Title

Abstract

Keywords：Frequency Selective Surface Polarization Insensitivity Three-layer Composite Structure

1 Introduction

The advent of deep learning has revolutionized numerous fields of science and technology, offering groundbreaking approaches in data analysis and problem-solving. In the realm of biomedical engineering, one of the critical challenges is the precise analysis of biological tissue slices. These analyses are crucial for various applications, ranging from medical diagnostics to research in pathology. Concurrently, in the domain of material science, assessing the wear and tear of cutting blades used in tissue slicing is pivotal for maintaining the integrity and accuracy of these analyses. This paper presents a novel approach, employing deep learning techniques, to address these intertwined challenges.

Deep learning, a subset of machine learning, excels in recognizing patterns and making predictions based on large datasets. This capability makes it an ideal candidate for interpreting complex biological structures and assessing tool wear, which are often nuanced and multifaceted in nature. In this study, we explore the potential of deep learning algorithms to predict the condition of biological tissue slices. This prediction is not only vital for the quality of biomedical analysis but also serves as an indicator of the cutting blade's condition. Worn or damaged blades can adversely affect the integrity of tissue samples, leading to inaccuracies in subsequent analyses.

Our approach utilizes convolutional neural networks (CNNs), a type of deep learning algorithm particularly adept at processing visual imagery, to analyze images of tissue slices. The CNNs are trained to detect subtle changes and anomalies in the tissue samples that are indicative of blade wear. By integrating this analysis with a predictive model for blade degradation, our method offers a dual benefit: enhancing the precision of tissue analysis and providing a predictive maintenance tool for the cutting equipment.

This paper details the development of this deep learning model, its training process, and the validation of its effectiveness. The results demonstrate not only the feasibility of using deep learning in this context but also its potential to significantly improve the accuracy and reliability of biological tissue analysis and cutting blade maintenance in biomedical settings.

2 Background and literature review

Deep Learning in Biological Tissue Analysis

Recent Developments: Deep learning, a subset of machine learning, has significantly transformed the way biological images are analyzed and interpreted. This transformation is underpinned by a collection of algorithms capable of deciphering the content of images, which is especially pertinent in cellular image analysis.[1]

Key Applications: The field has seen progress in various applications like image classification, segmentation, object tracking, and augmented microscopy. These advancements have rendered complex analyses more routine and enabled the execution of experiments that were previously impossible.[2]

Deep Learning in Material Science for Tool Wear Assessment

Industry Revolution: Deep learning has revolutionized the field of materials degradation by providing robust methods to interpret large quantities of data, crucial for detecting and modeling material deterioration.[3]

Detection Techniques: The detection of degradation in materials like steel, concrete, and composites is essential to prevent failure and ensure safety. This includes both direct detection methods (like visual inspection for corrosion or cracks) and indirect methods (like ultrasonic testing)[4]

3 Preliminary Work

3.1 Subsection 3.1

3.2 Subsection 3.2

4 Project plan, methodology and management

4.1 Subsection 4.1

4.2 Subsection 4.2

References

[1] Moen, E., Bannon, D., Kudo, T., Graf, W., Covert, M., & Van Valen, D. (2019). Deep learning for cellular image analysis. Nature Methods, 16(12), 1233-1246. https://doi.org/10.1038/s41592-019-0403-1

[2] Moen, E., Bannon, D., Kudo, T., Graf, W., Covert, M., & Van Valen, D. (2019). Deep learning for cellular image analysis. Nature Methods, 16, 1233-1246. Available at: https://www.nature.com/articles/s41592-019-0403-1.

[3] Nash, W., Drummond, T. & Birbilis, N. (2018). A review of deep learning in the study of materials degradation. npj Materials Degradation, 2, Article number: 37. Available at: https://www.nature.com/articles/s41529-018-0058-x

[4] Nash, W., Drummond, T. & Birbilis, N. (2018). A review of deep learning in the study of materials degradation. npj Materials Degradation, 2(1). Available at: https://www.nature.com/articles/s41529-018-0058-x

5 Example

This section includes some examples that are not commonly used

5.1 Enumerate

1. 1
2. 2
3. 3
4. 4

itemize

- 1
- 2
- 3
- 4

5.2 Table

5.2.1 Tables side by side

Table 5.1 Difference of Mild Steel

Loading	Difference	Difference rate
50N	0.01906 mm	16.5681%
100N	0.03803 mm	16.5298%
150N	0.05709 mm	16.5426%
Average		16.55%

Table 5.2 Difference of Alminium

Loading	Difference	Difference rate
50N	0.03944 mm	12.1856%
100N	0.07887 mm	12.1839%
150N	0.11831 mm	12.1845%
Average		12.18%

5.2.2 General table

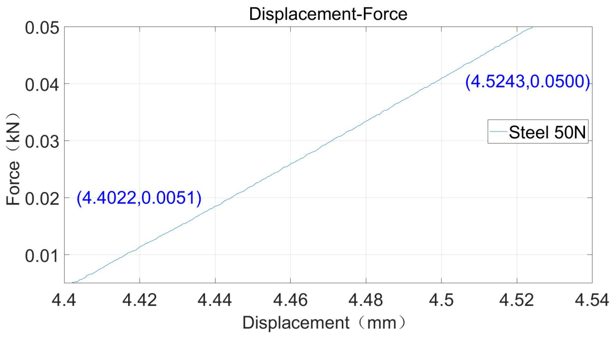
Table 5.3 The value of C_L

Value\Degree	0	5	10	15	17.5	20	22.5	25
C_L	0.034	-0.378	-0.658	-0.892	-0.954	-0.747	-0.717	-0.702

