

Using Machine Learning to Identify Product Styles [†]

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Abstract: The Waikato Environment for Knowledge Analysis (WEKA), a machine learning tool, was used to develop a model to identify product styles, and the style of classic chairs was determined using the model. Data used to develop the model consisted of 100 images of four styles of chairs such as Windsor, Shaker, Thonet, and Ming. After pre-processing the images using the image filters of WEKA, the images were used to train the model to classify chair styles. The accuracy of the model ranged from 96 to 98%. This validated the performance of the proposed method in classifying the styles of chairs, which helps the design of new chairs.

Keywords: product style; image recognition; machine learning

1. Introduction

In the field of industrial design, the style of a product may vary depending on the design concept, material, and function [1]. For the ever-changing needs of consumers, designers are looking for inspiration for better product designs. The design industry has been inspired by the art and styles of the past [2]. Product style is important in the communication of consumers with designers, allowing consumers to understand the function of the product and the concept and meaning of the product design [3]. Therefore, designers need to choose the most appropriate and accurate product style to meet the consumer's needs. Product style is defined by the visual impressions affected by shape, line, and decoration [4]. Designers categorize styles based on experience by referring to relevant image recognition theories. The following are the relevant theories of image recognition.

- Feature-matching theory: Things or shapes have attributes or features that must be analyzed while considering the quality and quantity of the attributes [5].
- Shape recognition: If the pattern is identified for each component, the recognition of the whole pattern is required with generalization, which is a bottom-up processing of the feature comparison theory. If the pattern is identified by the overall pattern, each component can be identified. This process is called a top-down process of the template comparison theory [6].

Manual classification is not rational or sufficiently scientific to classify product styles. Therefore, machine learning (ML) is used for classification models in design. ML imitates the central nervous system of humans to learn multi-level concepts and has been applied to image, motion, and speech recognition [7]. Image processing with ML is used to identify colors and textures in images to determine features [8]. Those features are used with hue saturation value (HSV) extraction and the gray level co-occurrence matrix (GLCM) calculation [9]. In the manufacturing industry, the inspection of parts is important. Therefore, deep learning (DL) is used to learn the correct object image and identify defective products [10]. Davis stated that it was difficult to define the boundaries of images but that ML could be used to build a database for the classification of images [11].



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The recognition of the product style belongs to image recognition and concept classification [3]. Thus, ML can be used as a tool for the development of products and designs. In industrial design, the product style is determined according to the design concept, material, and function [1]. Thus, it is necessary for designers to accurately identify the product. The purpose of this study is to investigate whether Waikato Environment for Knowledge Analysis (WEKA) can be used as an effective method for the categorization of the product style. In this study, we used the designs of chairs to investigate the use of the WEKA model for the extraction of the features of the images. The model was trained to recognize and classify product styles. The result helps develop new products and their styles that are preferred by consumers.

2. Method

2.1. Chairs

There are a variety of design styles for chairs according to history, region, designer, or thought. Whether it is modern or classical; Chinese or European; or made of solid wood, steel, bamboo, or man-made materials, each style represents the history and design philosophy [4]. Therefore, the most representative and influential chairs were selected in this study. In the history of furniture, the Windsor chair represents the origin of the chair. For hundreds of years, throughout Europe and the United States, it has been used, and this has greatly contributed to the popularization of the chair [12]. Mr. Sanshiro Ikeda of Matsumoto Folk Art Furniture, who made the Windsor chair in Japan, said, “The Windsor chair is the ultimate chair [13]. This shows that the style of the Windsor chair really influenced the development of the chair in the future”.

After the Second World War, Wegner’s “The Chair”, with its organic curves from the back to the arms and legs made of teak wood, became a model of Danish organic design [14]. Hans Wegner designed more than 500 chairs in his lifetime, the most classic being the Chinese Chair designed in 1944. His design concept was inspired by the ancient tradition of Corinthian design, and he developed this, bringing the essence of the Chinese Ming-style circle chair [15]. The smooth lines show a deep Chinese flavor and foundation of the Ming-style chair. Shimazaki said that in the history of chairs, whenever a new material was developed, an epoch-making chair was introduced [16]. Therefore, in the case of chairs made of wood, the wood-bending technology developed by Thonet allows for a wider range of chair designs. It is even possible to produce a curved surface that conforms to the human body, and mass production is also possible. Thonet’s wood-bending technology developed the furniture manufacturing industry and influenced the furniture of future generations. Therefore, we selected the Windsor chair, the Thonet chair, the Ming chair, and the Shaker chair for this study.

