euspen's 24th International Conference & Exhibition, Dublin, IE, June 2024
www.euspen.eu

Artificial neural network-based tool condition monitoring of titanium alloy end mill process using time series data

Kangseok Kim[1], Miru Kim[2], Deugwoo Lee[1]

[1]Department of Nano Energy Engineering Pusan National University, Busan, Republic of Korea
[2]Dongnam Division, Korea Institute of Industrial Technology, Jinju, Republic of Korea

kimkng@pusan.ac.kr

Abstract

Titanium alloy, one of the representative difficult-to-machine materials, is light, has high high-temperature strength, and has excellent mechanical properties, so it is widely applied to major parts such as aviation and space. However, due to low thermal conductivity during cutting, a lot of heat is generated, so tool life is short and tool management is difficult. When machining titanium alloy, it is important to detect the condition of the tool and determine the appropriate replacement time when machining with one tool for a long time or when a large amount of machining is required. To monitor a tool during machining, it is necessary to measure signals generated during machining and find a way to determine the relationship between the condition of the tool and the machining signal. For this, it is useful to apply an AI-based analysis model. In this paper, a machining experiment of titanium alloy was conducted using an end mill tool with a diameter of 16mm to obtain the necessary data, and a monitoring system was created by attaching an acceleration sensor to the main axis of the machining equipment. In addition, tool wear was periodically measured using an optical microscope and used for data collection and tool condition analysis. In order to apply it to the AI-based analysis model, the signal from the acceleration sensor generated during processing was obtained as time series data. The acquired time series data was directly applied to an AI model combining CNN, LSTM, and MLP (Multi-Layer Perceptron) to train an AI model for multi-class classification that determines tool status according to signals generated during machining. Tool monitoring during the titanium alloy end mill process was performed and evaluated through an AI model learned using the acquired time series data.

End mill, Titanium alloy, Tool monitoring, AI model, Time series data

1. Introduction

Drilling and milling processes are among the oldest machining process that are still vastly practiced in the recent manufacturing industry. Modern machining sector has been establishing an effort in developing automated machines that are competent of precisely detecting tool defects to avert machining processes from continuously running with defected tools. A study disclosed that the manufacturing and production industries spend most of the whole operating costs on machine maintenance [1]. Estimating tool life is crucial, but challenging to be achieved and although tool manufacturer provides an estimated period of tool life [2], the information provided could not be fully relied on due to the fluctuation of tool lifespan [3], and implemented machining parameters.

Certain characteristics of the work materials such as low thermal conductivity, strong chemical reactivity with the cutting tool materials at high temperatures, and relatively low elastic modulus, make Titanium alloy as one of the difficult-to-cut materials [4]. The deformation or damage of the sharp edges of the cutting tool due to the interaction between the tool and the workpiece during machining is called tool wear. Deterioration of product quality due to tool wear and increase in product cost due to frequent tool replacement are major issues in machining difficult-to-cut-materials. In manufacturing, cutting tool failure increases costs and maintenance time and reduces production rates. When machining titanium alloy, it is important to detect the condition of the tool and determine the appropriate replacement time when machining with one tool for a long time or when a large amount of machining is required. To monitor a tool during machining, it is necessary to measure signals generated during machining and find a way to determine the relationship between the condition of the tool and the machining signal.

Signals obtained from sensors during processing are large amounts of complex time series data, making it difficult to find patterns. Therefore, in the case of time series data, machine learning is mainly used to process the data by characterizing it with a statistical model to find appropriate patterns and learn them. Deep learning, which even learns the process of recommending and selecting features from learning data, is suitable for real-time monitoring because it can be applied directly to time series data without characterizing it with a statistical model. Therefore, in this study, we designed deep learning models consisting of a combination of CNN MLP and CNN LSTM MLP, and examined the model's performance by directly applying time series data to the designed AI model. Vibrations generated during machine tool processing are measured using an acceleration sensor and analyzed using an AI-based analysis model to identify the relationship between the processing state of the machine tool and the tool condition. Signals that fluctuate according to the processing state of the machine tool were collected, and an AI model for multi-class classification was designed and evaluated by combining CNN, LSTM, and multi-layer perceptron (MLP).

