Predicting Surface Roughness in Titanium Alloy Milling Machining Through Tool Wear Images

Hariyanto Gunawan
Department of Mechanical Engineering
Chung Yuan Christian University
Taoyuan, Taiwan
e-mail: harrywey@cycu.edu.tw

AM Mufarrih
Department of Mechanical Engineering
Chung Yuan Christian University
Taoyuan, Taiwan
e-mail: mufarrih@polinema.ac.id

Chi-Min Chang
Department of Mechanical Engineering
Chung Yuan Christian University
Taoyuan, Taiwan
e-mail: jimmy21262353122385@gmail.com

Zheng-Xin Su
Department of Mechanical Engineering
Chung Yuan Christian University
Taoyuan, Taiwan
e-mail: aa891119@gmail.com

***Abstract*—This study presents a deep learning-based approach to predict surface roughness in the Computer Numeric Control (CNC) milling of Ti-6Al-4V, integrating You Only Look Once (YOLO)v7 for tool wear detection with Long Short-Term Memory/Bidirectional Long Short-Term Memory (LSTM/BiLSTM) for time-series prediction. Images of tool wear are analyzed to extract wear features, which are combined with machining parameters to forecast surface roughness. Experiments were conducted on a vertical milling machine to confirm the effectiveness of the model. YOLOv7 achieved a wear detection accuracy of 92.4%, while BiLSTM attained a prediction of 82.61%, outperforming traditional LSTM. The proposed system offers a reliable solution for intelligent tool condition monitoring and machining quality control.**

Keywords-YOLOv7; BiLSTM; tool wear; surface roughness.

I. INTRODUCTION

In modern manufacturing industries, titanium alloys are widely used in aerospace, biomedical, and marine engineering due to its strength and corrosion resistance [1]. Machining Titanium alloy (Ti-6Al-4V) poses significant challenges, including rapid tool wear because its high hardness, low thermal conductivity, and chemical reactivity. Tool wear significantly impacts surface roughness, influencing dimensional accuracy and production costs [2-4]. Traditional methods to monitor tool wear and surface roughness are offline, time-consuming, and lack predictive capabilities [5]. In recent years, incorporating Artificial Intelligence (AI) and Internet of Things (IoT) has further enhanced the intelligence system of CNC [6]

To address these challenges, this study proposes a hybrid approach that combines vision-based tool wear detection using YOLOv7 with LSTM/BiLSTM based time-series prediction of surface roughness. By integrating machine vision and deep learning, the system aims to provide real-time monitoring and prediction, ultimately supporting process optimization in smart manufacturing.

The structure of this paper is as follows: In section 2, we describe the methodology used, including data collection, preprocessing, and model design. Section 3 presents the experiment design and results. Also, the discussion of the findings and comparative analysis with prior work. Finally, Section 4 concludes the paper and outlines future directions.

II. METHODOLOGY

The proposed framework consists of image acquisition, wear detection, data preprocessing, predictive modeling, and performance evaluation. (1) Tool wear detection. TiAlN-coated tungsten carbide end mills are used for milling Ti-6Al-4V under eight combinations of process parameters (defined via Taguchi L8 orthogonal array). After each trial, the tool wear is examined using a SUPEREYES B008 digital microscope. (2) YOLOv7 model [7]. Tool wear images are annotated into wear and tool regions. YOLOv7 is trained to detect and classify wear into five levels based on the wear area ratio. The tool wear score is calculated as the wear area percentage of the total tool face. (3) Surface roughness measurement. Surface roughness (Ra) is measured at five fixed points on each machined surface using a FBT-650 surface roughness tester. The average Ra is used for model training. (4) Data integration and modeling. The wear scores, tool diameters, spindle speeds, feed rates, and cutting depths form the input features. LSTM and BiLSTM models are trained using 80% of the dataset, while the remaining 20% is used for testing. (5) Model evaluation. Performance is assessed using Mean Absolute Percentage Error (MAPE), accuracy rate, and model loss.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental framework of this study is illustrated in Figure 1. The experiment is structured using the Taguchi L_8 orthogonal array to test four factors at two levels: tool

Courtesy of IARIA Board and IARIA Press. Original source: ThinkMind Digital Library https://www.thinkmind.org

Copyright (c) IARIA, 2025. ISBN: 978-1-68558-286-9

diameter 3 and 4 mm; spindle speed 3000 and 5000 rpm; feed rate 247 and 300 mm/min; depth of cut 0.5 and 1 mm. Each condition is repeated three times, producing 24 samples. Tool wear image and surface roughness values are recorded for each trial. Figure 2 shows the bounding box and label of the tool and Not Good (NG) for wear characteristics.

The trained YOLOv7 model successfully identifies tool and wear regions with an overall classification accuracy of 92.4%. Five wear grades were established based on wear score distribution (2.1 to 4.9%). Figure 3 shows an example of tool wear level 5 (4.9%). The confusion matrix showed high performance with a precision of 95% and a recall of 93%.

