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ARTICLE

Identifying Brand Consistency by Product Differentiation Using CNN

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ABSTRACT

This paper presents a new method of using a convolutional neural network (CNN) in machine learning to identify brand consistency by product appearance variation. In Experiment 1, we collected fifty mouse devices from the past thirty-five years from a renowned company to build a dataset consisting of product pictures with pre-defined design features of their appearance and functions. Results show that it is a challenge to distinguish periods for the subtle evolution of the mouse devices with such traditional methods as time series analysis and principal component analysis (PCA). In Experiment 2, we applied deep learning to predict the extent to which the product appearance variation of mouse devices of various brands. The investigation collected 6,042 images of mouse devices and divided them into the Early Stage and the Late Stage. Results show the highest accuracy of 81.4% with the CNN model, and the evaluation score of brand style consistency is 0.36, implying that the brand consistency score converted by the CNN accuracy rate is not always perfect in the real world. The relationship between product appearance variation, brand style consistency, and evaluation score is beneficial for predicting new product styles and future product style roadmaps. In addition, the CNN heat maps highlight the critical areas of design features of different styles, providing alternative clues related to the blurred boundary. The study provides insights into practical problems for designers, manufacturers, and marketers in product design. It not only contributes to the scientific understanding of design development, but also provides industry professionals with practical tools and methods to improve the design process and maintain brand consistency. Designers can use these techniques to find features that influence brand style. Then, capture these features as innovative design elements and maintain core brand values.

KEYWORDS

Machine learning; product differentiation; brand consistency; principal component analysis; convolutional neural network; computer mouse

1 Introduction

There is an increasing research interest in the impact of artificial intelligence (AI) technologies on products [1]. While much research focuses on the impact of AI on how designers work (e.g., [2]) or how they think (e.g., [3]), there is little investigation into AI regarding the design of the brand product, design style, and design features. Among the AI technologies, machine learning-based and deep learning-based AI models can be applied to product styling [4]. We believe that these techniques can also be applied to analyzing design style and branding.

Analysis of product styling trends is critical in the consumer products industry because it can identify design information to manage the consistency of product styling and branding. This analysis depends largely on the accurate classification of mixed styles as defined by industrial design experts, who typically use a collection of images of various design styles, e.g., adopted from [5], through focus group interviews. Obviously, this qualitative method is not only subjective because the style criteria determined by the experts are vague, but also requires experienced design experts, time, and money [6].

In contrast, since machine learning-based and deep learning-based AI models have allowed automated image classification by capturing human-unrecognizable features, they are supposed to be able to automatically classify product styling images. The classification techniques have been explored in fashion style analysis and architectural style classification with a wide range of accuracy. For example, the former's accuracy could range from about 70% to 97% (see [7–9]), while the latter's accuracy is about 65% to 95% (see [10–12]). Like architecture, style classification in product design is not a standard classification problem. We can find different expressions in the same design style with the same design feature, and in turn, we can also find very similar expressions in the same product component without a different design style. Thus, feature extraction becomes difficult in product style classification. In addition, we require high-quality datasets with a large number of samples to train the model to capture the features. Since the generation of design styles evolves as a gradual process, the acquisition of high-quality balanced data could be very difficult.

In this context, the present study retrieved the product design information from design datasets and transformed it into design knowledge. Previous research has used machine learning techniques to determine vehicle styles and their design features in the transitional period [13]. In the present research, a period style is a set of defining characteristics that distinguish the design expressions of products in a historical framework. We followed the biological metaphor of period style [14], in which every style has boundaries to places where it begins and ends; every style begins with its birth (the early phase), progresses to maturity (the middle or classic phase), a decline (the late phase) and, finally, disappearance. The concept of period style provides an essential framework for determining the balance of the consistency of a brand style and the product appearance variation.

Still, the biological metaphor of period style implies that a period style can evolve, and adaptability and evolution are important considerations for it. In other words, the period style evolves between consistency and change.

Period style can be applied to various fields such as art, architecture, literature, fashion, and of course, design. For example, in architecture, different historical periods often have specific stylistic elements that define the works created during that time. The Renaissance, Baroque, Gothic, and Rococo are examples of architectural periods, each with its own unique style. In fashion and design, period style encompasses the clothing, accessories, and aesthetic preferences that were prevalent during a particular historical epoch. From this viewpoint, understanding period style involves recognizing and appreciating the nuances and characteristics that define the design sensibilities of a specific time in history.