2. Experiments

The machining experiment of titanium alloy (Ti-6Al-4V) was conducted using an end mill tool with a diameter of 16mm to obtain the necessary data, and a monitoring system was created by attaching an acceleration sensor (Kistler 8688A10) to the spindle of the machining equipment as shown in figure 1. A case for installing the accelerometer was manufactured and attached to the non-rotating part of the spindle with adhesive. NI-9234 and cDAQ-9178 were used for data acquisition, and the sampling rate was 20kHz. The cutting conditions (cutting speed: Vc, feed: fz, axial depth of cut: Ap, radial depth of cut: Ae) are showed in table 1. Side milling was applied as shown in figure 2(a), and figure 2(b) shows the state of the workpiece after processing. In addition, tool wear was periodically measured using an optical microscope and used for data collection and tool condition analysis.

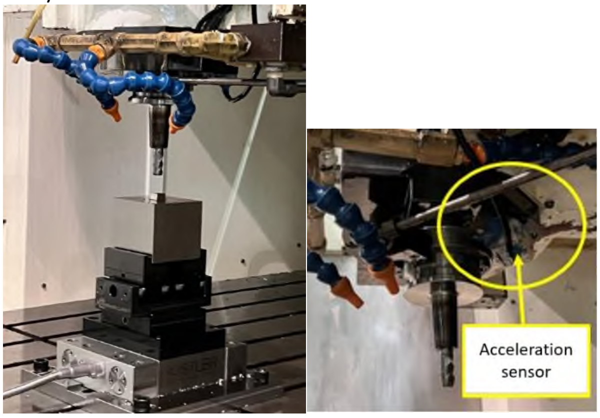
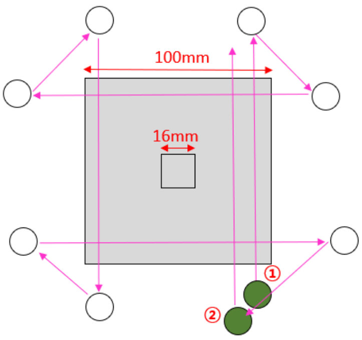


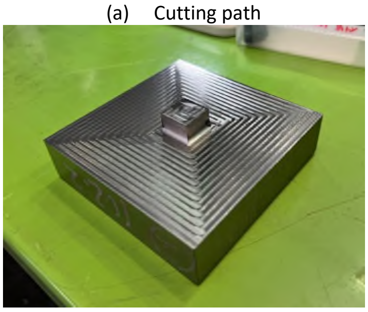
Figure 1. Experimental Set-up and installation of acceleration sensor

Table 1 Cutting conditions

Vc (m/min)	fz (mm/tooth)	Ap (mm)	Ae (mm)
80	0.1	5.0	3.0



(a) Cutting path



(b) Workpiece after cutting

Figure 2. Cutting path and workpiece after cutting

Figure 3 shows the signal of acceleration sensor and the relation between obtained signal and tool wear. In order to obtain processing characteristic signals according to tool wear, the tool states are classified into 6 categories such as no wear (first point), very light wear (second point), light wear (third point), moderate wear (fourth point), and severe wear(max. peak of the graph), and tool failure (fifth point).

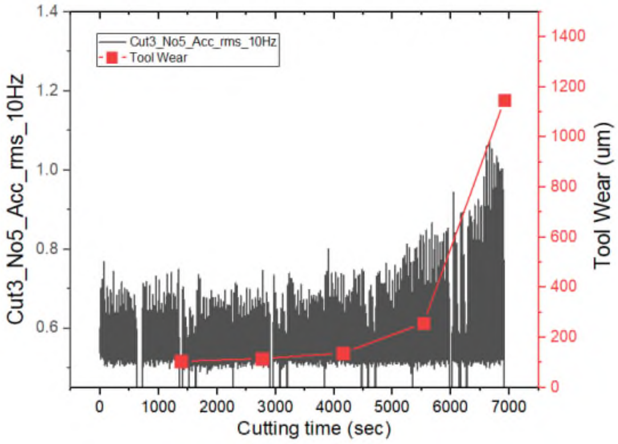


Figure 3. Data comparison between the signal of acceleration sensor and tool wear

