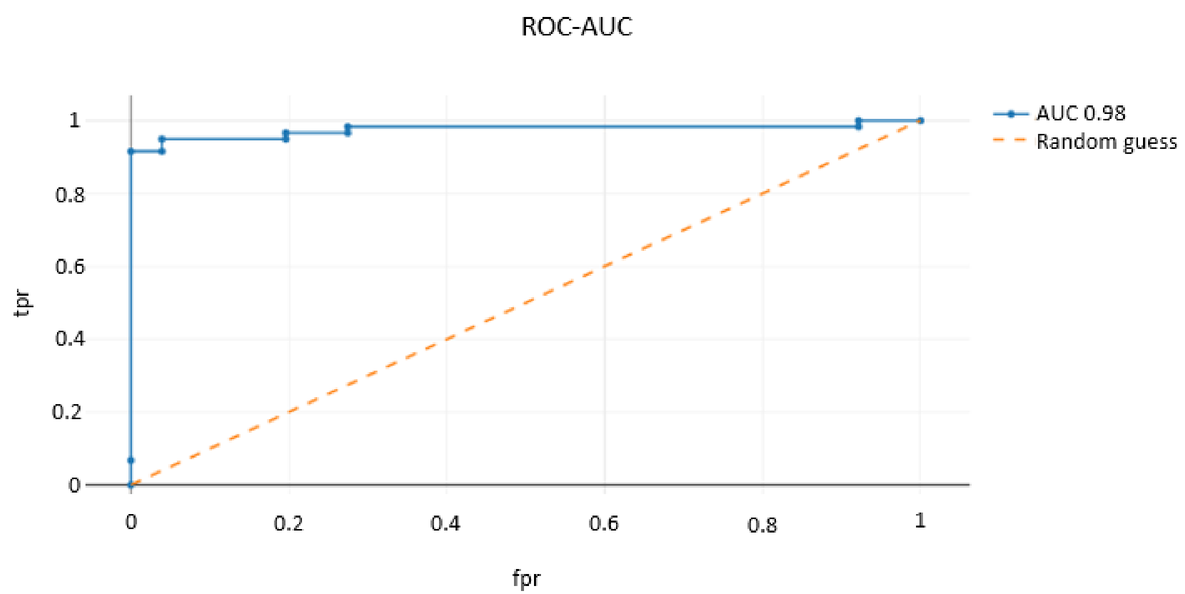


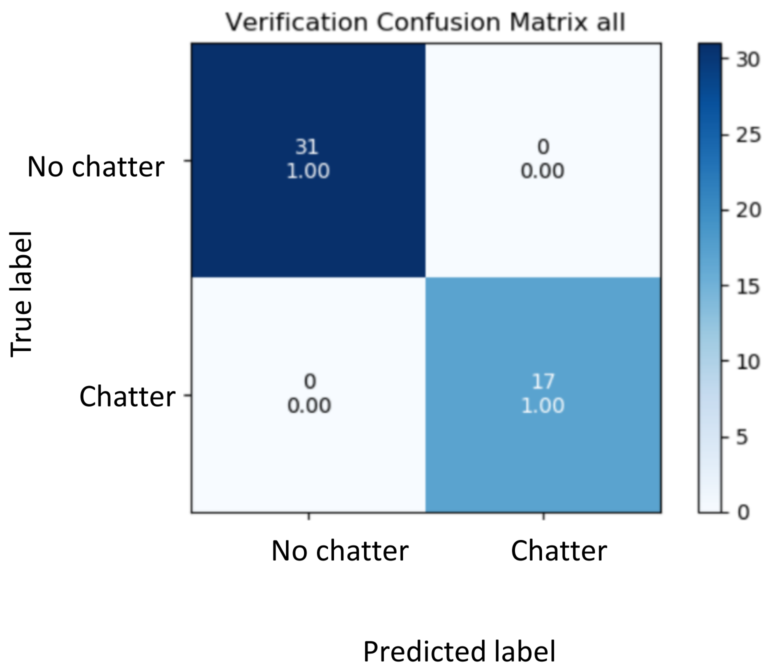
Figure 19: Receiver Operating Characteristic Area Under Curve (ROC-AUC)

Results and Verification

- After the results were obtained, verification cut were conducted with 6 different input parameters.
- A total of 48 data is labeled according to chatter detection analysis and given to the CNN model in verification step.
- During the cut acoustic emission data is collected and chatter is analyzed with the afforementioned methdod.
- True labels are identified according to the chatter detection analysis and compared with the CNN results. CNN algorithm pedicted all the labels correctly.