There is a symbiotic relationship between period style of product and brand style. "Brand style" refers to the unique and consistent visual and verbal elements that a brand uses to convey its identity and communicate with its audience. It encompasses the brand's logo, color scheme, typography, tone of voice, imagery, and other design elements that distinguish it from competitors and create a cohesive and recognizable brand image. In this paper, we focus on the brand identity expression associated with the period styles of its products. Therefore, the common characteristic of period style and brand style is the evolution between consistency and change. A well-managed evolution of the brand style allows for updates and adjustments while retaining core elements. Thus, it ensures that the brand remains relevant over time without losing its identity. In this way, we can assume that the higher appearance variation of a period style of a product or a brand style, the higher classification accuracy of the AI models could be trained, and vice versa. Since the consistency and change of a period style of the product have an inverse relationship, thus we can assume that the higher classification accuracy, the lower brand consistency.

To sum up, the questions of this study are threefold as follows:

RQ1. To what extent can machine learning methods identify design expression characteristics of products within a brand?

RQ2. To what extent can deep learning methods classify products by periods?

RQ3. To what extent the above methods can evaluate the consistency of a brand style with variation in product appearance?

2 Period Styles of Computer Mouse

In this section, we briefly trace the evolutionary journey of the mouse as a pivotal input device for personal computers in chronological order: (1) three-button mouse, (2) scroll wheel mouse, (3) functional and wireless mouse, (4) creative and diverse mouse, to (5) multifunctional and affordable mouse. Adopting the chronological classification, we regard the mouse devices with common design features in each period as having the same period style. Thus, we will use the above five periods as the period styles in this study.

2.1 Three-Button Mouse

In computer peripherals, the mouse represents a ubiquitous and indispensable tool for interacting with personal computers. The origins of this device trace back to 1963 when Douglas Engelbart invented the first mouse [15]. However, it was not until the 1980s that personal computers gained widespread popularity, and the mouse evolved into an essential component of the digital age. Microsoft introduced a mouse with two green buttons in 1982, celebrating a pivotal moment, and subsequent iterations by various companies propelled the functionality of the mouse. One notable innovation during this period was the scroll wheel, developed by Kunio Ono et al. in 1985 [16]. Microspeed company became a player in 1987, launching a trackball device with a vertical scroll wheel two years later. However, the product was substituted by the new mouse design with a scroll wheel [17,18]. The evolution continued to replace trackball devices with mouse devices with scroll wheels.

While the Mouse System company applied for a killer patent for the scroll wheel mouse used in the Windows system, its acquisition by Taiwan-based KYE Systems Corp. in 1990 further influenced the trajectory of mouse development [19]. Before acquiring, KYE had launched its first three-button mouse with a small logo on the end of the front stylish cover in 1986, followed by an own-brand mouse named Genius. In 1993, Microsoft began to develop a scroll wheel design for the user needs of scrolling website homepages or spreadsheets. Therefore, the mouse and the scroll wheel were undoubtedly necessary for the Windows environment and applications. Since the Mouse System company continued to develop new mouse devices with scroll wheels independently, KYE's mouse adopted its appearance design and mechanical structure in 1996 [20]. In summary, we refer to the period from 1986 to 1996 as the rise of the three-button mouse.

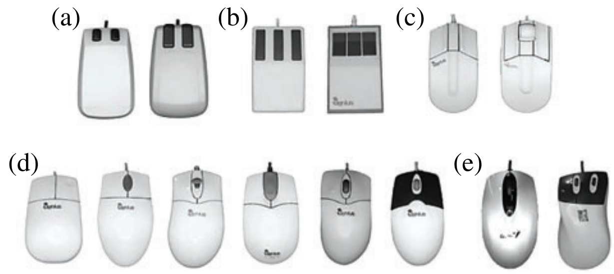

Figure 1: The mouse devices of Microsoft, KYE, and A4tech

They are from left to right in Fig. 1: (a) Green eye and grey eye; (b) Phys and F6; (c) hi mouse and ProAgio; (d) Easy mouse, easy mouse, new scroll, net mouse, net scroll, and power scroll; (e) Traveler 320 and WinBest 4D+ (The mice are from the author's collection and photographed by the author).

