The Property Prediction of Metal Additive Manufacturing Products with Textural Features Extraction based on Machine Learning

Lien-Kai Chang [1,2†], Ri-Sheng Chen [2†], Mi-Ching Tsai [1,2†], Rong-Mao Lee [5†], Ching-Chih Lin [2†], Jhih-Cheng Huang [1,2†], Tsung-Wei Chang [1,2] , Ming-Huwi Horng [3,4*]

[1] Electrical Motor Technology Research Center, National Cheng Kung University, Tainan 700, Taiwan

[2] Department of Mechanical Engineering, National Cheng Kung University, Tainan 700, Taiwan

[3] Department of Computer Science and Information Engineering, National Cheng Kung University, Tainan 700, Taiwan

[4] Academy of Innovative Semiconductor and Sustainable Manufacturing, National Cheng Kung University, Tainan 700, Taiwan

[5] Department of Intelligent Automation Engineering, National Chin-Yi University of Technology, Taichung 411, Taiwan

[*]Corresponding author(s). E-mail(s): horng@mail.ncku.edu.tw;

Metal additive manufacturing (AM) has been increasingly applied across various industries, including healthcare, manufacturing, and aerospace, owing to its advantages in customization and rapid production. However, acquiring accurate product properties necessitates repetitive and time-consuming measurements, which risk damaging the product. Thus, there is a pressing need to develop automated mechanisms to predict product properties. In this study, to forecast these properties, we developed details related to metal additive manufacturing products, encompassing both the process parameters and textural features. These texture features were extracted from layer-by-layer images using the three dimensional gray-level co-occurrence matrix (GLCM) and selected powerful features. Subsequently, we employed machine learning (ML) models, such as logistic regression, support vector regression (SVR), XGBoost, and LightGBM, to predict product properties and compare their performances. The experimental results reveal a strong correlation between process parameters and certain textural features with product properties. It highlights a notably higher correlation for three-dimensional textural features compared to two-dimensional ones. Additionally, the models exhibit high predictive accuracy, especially XGBoost, and LightGBM achieve R2 scores approaching 0.9 for all properties. These findings highlight the superiority and feasibility of the proposed approach. Moreover, this proposed approach holds promise in accurately predicting diverse product properties, meeting the demands of multiple application contexts.

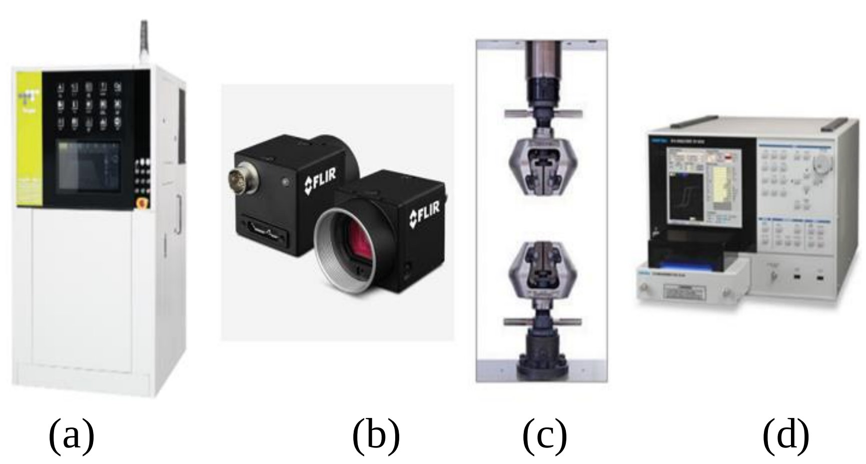

Fig. 1 Experimental equipment. **a** AMP-160. **b** BFS-U3-200S6M-C. **c** MWG-100KNA. **d** SY-8219.