2.2. Research Methodology

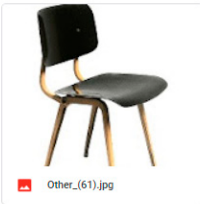
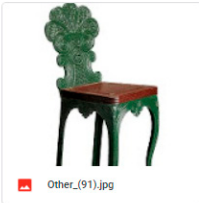
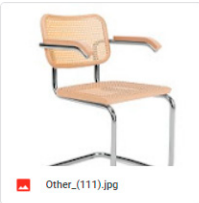
To use the WEKA model to identify the product style, appropriate images needed to be chosen for the model to learn. A total of 100 pictures of each style of the four chairs were collected as shown in Table 1. Categories were defined (Table 2) for the chairs that did not belong to these four styles to help the model detect the style of chairs accurately. The final database was imported into the data for learning. The styles of the chairs were classified into five categories (Figure 1).

In the first phase of this study, we identified the filter to extract the image features and the classifier to classify the recognized image features for ML. In the second phase, we investigated whether the proposed WEKA model classified the styles of chairs accurately. Table 3 shows the result of the classification of the chair style with different filters. The best accuracy was obtained with JpegCoefficientFilter. Compared with the other filters, the accuracy (95%) of JpegCoefficientFilter was higher with a lower absolute difference, which means that the stability of this filter was higher. The filter captured features by calculating quantile coefficients in the image that were not visible to humans. The absolute difference was the other way to verify the feature extraction.

Table 1. Four types of chair styles.

Images																
																
																
																
Chair	Shaker				Ming				Thonet				Windsor			

Table 2. Chairs not classified as these four styles.

Figures				
				
				
Chair	Other			

Selected attribute				
Name: class		Distinct: 5		Type: Nominal
Missing: 0 (0%)				Unique: 0 (0%)
No.	Label	Count		Weight
1	Ming	100		100
2	Other	110		110
3	Shock	110		110
4	Thonet	110		110
5	Windsor	110		110

Figure 1. Five categories for machine learning training.

Table 4 shows that the correctness of each classifier was similar, but the performance of SMO was significantly lower than the other classifiers in terms of failure rate and absolute difference. This indicated that SMO was more stable in classification.

Table 3. Accuracy of four methods with different image filters.

Filter	Function	Accuracy	Absolute Dispersion
BinaryPatterns PyramidFilter	Extraction of rotation-invariant numerical histograms of local binary patterns from images.	90%	25%
EdgeHistogramFilter	A filter for extracting MPEG7 boundary histogram features from pictures.	85%	37%
JpegCoefficientFilter	A batch filter for extracting JPEG coefficients from images	95%	11%
PHOGFilter	A filter for extracting the directional gradient histogram value PHOG from the image.	90%	26%

Table 4. Accuracy rates of the five methods with different classifiers.

Classifier	Success Rate	Failure Rate	Absolute Dispersion
SMO	98%	0.073	8%
J48	96%	0.097	16%
RandomForest	99%	0.096	19%
RandomComitee	99%	0.097	16%
RandomSubspace	99%	0.097	18%

The JpegCoefficientFilter filter and the SMO classifier were tested in the first phase for image recognition and the most stability. Then, they were tested in the second phase to classify the chair styles. The accuracy of the training was 100%, which implied that the WEKA model accurately learned the images (Figure 2).

Correctly Classified Instances	620	100	%						
Incorrectly Classified Instances	0	0	%						
Kappa statistic	1								
Mean absolute error	0.0625								
Root mean squared error	0.1749								
Relative absolute error	97.1721 %								
Root relative squared error	97.8816 %								
Total Number of Instances	620								
=== Detailed Accuracy By Class ===									
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Ming
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Other
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Shock
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Thonet
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Windsor

Figure 2. Numerical result of classification of five categories.

The chairs in Figure 3 were used to train the model for the prediction and classification of chair styles. The results are shown in Figures 3–5. Chairs 5, 6, 7, and 8 in Table 2 were classified as Ming style. Chair 9 was classified as a new style. This prediction was accurate because the WEKA model accurately classified chairs. The WEKA model can be used to classify other product styles without manual classification and the influence of subjectivity and uncertainty.

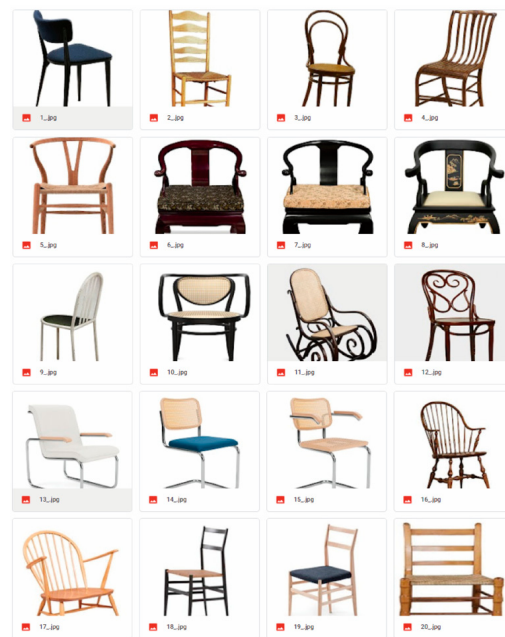


Figure 3. Random chair images.