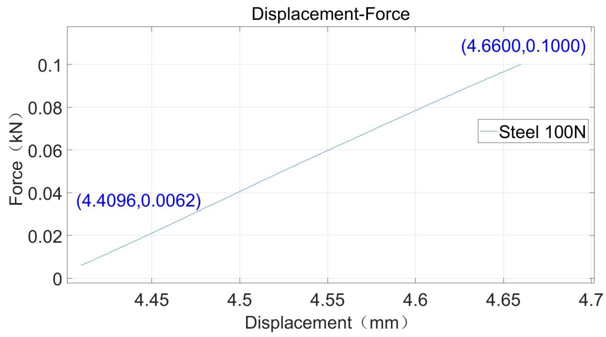
5.3 Picture

5.3.1 Pictures side by side

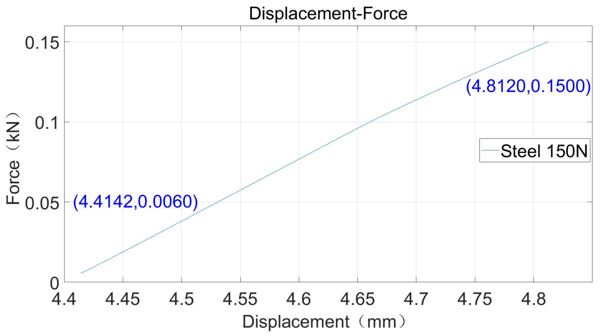
Images side-by-side, each with its own subheading but sharing large headings and tags



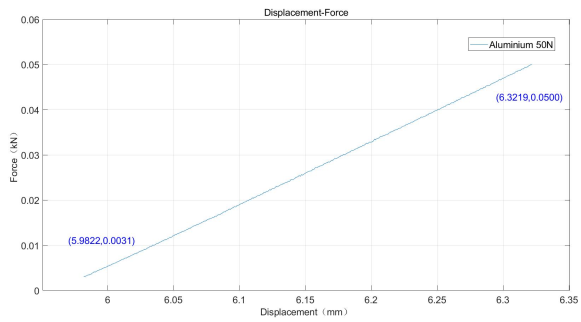
(a) 50N loading Mild Steel



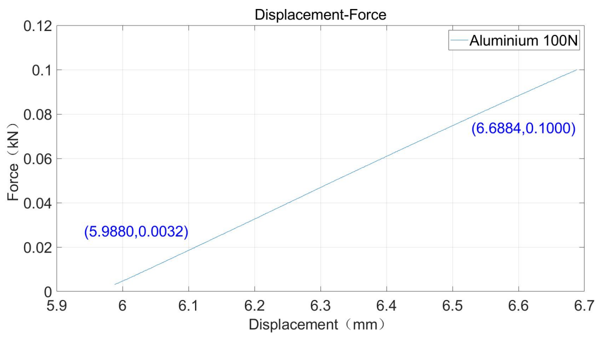
(b) 100N loading Mild Steel



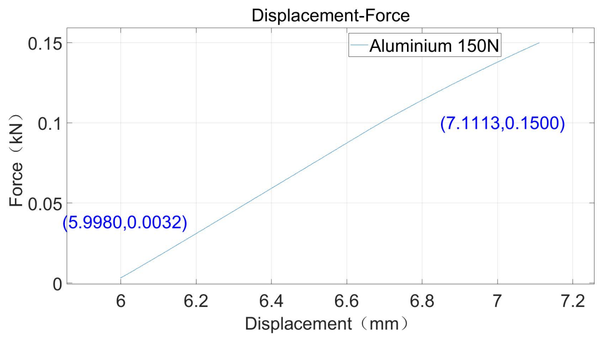
(c) 150N loading Mild Steel



(d) 50N loading Aluminium



(e) 100N loading Aluminium



(f) 150N loading Aluminium

Figure 5.1 Results of experiments with Steel and Aluminium

5.3.2 picture name adjust

Table 2.1 Result of the maximum bending displacements

Bending Displacement	Mild Steel	Aluminium
δ_{AN_1} (P = 50 N)	0.1341 mm	0.3631 mm
δ_{AN_2} (P = 100 N)	0.2681 mm	0.7262 mm
δ_{AN_3} (P = 150 N)	0.4022 mm	1.0893 mm

5.4 Equation

Editing by Axmath or python pix2tex (cmd input latexocr if you have been install pix2tex in your system)

$$\begin{cases} \delta_{An\_1} = \frac{P_{50N}L^3}{48E_sI} = \frac{50\times0.1^3}{48\times172.6698\times10^9\times4.5\times10^{-11}} = 0.1341\times10^{-3}m \\ \delta_{An\_2} = \frac{P_{100N}L^3}{48E_sI} = \frac{100\times0.1^3}{48\times172.6698\times10^9\times4.5\times10^{-11}} = 0.2681\times10^{-3}m \\ \delta_{An\_3} = \frac{P_{150N}L^3}{48E_sI} = \frac{150\times0.1^3}{48\times172.6698\times10^9\times4.5\times10^{-11}} = 0.4022\times10^{-3}m \end{cases} \quad (5.1)$$