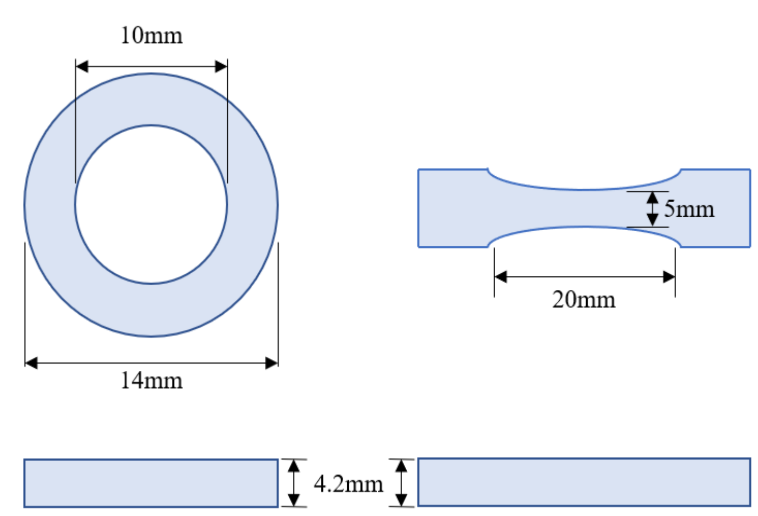

Fig. 2 Experimental items. **a** Ring specimen. **b** Tensile specimen.

Table 1 Specified ranges of SLM parameters

SLM parameters	Range
Oxygen concentration (ppm)	0 ~ 6,000
Laser power (W)	150 ~ 250
Scanning speed (mm/s)	300 ~ 1,000
Layer Thickness (mm)	0.05 ~ 0.2
Energy density (J/mm³)	25 ~ 200

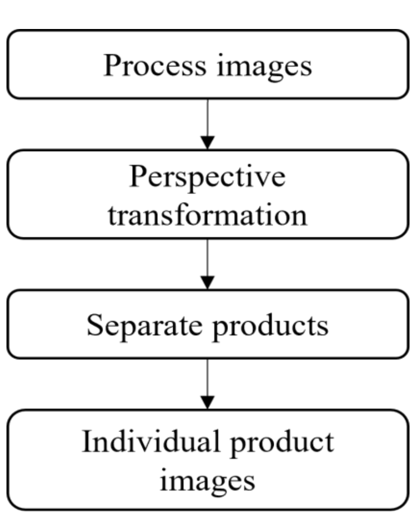

Fig. 3 Process of separating workpieces

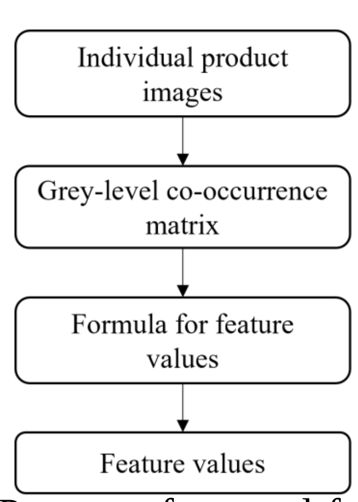

Fig. 4 Process of textural features transformation.

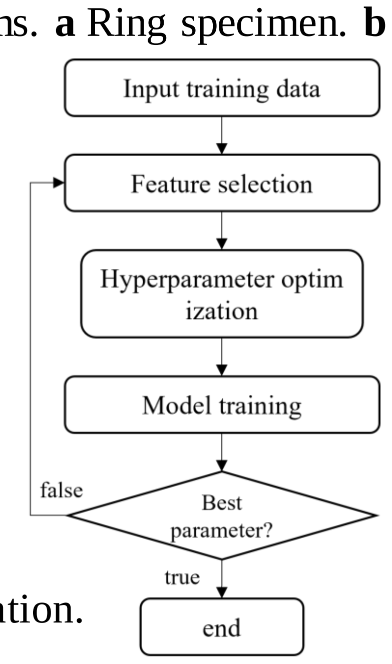

Fig. 5 Process of training model.