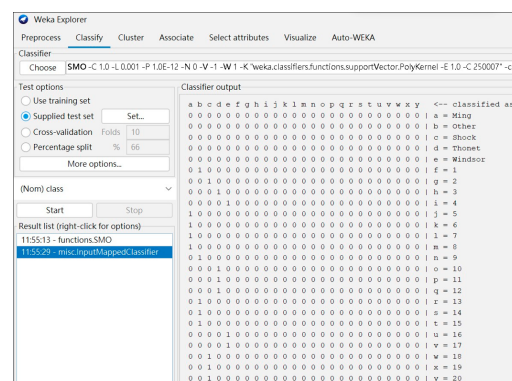


Figure 4. Classification matrix.

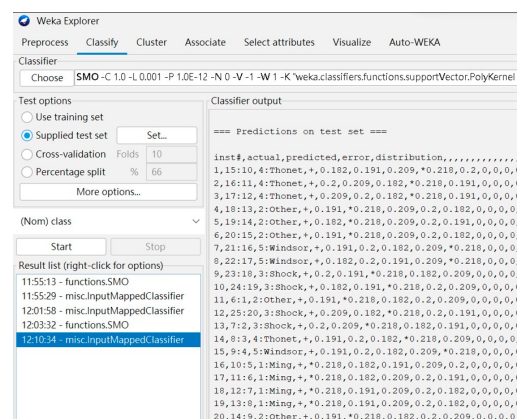


Figure 5. Predicted data by WEKA model.

3. Conclusions

We demonstrated the effectiveness of the Weka model in classifying the four styles of 100 chairs. The results indicated that industrial designers could use the proposed model to classify and identify product styles. New applications of ML could be developed for

product design based on the result of this study. Future research is required to classify and identify product styles using AI technology.

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References

1. Tsai, H.-C. An Analysis of Study on the Features Design from Hans J. Wegner in Denmark. Master's Thesis, National Taiwan Normal University, Taipei, Taiwan, 2011.
2. Bhaskaran, L. *Design of THE Times: Using Key Movements and Styles for Contemporary Design Paperback*; RotoVision: Brighton, UK, 2005.
3. Chan, C. Exploring individual style in design. *Environ. Plan B Plan. Des.* **1992**, *19*, 503–523. [\[CrossRef\]](#)
4. Qiu, M.; Cheng, Y.; Chen, P. *Taiwanese Wood Furniture New Craftmanship*; Jackwood Culture: Taipei, Taiwan, 2007.
5. Cheng, C. *Cognitive Psychology—Theory and Practice*; Laureate Publishing: Slaton, TX, USA, 1993.
6. Pahl, G.; Beitz, W. *Engineering Design: A Systematic Approach*; The Design Council: London, UK, 1988.
7. Kuo, P. *Image Super Resolution Based on Deep Learning*; National Cheng Kung University: Tainan, Taiwan, 2015.
8. Kim, D.; Shin, K.; Woo, J. Displacement Measurement of Steel Pipe Support Using Image Processing Technology. *J. Image Graph.* **2020**, *8*, 80–84. [\[CrossRef\]](#)
9. Vimina, E.R.; Poulouse, K. Content Based Image Retrieval Using Low Level Features of Automatically Extracted Regions of Interest. *J. Image Graph.* **2013**, *1*. [\[CrossRef\]](#)
10. Syakirin, N.; Fauadi, M.; Awang, N. Some Technique for an Image of Defect in Inspection Process Based on Image Processing. *J. Image Graph.* **2016**, *4*, 55–58. [\[CrossRef\]](#)
11. Haffey, M.K.D.; Dufty, A.H.B. Knowledge discovery and data control mining in design environments. In *From Knowledge Intensive CAD to Knowledge Intensive Engineering*; Cugini, U., Wozny, M., Eds.; ITIFIP; Springer: Boston, MA, USA, 2000; Volume 79, p. 59.
12. Kane Watanabe, W. *Western Furniture Integration*; Kodansha Ltd.: Tokyo, Japan, 1980.
13. Nishikawa, R. *Illustrated Classic Chairs*; Taiwan Tohan: Taipei, Taiwan, 2015; pp. 93, 224.
14. Hauffe, T. An Analysis of Study on the Features Design from Hans J. Wegner in Denmark. In *Design: A Concise History*; Laurence King: London, UK, 1998; pp. 126–127.
15. Fang, H.; Hu, J.; Peng, L. *History of Modern Furniture in the World*; Central Compiler: Beijing, China, 2005; pp. 270–275.
16. Shimazaki, S. *Japanese Chairs*; Seibundo Shinkosha: Tokyo, Japan, 2007.

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