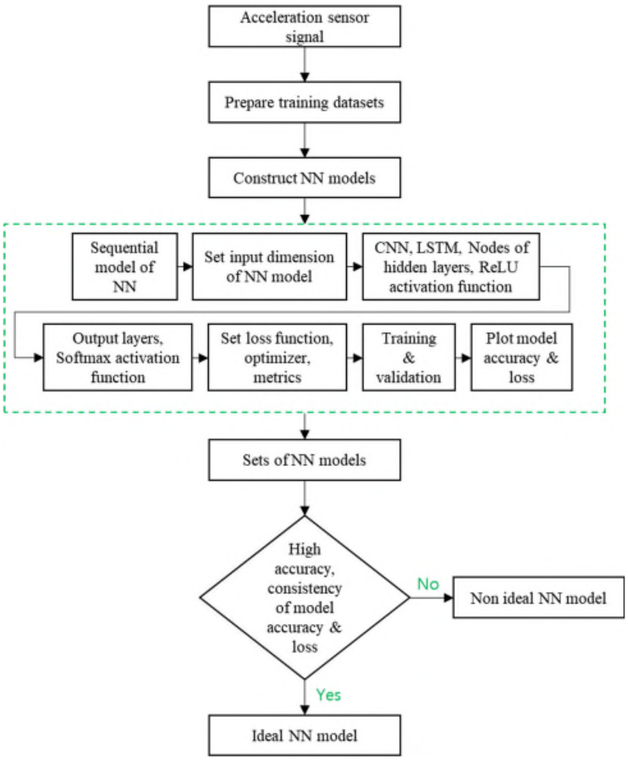


Figure 4. Flowchart of the signal analyzation through CNN LSTM MLP

3. Data analyzation methods

Recently, in the case of AI models that combine CNN (Convolution Neural Network) and LSTM (Long Short-Term Memory), there have been many reported cases of designing AI models with high accuracy and reliability by directly applying time series data to find the best features [5 - 6].

To analyze the state of the tool using the processing signal of the machine tool, we designed and trained an AI model for multi-class classification by combining CNN, LSTM, and multi-layer perceptron. The process of learning by applying acceleration sensor signals for each tool wear condition to the AI model is summarized in figure 4. A study was conducted to predict the tool wear by directly applying time series data to an AI model created using CNN and hybrid deep learning techniques, and various models combined CNN MLP and CNN LSTM MLP were reviewed.

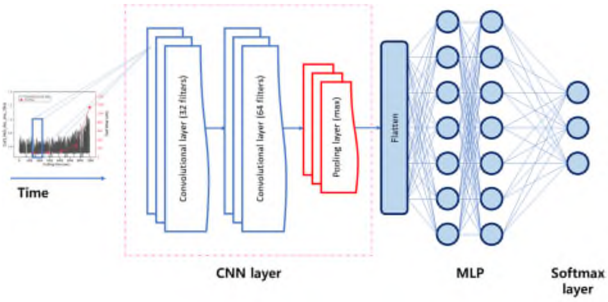


Figure 5. Architecture of CNN MLP for deep learning

Figure 5 and figure 6 show the structure of a model combining CNN MLP and CNN LSTM MLP. Figure 5 is the architecture of a model designed with an input layer, CNN layer, Dense layer, and output layer, and figure 6 is the architecture of a model designed with an input layer, CNN layer, LSTM layer, Dense layer, and output layer.

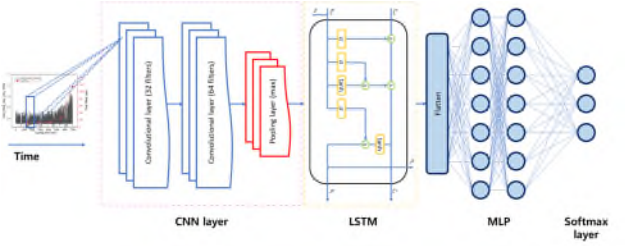
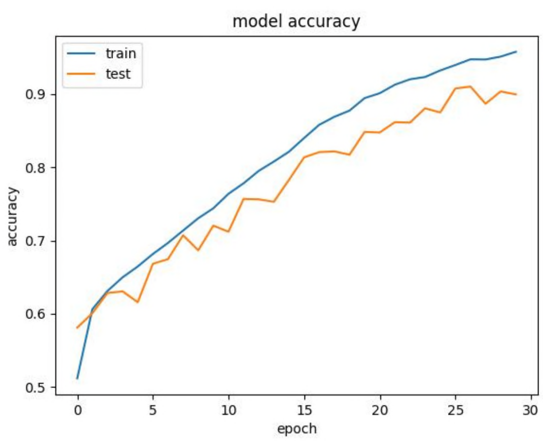