Table 2 Influence of neighboring images

R^2 score	XGBoost		LightGBM		SVR		Linear	
2D/3D	2D	3D	2D	3D	2D	3D	2D	3D
Tensile strength	0.92	0.93	0.93	0.93	0.93	0.93	0.74	0.77
Magnetic permeability								
50 Hz	0.94	0.93	0.93	0.94	0.92	0.92	0.72	0.77
200 Hz	0.88	0.88	0.85	0.88	0.83	0.86	0.72	0.77
400 Hz	0.92	0.92	0.91	0.92	0.87	0.91	0.71	0.78
800 Hz	0.91	0.91	0.92	0.92	0.91	0.91	0.66	0.73
Iron loss								
50 Hz	0.94	0.96	0.95	0.96	0.93	0.96	0.74	0.77
200 Hz	0.95	0.96	0.95	0.95	0.93	0.94	0.72	0.75
400 Hz	0.95	0.96	0.95	0.96	0.94	0.95	0.75	0.77
800 Hz	0.95	0.96	0.96	0.96	0.93	0.95	0.77	0.80

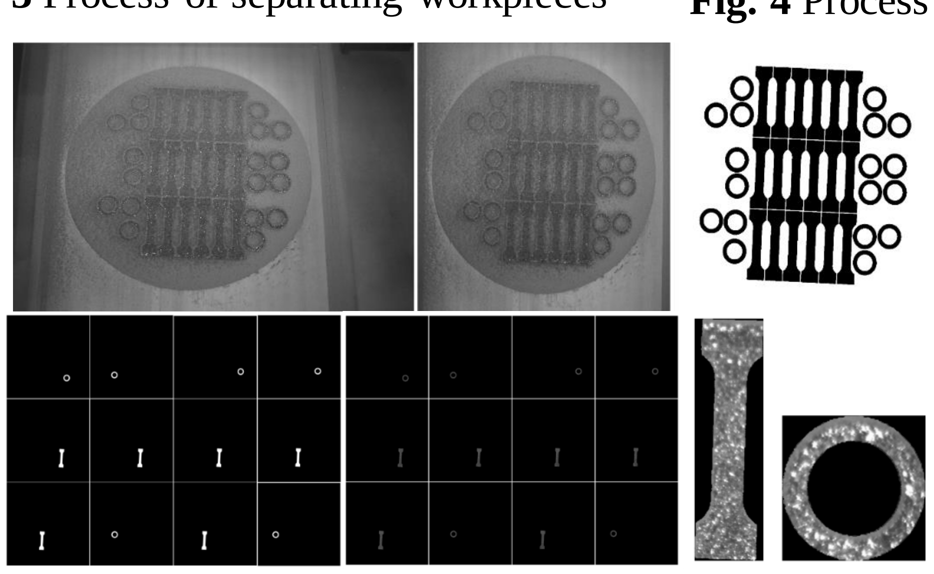

Fig. 6 Separate workpieces. **a** Original process image. **b** Image post-perspective transformation. **c** Mask image. **d** Mask image post-edge detection. **e** Image post-logical operation. **f** Layer-by-layer image of the tensile specimen. **g** Layer-by-layer image of the ring specimen.

Table 3 Influence of textural features

R^2 score	XGBoost		LightGBM		SVR		Linear	
Use textural features	No	Yes	No	Yes	No	Yes	No	Yes
Tensile strength	0.902	0.924	0.905	0.930	0.903	0.930	0.725	0.742
Magnetic permeability								
50Hz	0.917	0.940	0.916	0.937	0.903	0.920	0.707	0.727
200 Hz	0.851	0.882	0.835	0.850	0.819	0.831	0.703	0.721
400 Hz	0.902	0.924	0.893	0.919	0.852	0.877	0.702	0.719
800 Hz	0.896	0.918	0.906	0.927	0.908	0.911	0.630	0.669
Iron loss								
50 Hz	0.928	0.949	0.913	0.956	0.919	0.930	0.725	0.744
200 Hz	0.923	0.953	0.923	0.952	0.913	0.935	0.708	0.728
400 Hz	0.930	0.957	0.930	0.957	0.927	0.944	0.761	0.753
800 Hz	0.932	0.959	0.923	0.967	0.927	0.938	0.755	0.775