2.2 Scroll Wheel Mouse

By 1996, many people were using the traditional three-button mouse and trackball. Due to the computer systems such as Windows 95 and the scroll wheel mouse had just been launched. The scroll wheel mouse was not popular at that time. No one knew what mainstream input device would be used in the future. Perhaps the future input device was predicted to be a trackball or a stylus. There were a lot of alternative devices to the scroll wheel design on the mouse.

Therefore, KYE invented several alternative devices like the scroll wheel, including the pushing rod type, the single button type, and the type with up and down buttons in the following three years. Other companies, including Mizumi, launched a mouse design with a function similar to the famous red dot function of International Business Machines Corporation. In addition, the subsequent Apple Computer developed a mouse with similar functions. These mouse devices by KYE applied the scroll wheel-like innovative designs, such as Net Mouse Pro and New Scroll, and won the Taiwan Excellence Award.

The Microsoft R&D Centre began researching and developing similar scroll wheel designs in 1993. However, the speed of applying for scroll wheel design patents was still slower than Mouse System Company. Microsoft quickly followed suit and started to apply for a mouse scroll wheel patent. In 1999, Microsoft achieved another important goal to utilize optic sensors in its mouse devices replacing the traditional mechanical rolling ball structure. These evolutions came up with the application of these technologies. The differences between optics sensors and mechanism design are significant. In addition, there were slight changes in the wheel scroll appearance of the mouse devices produced by Microsoft in just three years before 2000. Another well-known mouse manufacturer, Logitech, also developed a wireless mouse in 1991. Thus, these three critical technologies included wireless, scroll wheel, and optics sensor. The design of the computer mouse entered a new generation after 2000. To sum up, we refer to the period from 1995 to 2000 as the popularization of the scroll wheel mouse.

2.3 Functional and Wireless Mouse

In 2000, Microsoft developed the scroll wheel and applied for a patent slightly behind KYE. Therefore, KYE exchanged patents for scroll wheel patents with Microsoft, which let KYE produce mouse devices for Microsoft. Through this mutually beneficial relationship, Microsoft and KYE enjoyed profitable results. However, Microsoft R&D Centre continued developing related new scroll wheel technologies, including a four-way scroll wheel. Based on the different structures, KYE developed a similar four-way scroll wheel function and applied the technology to its brand products. In addition, even more mouse devices with the four-way scroll wheel function were launched on the market after 2004.

Another mouse manufacturer in Taiwan, A4tech, also simultaneously invented a new type with two scroll wheels. It involved the psychological cognition of human factors. One scroll wheel represented front and back scrolling, but what was the function defined by the other vertical scroll wheel? This caused the user to doubt whether the mouse was based on the user-centered design or just the designer's thoughts. Coincidentally, the manufacturer A4tech soon developed another model with a vertical and a horizontal scroll wheel. This design seemed easier for users to understand, one was vertical scrolling, and the other was horizontal scrolling. Therefore, we refer to the period from 2000 to 2009 as the functionality and wireless mouse.

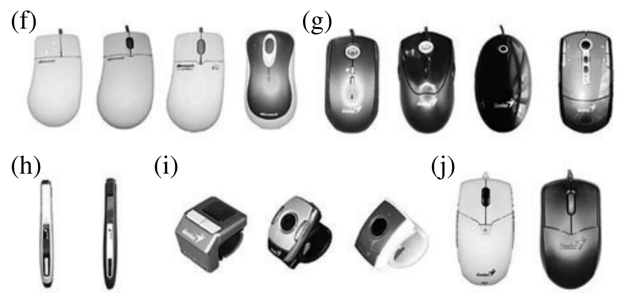

Figure 2: Microsoft and KYE systems corp mouse devices

From left to right in Fig. 2: (f) Microsoft Mouse 2.0, IntelliMouse (scroll wheel), IntelliMouse optical and wireless optical mouse 2000; (g) Traveler 355 Laser, NetScroll T220 Laser, Scrolltoo T355, and Navigator T835 Laser; (h) Pen mouse and pen mouse V2; (i) Ring mouse, ring mouse 2, and ring presenter; (j) Cam mouse and net scroll 310X (The mouse devices are from the author's collection and photographed by the author).