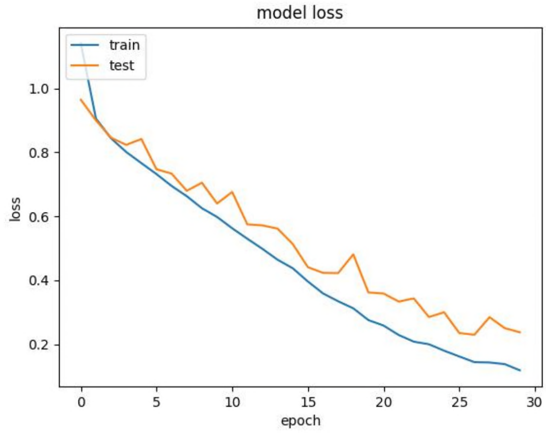
Figure 6. Architecture of CNN LSTM MLP for deep learning

4. Results and discussion

The learning curves composed of the model accuracies and losses of each CNN MLP architecture and CNN LSTM MLP architecture are presented in figure 7 and figure 9. The confusion matrix was plotted for each CNN MLP architecture and CNN LSTM MLP architecture, as shown in figure 8 and figure 10, based on the predicted and true labels for each tool condition. The evaluation metrics of the confusion matrix for each AI model is summarized in table 2. As a result of verifying the learned model with test data, the accuracy and evaluation indexes of CNN LSTM MLP architecture was higher than that of CNN MLP architecture. As a result of evaluating the AI model of CNN LSTM MLP architecture with test data, the accuracy was over 95% and the developed model was able to classify each data precisely based on the true label.



(a) Training score



(b) Model loss

Figure 7. Training score and model loss curve by test data (CNN MLP architecture)

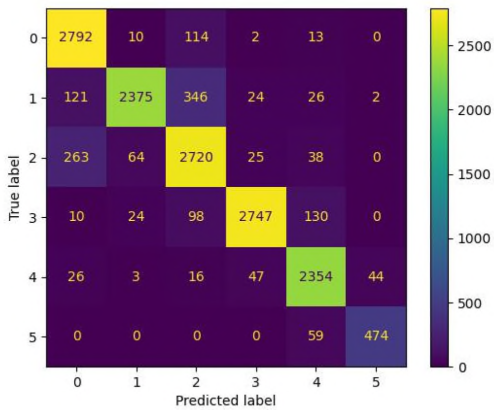
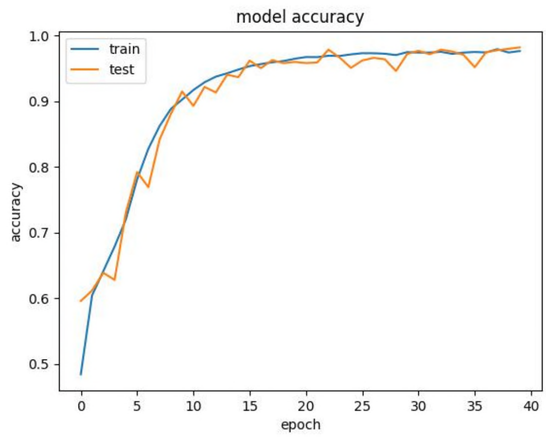
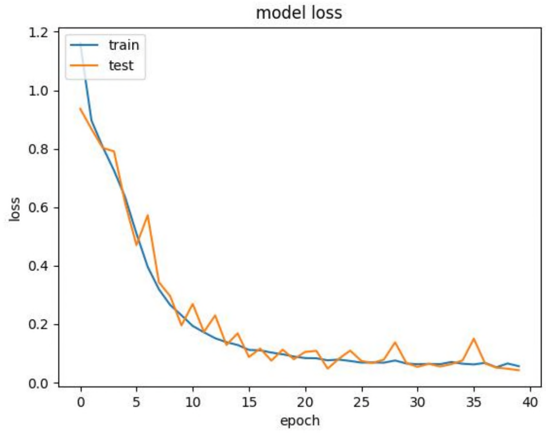