The LSTM model achieved a peak test accuracy of 77.12%, while BiLSTM outperformed it with an accuracy of 82.61%. Figures 4 and 5 show the LSTM and BiLSTM prediction accuracy. The BiLSTM model also exhibited better convergence with a smoother loss curve and lower final error (MSE ≈ 0.005) as shown in Figure 6. The use of bidirectional processing helps capture temporal dependencies more effectively. Taguchi analysis of signal-to-noise (S/N) ratios revealed that feed rate and tool diameter have the greatest impact on Ra. Lower feed (247 mm/min) and smaller tool diameter (3 mm) result in lower surface roughness, as shown in Figure 7.

The results affirm the efficacy of combining vision-based tool wear detection with time-series prediction. BiLSTM is notably superior due to its dual-directional processing, making it suitable for capturing complex temporal features in tool wear evolution. Lower feed rate and shallow depth of cut help maintain surface quality. The approach reduces reliance on offline inspection and enhances adaptive process control.

IV. CONCLUSIONS

This study presents a hybrid intelligent framework that integrates computer vision and deep learning for predictive surface roughness analysis in CNC milling of Ti-6Al-4V. The YOLOv7 model effectively detects and quantifies tool wear, while BiLSTM excels in forecasting surface quality using historical and real-time data. The results validate the models' capability in capturing temporal dependencies and supporting data-driven decision-making in manufacturing. Future work may explore adaptive control and real-time integration with CNC systems.

REFERENCES

[1] Q. Zhao and Q. Sun, "High-strength titanium alloys for aerospace engineering applications: A review on melting-forging process," Mater. Sci. Eng. Vol. 845, pp. 143260-1432642, 2022.

[2] P. M. Huang and C. H. Lee, "Estimation of tool wear and surface roughness development using deep learning and sensors fusion," Sensors. Vol 21(16), pp. 5338-5359, 2021.

[3] R. Kang, H. Ma, Z. Wang, Z. Dong, and Y. Bao, "Effect of tool wear on machining quality in milling Cf/SiC composites with PCD tool," J. Manuf. Process. Vol. 105, pp. 370-385, 2023.

[4] H. Demirpolat, R. Binali, A. D. Patange, S. S. Pardeshi, and S. Gnanasekaran, "Comparison of tool wear, surface roughness, cutting forces, tool tip temperature, and chip shape during sustainable turning of bearing steel," Materials. Vol. 16(12), pp. 4408-4421, 2023.

[5] Q. Wang, H. Wang, L. Hou, and S. Yi, "Overview of tool wear monitoring methods based on convolutional neural network," Appl. Sci. Vol. 11(24), pp. 12041-12063, 2021.

[6] S. Du, "Analysis of the application of intelligent CNC technology in machinery manufacturing," J. Phys. Conf. Ser. Vol. 2649, pp. 012010-012014, 2023.

[7] L. Zhao and M. Zhu, "MS-YOLOv7: YOLOv7 based on multi-scale for object detection on UAV aerial photography," Drones Vol. 7(3), pp. 188-205, 2023.

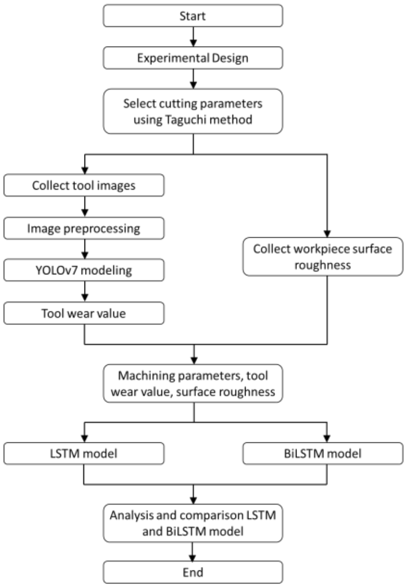

Figure 1. Research workflow

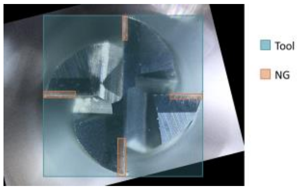

Figure 2. YOLOv7

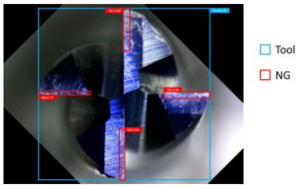

Figure 3. Tool wear level 5 (4.9%)

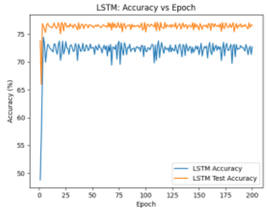

Figure 4. LSTM model accuracy

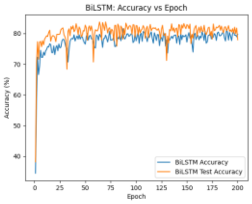

Figure 5. BiLSTM model accuracy

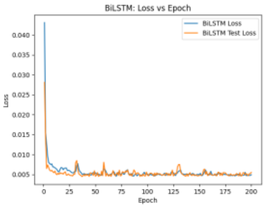

Figure 6. BiLSTM model loss

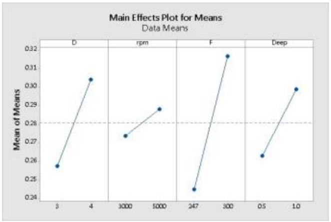

Figure 7. Main effect of surface roughness

Courtesy of IARIA Board and IARIA Press. Original source: ThinkMind Digital Library https://www.thinkmind.org

Copyright (c) IARIA, 2025. ISBN: 978-1-68558-286-9