2.4 Creative and Diverse Mouse

In 2007, KYE wanted to make a breakthrough in new-generation scroll wheel technology. Therefore, it started developing an optical scroll wheel. The appearance of an optical scroll wheel is different from traditional ones. The new generation of optical scroll wheel technology became more feasible and looked like a touchpad. After this technology became obsolete, it was used in Genius brand mouse devices, named TC module. Meanwhile, Microsoft also developed a touch-based scrolling technology and used it in Microsoft's mouse.

Two years later, KYE began to develop pen-type input devices, including the pen mouse. Although KYE was not the first company to develop such a device, it still encountered some issues. One of the problems was how to add a scroll wheel to the form of the pen. Putting the scroll wheel in the pen mouse regarding mechanism design and appearance was challenging. Finally, the pen mouse used buttons instead of the scroll wheel. KYE developed another new product: a ring-shaped mouse at the same time. The ring mouse applied the optical scroll wheel technology mentioned earlier. KYE has produced several generations of ring-shaped mouse devices. Besides the touch-like optical scroll wheel, there are some changes in its appearance between these ring-shaped mouse devices. However, the ring mouse, which applied optical scroll wheel technology, not only has the function of a scroll wheel but also becomes the function of mouse cursor movement. In addition, another ring-type mouse manufacturer used the traditional scroll wheel to control the cursor.

Another interesting issue with the ring mouse was using the optical scroll wheel to move the mouse cursor. Turning the mouse over and touching the optical sensor with your finger is difficult. Also, it is slow to move the mouse cursor on the screen. It is not easy to control. The behavior involved a control/response ratio of human factors engineering [21]. For the user to have their fingers control the mouse cursor was challenging. For example, the user could quickly do tasks with a mouse, but when operating a ring mouse, he would have to slowly move his finger to control the mouse cursor to complete the task. In sum, we refer to the period from 2007 to 2016 as the creative and diverse mouse.

2.5 Multifunction and Affordable Mouse

In 2013, KYE launched a multifunction mouse that combined two different functions. For example, a mouse combines a charging and mouse function or a camera and mouse function. In addition, another wired mouse could store the wire on the mouse inside. This was also the end of the creative diversification period style and the start of the affordable or low-cost mouse period style.

In the low-cost period, KYE's mouse style tended to be simple and colorful, representing a feeling of youthfulness. Moreover, their mouse devices with LED lighting revealed a sense of high-tech. Mouse devices during this period essentially boosted their value by enhancing the product appearance, rather than improving performance by adding functions.

However, during this period, KYE developed a new mouse, the Net Scroll 310X, with a top shell that combined the button's function and front cover shell structure. Simply put, it was to make the buttons function on the front cover and achieve the elastic effect. Thus, when the mouse's front cover and bottom are assembled, the user clicks the button on the front cover to have the button function. Lastly, we refer to the period from 2013 to 2022 as the multifunction and affordable mouse.

We believe the above periods of mouse devices can be classified using artificial intelligence. The following section will briefly introduce the application of artificial intelligence in design and present the research methods used in this study.

3 Method

The application of artificial intelligence in design includes using artificial neural networks, fuzzy theory, genetic algorithms, deep learning, cluster analysis, expert systems, and rule-based design. The knowledge expression of rule-based design can be extracted from experts and is understandable. Interesting examples include the automatic diagnosis system [22] and shape grammar [23]. In particular, the half-hexagon table grammar in [24], and the structure grammar implementation in [25]. Although the rule-based design is understanding and explainable, it could produce inappropriate design solutions. Another approach is case-based reasoning, which uses the solutions of previous cases to solve the new problem [26,27]. The IDEATE program of Industrial Design at TU Delft in the Netherlands is an example of a case-based design system, a conceptualization process for industrial design research [28]. Finally, an example of deep learning is using the CNN model to reconstruct artwork with specific characteristics [29].