Figure 8. Confusion matrix of CNN MLP architecture plotted based on true and predicted data



(a) Training score



(b) Model loss

Figure 9. Training score and model loss curve by test data (CNN LSTM MLP architecture)

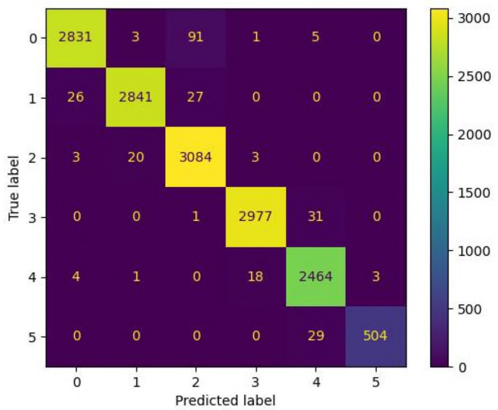


Figure 10. Confusion matrix of CNN LSTM MLP architecture plotted based on true and predicted data

Table 2 Evaluaiton metrics of the confusion matrix for each AI model

AI model	Macro precision (%)	Macro recall (%)	Macro F1-score (%)	Accuracy (%)
CNN + MLP	90	90	90	89.9
CNN + LSTM + MLP	98	98	98	98.2

5. Conclusion

In order to predict and monitor the state of the tool during processing of titanium alloys, an AI model for multi-class classification was designed and trained by combining CNN, LSTM and a multi-layer perceptron to analyze the state of a tool using processing signals of a machine tool. The performance of the AI model, which classifies the tool states into 6 categories.

To predict the tool wear by directly applying time series data obtained from acceleration sensors during machining to an AI model created using CNN and hybrid deep learning techniques, various models combined CNN MLP and CNN LSTM MLP were reviewed and evaluated. As a result of verifying the learned model with test data, the accuracy and evaluation indexes of CNN LSTM MLP architecture was higher than that of CNN MLP architecture. As a result of evaluating the AI model of CNN LSTM MLP with test data, the accuracy was over 95% and the tool state was successfully predicted. In the future, it is believed that collecting and analyzing more data can develop into predictive maintenance technology that can predict tool state abnormalities during processing.

Acknowledgment

This research was funded by "(Details2) AI-based high-reliability large vertical turning center" of the Ministry of Trade Industry and Energy (MOTIE), Korea (Grant No. 20021890).

References

[1] R.K. Mobley, 2002, An introduction to predictive maintenance, 2nd Edition, Elsevier. https://doi.org/10.1016/B978-0-7506-7531-4.X5000-3
[2] R. Heinemann, S. Hinduja. 2012 A new strategy for tool condition monitoring of small diameter twist drills in deep-hole drilling. International Journal of Machine Tools & Manufacture, 52, 69-76
[3] S. Soederberg, O. Vingsbo, M. Nissle. 1982 Performance and failure of high speed steel drills related to wear. Wear, 75, 123-143
[4] E.O. Ezugwu, Z.M. Wang, 1997 Titanium alloys and their machinability a review, Journal of Materials Processing Technology 68, 262-274
[5] G. Ercolano, S. Rossi, 2021, Combining CNN and LSTM for activity of daily living recognition with a 3D matrix skeleton representation, Intel Serv Robotics, 14, 175–185. https://doi.org/10.1007/s11370-021-00358-7
[6] A. Borré, L.O. Seman, E. Camponogara, S.F. Stefenon, V.C. Mariani, L.d.S. Coelho, 2023, Machine Fault Detection Using a Hybrid CNN-LSTM Attention-Based Model, Sensors, 23(9), 4512. https://doi.org/10.3390/s23094512