Table 2: Verification test results

Experiment No:	**Input Parameters**		**True Labels**	**CNN Results (%)**	
	Depth of Cut (mm)	Spindle Speed (rpm)		No chatter	Chatter
1	1	4000	No chatter	100	0
2	2	3300	No chatter	100	0
3	2	5400	No chatter	100	0
4	3	6300	Chatter	0	100
5	4	9500	Chatter	0	100
6	5	7500	Chatter	0	100



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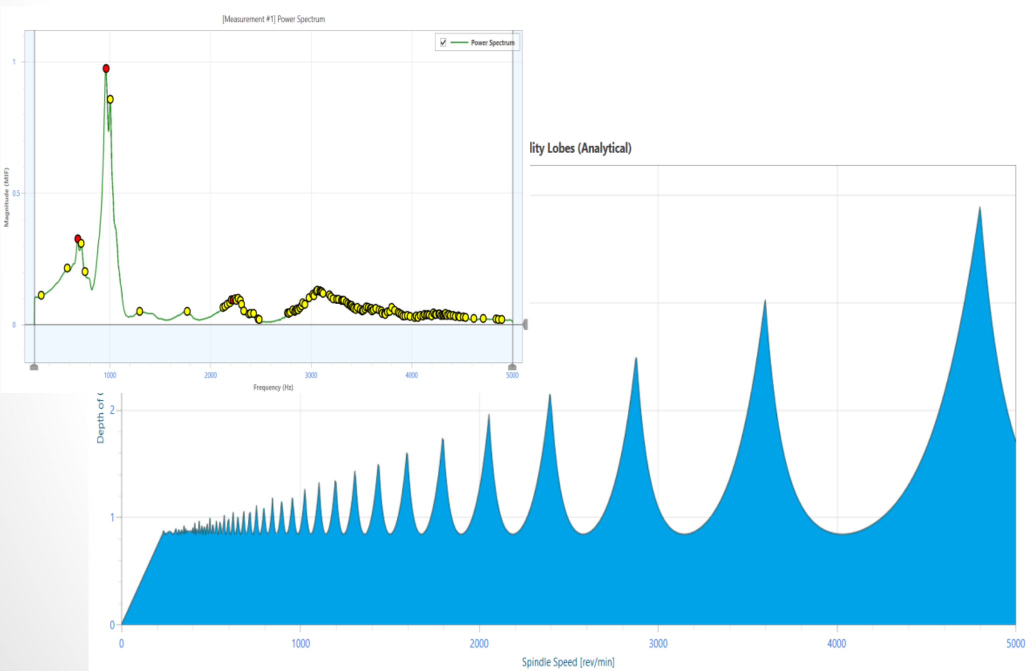
Conclusion

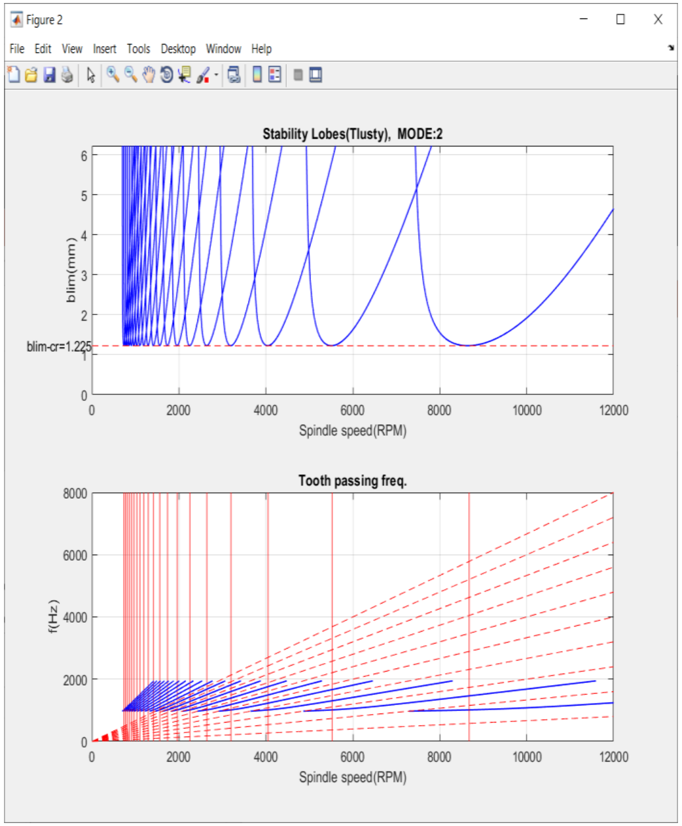
- In this study, a CNN based model that use AE data for chatter detection is developed.
- The time-series data converted into spectrograms because a CNN based model use image features. Afterwards, the spectrograms were labeled as stable and unstable in order to train CNN based prediction model for chatter detection.
- The CNN based estimation model developed in this study predicts stable and unstable situations with 92% accuracy, that proves promising results for further R&D study on machining using Deep Learning.

Ongoing and future works

- Chatter identification and classification based on stability lobes
- Detection of regenerative chatter with deep learning



Stability lobes (Cutpro^{TM} by MAL Inc.)



Stability lobes AISI304 (Tlusty method)

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