On the other hand, brand and emotional issues are explainable by quantitative methods. For example, a knowledge base application of automotive headlights is used to improve the quality of styling aesthetics by visually inspecting styling surfaces [30]. In addition, the utility of helping product designers understand whether to achieve the desired aesthetic design links physical design details with customer response psychology [31]. Also, communication between producers and consumers can increase to obtain information related to visual acuity [32]. The different design features noted by consumers in different regions may also be various [33]. In general, using quantitative methods to explain the brand and emotional issues can make people more aware of the abstract and interesting but unknown parts.

This study contains two experiments to investigate the Genius mouse devices produced by Taiwanese manufacturer KYE Systems Corp. The dataset of Experiment 1 comprised 50 Genius mouse devices of the five periods described in Section 2. Period Styles of Computer Mouse. In Experiment 2, we simplified the original five-period styles into two stages. The Early Stage (A period) encompassed the period style of (1) three-button mouse, (2) scroll wheel mouse, and (3) functional and wireless mouse. The Late Stage (B period) contained the period style of (4) creative and diverse mice, to (5) multifunctional and affordable mice. The dataset of Experiment 2 consisted of 6042 images of Genius mouse devices of the two stages. The core concept is transforming the product appearance variation into a classification problem for machine learning and deep learning.

3.1 Product Dataset of Machine Learning and Deep Learning

The dataset in the first experiment consisted of fifty Genius mouse devices produced by KYE for several periods from 1986 to 2020. The data samples spanning thirty-five years were selected to be representative mouse datasets as a statistical dataset.

Then principal component analysis (PCA) was applied in this investigation. The dataset captured the data on size and design features. The styles of scroll wheel features include without scroll wheel design, traditional scroll wheel design, scroll wheel-like designs, and optical scroll wheel design.

The element of the scroll wheel is applied to a mechanical or optical scroll wheel. The mouse devices also have two signal transmission methods: wired and wireless mouse. During the period from without scroll wheel design to traditional scroll wheel design, there were some transitional mouse devices with scrolling-like functions, which can facilitate the scrolling-like in the application of windows. Experiment 1 divided the dataset into fifty mouse devices to facilitate the data visualization of principal component analysis (see Fig. 3). The reason was to avoid too many model names and points occupying the entire chart and losing data visibility.

The division of stages A and B is not based on some criteria of appearance differentiation. Instead, it is based on the functions followed by the appearance. Stages A include the period of the three-button mouse, scroll wheel mouse, and functional and wireless mouse. Stage B includes the period of creative and diverse mice and multifunction and affordable mice. Therefore, we can see that the appearance features of Stage A include the large mouse, a three-button mouse but no scroll wheel, the touch scroll mouse, a plating decorative design, a side rubber material design, and a wedge-shaped design. The appearance features of Stage B include the small mouse, adding retractable cable design, bright appearance, spray painting region in the key button, and polishing design of the mouse middle part.

In Experiment 2, convolutional neural networks were successfully used in various applications for computer mouse images. The database of this study collected 6042 images saved in JPG or PNG formats and reduced the size of each image in the database to 120 $\times$ 120 pixels. Experiment 2 uses the convolutional neural networks of the deep learning method. The study applies the VGG16 model in deep learning. The related research combined with VGG16 and the product included product repairability [34], circuit manufacturing defects [35], and product classification [36]. CNNs have two essential functions inside, called convolution and pooling. Inside a convolution, several filters are used for scanning the input image, increasing its size and scale. Later, pooling is used to compress the images and cut down the size but maintaining the same scale. Fig. 4 show the CNN architecture based on the VGG16 model.

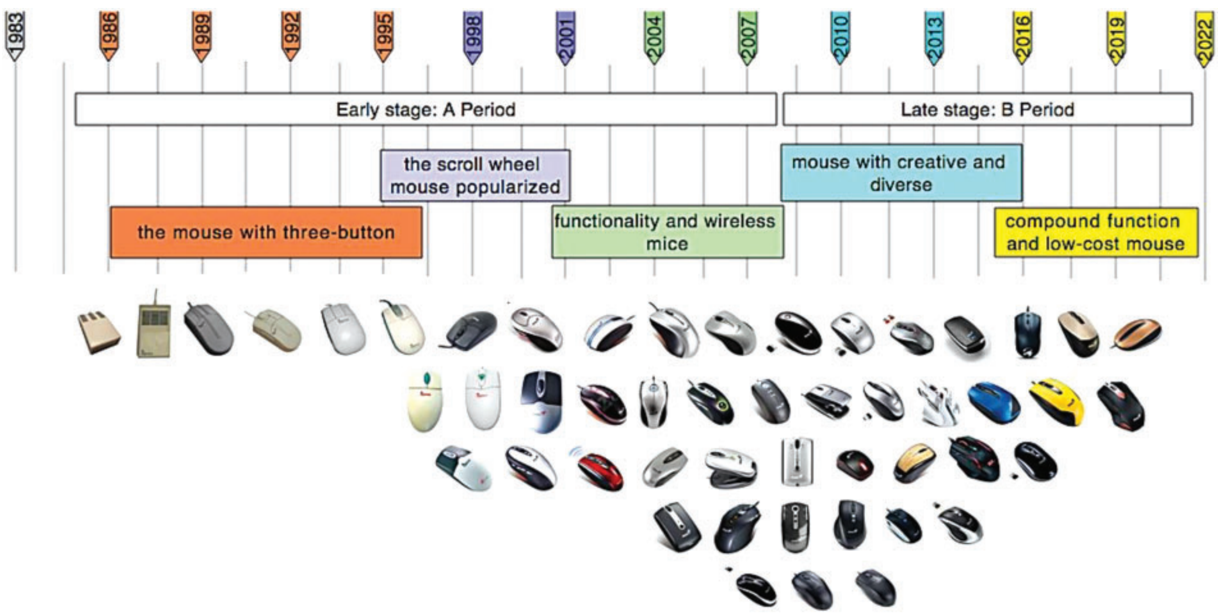

Figure 3: The research captured 50 out of 233 Genius mice

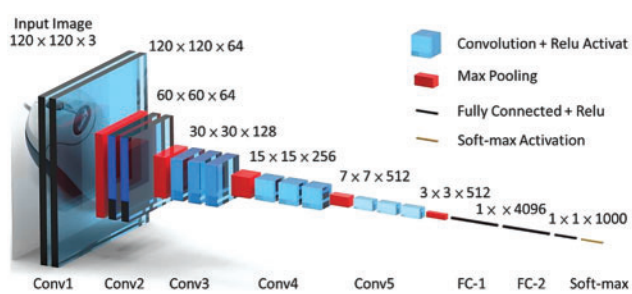

Figure 4: CNN architecture based on the VGG16 model

In preprocessing and parameter tuning, the Keras ImageDataGenerator class is employed to augment training images with various transformations like rescaling, rotation, shifting, shearing, zooming, flipping, and fill mode. This enhances the model's ability to generalize to diverse data variations. The code snippet also involves setting up a validation image data generator, preparing data, and visualizing predictions for training and validation sets. The CNN model combines a pre-trained VGG16 base with a custom top model for image classification through transfer learning. Input images are shaped with width, height, and RGB channels. The VGG16 base, with pre-trained ImageNet weights, excludes fully connected layers (include_top = False). A sequential model forms the custom top, incorporating flattening, ReLU dense layer, batch normalization, dropout, and softmax dense layer. The fusion of VGG16 and the top model yields the final model, preserving pre-trained information by freezing VGG16 layers up to 15 during training. This approach optimally adapts pre-trained VGG16 features for image understanding to a specific classification task.

The dataset of 6042 images with a size of 120 × 120 pixels is divided into 4412 images (73%) for training the model, 1630 images (27%) for verification with hyperparameter tuning, and an additional 99 images for testing the final model's performance. The dataset description is displayed in Table 1.

Table 1: Dataset description of the computer mouse style classification (only for Experiment 2)

Item	Description
Dataset name	KYE computer mouse style classification.
Image data	Each sample in the dataset consists of an image representing a KYE mouse.
	The 6042 images are in standardized JPG or PNG formats, with consistent dimensions of 120 × 120 pixels.
Labels	Each image in the dataset is associated with a single. corresponding period label, namely the early stage and the late stage.
Data split	The dataset is divided into two parts: training and validation.
	The split is 73% for training, 27% for validation, and an additional 99 images for testing.

3.2 Relationship between Product Appearance Variation

This study uses PCA in machine learning and CNN in deep learning to identify characteristics of the design expression of products of a brand, predict period styles of the products, and evaluate product appearance variation. To simplify, the five chronological order of period styles is split into two stages: the Early Stage and the Late Stage. For example, Porsche cars have showcased a recognizable aesthetic that combines timeless elegance with sporty proportions. While the specific details may evolve with each new generation, the fundamental design DNA, as exhibited in the iconic Porsche 911 sports car, remains consistent. The degree to which consistency is maintained in a certain brand might be explored by using image classification with CNN.

It is quite challenging to find the relationship between different time series, product differentiation, and brand style continuity based on machine learning or deep learning. Therefore, this study simplifies the problem and only discusses the continuity of the same brand style under two different time series. The results are divided into the following four types (see Fig. 5):

1. The first type is an extreme case full of brand continuity but almost no product appearance differentiation.
2. The second type is an extreme case full of appearance differentiation but almost no brand continuity.
3. The third type is the difference in product appearance is greater than the continuity of brand style.
4. The fourth type is the continuity of brand style is greater than the difference in product appearance.

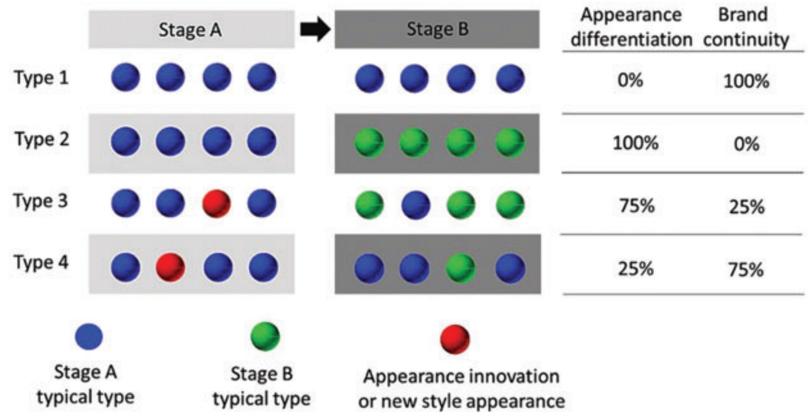

Figure 5: The four different types with product appearance differentiation and brand style continuity

3.3 Evaluating Brand Consistency

We see brand style consistency as a problem of classification with deep learning. The recognition rate of deep learning corresponds to the degree of the product appearance variation. The brand style consistency score and product appearance variation score are complementary of each other; their sum equals 1. Note that the product appearance variation refers to the degree of product appearance that cannot be classified to a certain period style, instead of the degree of innovation. For example, when a KYE mouse device of the different stages got an accuracy of 81.4% based on deep learning, we can convert the accuracy to the product appearance variation score (0.64) and brand style consistency score (0.36).

In a certain period, the accuracy rate of identifying a specific brand style, X_{AI}, is regarded as the ratio of product appearance variation. It is the average of the last ten predictions, calculated by

$$X_{AI} = f(X) = \frac{1}{n}\left(\sum\nolimits_{i=(t-n+1)}^{n} Xi\right) \tag{1}$$

where

n: the times of the last predictions and set to 10,

t: the value of epochs of the deep learning and set to 100, and

X_i: the accuracy rate in the *i-th* epoch by the deep learning method.

X_{AI} is the accuracy rate of a product brand identifying a specific style in a certain period based on deep learning. The value could be regarded as the ratio of product appearance difference. X_{SC} is the ratio of brand style consistency, calculated by

$$Score\ X_{SC} = f(X_{SC}) = 1 - \left(\left(X_{AI} - X_{AI(Type\,1)}\right) / \left(X_{AI(Type\,2)} - X_{AI(Type\,1)}\right)\right) \tag{2}$$

In addition, to reduce the dimensions of the dataset while preserving as much variability as possible, PCA is employed for its related advantage [37]. PCA can be seen rotating the original axes to a new set of orthogonal axes [38]. In the process, PCA uses singular value decomposition (SVD) to obtain eigenvector and eigenvalue. The singular value decomposition of a matrix M to be decomposed is a factorization of the form.

$$M = U\Sigma V' \tag{3}$$

where

U: left singular matrix,

Σ: diagonal matrix containing singular eigenvalues, and

V^t: right singular matrix or the conjugate transpose of V.

To determine the consistency of brand style over two periods of time, we use the following formula:

$$TPR = \frac{No\ of\ correctly\ identifying\ early - stage\ style}{Total\ no\ of\ early - stage\ style} = \frac{TP}{TP + FN} \tag{4}$$

$$TNR = \frac{No\ of\ correctly\ identifying\ later - stage\ style}{Total\ no\ of\ later - stage\ style} = \frac{TN}{FP + TN} \tag{5}$$

$$Accuracy\ Rate = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where

TP: True Positive-Values that are actually positive and predicted positive.

FP: False Positive-Values that are actually negative but predicted to positive.

FN: False Negative-Values that are actually positive but predicted to negative.

TN: True Negative-Values that are actually negative and predicted to negative.

TPR: True Positive Rate-The ratio of the products of a brand in Early Stage that is correctly predicted as Early Stage style.

TNR: True Negative Rate-The ratio of the products of a brand in Later Stage that is correctly predicted as Later Stage style.

3.4 Defining Design Requirements

The research procedure of this investigation consists of six main steps. The first step is to select 50 out of 233 mouse devices of the Genius. The second step is applying PCA to classify the style. The third step is to find the change in body size between wired and wireless mouse devices. The fourth step is to collect 6042 Genius mouse images as a dataset in two different stages and use CNN with deep learning to classify the style. The fifth step is applying heat map analysis of the CNN to recognize features. The last stage is to evaluate the brand consistency by the product appearance variation. These six steps are shown in Fig. 6.

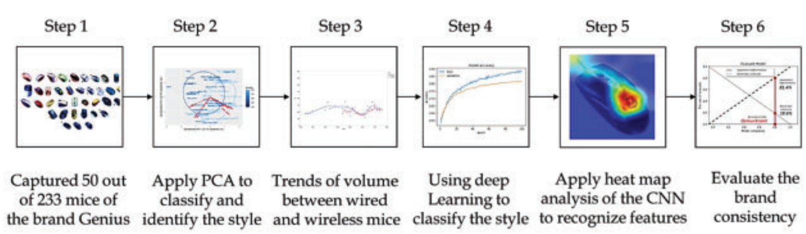

Figure 6: The research procedure

Regarding heat map analysis, experience has shown that heatmap-based methods can improve classification confidence to varying degrees depending on the dataset but have not yet been widely used for design style classification. For example, empirically, heatmap-based methods can improve classification confidence to varying degrees depending on the dataset [39]. Furthermore, the integration of PCA and heatmaps helps highlight correlations between variables and quantitative differences in expression levels and provides more readable visualizations of large amounts of data [40]. However, in some cases, heat maps still fail to provide useful explanations for the predictions of classification models. For example, domain experts believe that heatmaps used to explain deep neural networks predicting gender based on electrocardiograms cannot be applied to obtain new medical knowledge [41]. Further exploring the comprehensive interpretation of heatmaps for classification models is clearly beyond the scope of this study, but future efforts should be directed toward developing holistic interpretation predictions that cover all aspects of the model from development to real-time.

4 Results

This chapter contains three sections. The first section depicts the evolution of design characteristics of the Genius mouse devices in different periods, focusing on the classification with time series. The second section presents the visualization of the classification using PCA, while the third section exhibits the prediction of brand styles with CNN.

4.1 Classifying with Time Series

The result shows that most of the data samples in the Early Stage were wired mouse devices. The first wireless mouse was launched to the market in 2002. The length of the wired mouse devices reached its maximum size in 2005. The trend of wireless mouse devices is roughly in line with wired mouse devices. The reason could be two-fold. First, the miniature wireless mouse appeared in 2009, but the miniature wired mouse appeared later. Second, the appearance of the miniature mouse for portability needs accompanies the appearance of the notebook computer.

The evolution in the average length and volume of wireless and wired mouse devices each year shows that wireless mouse devices are generally shorter than wired mouse devices, as shown in Fig. 7. But, around 2010, wired mouse devices' average length was shorter than that of the wireless mouse devices. There are two possible explanations. One is that during that period, wired and wireless mouse devices often shared the same mold, so the length and volume would not be any different. The length of wireless mouse devices was mainly maintained at 100 to 110 mm from 2010 to 2019. Between the intervals, the size is almost the same as that of a wired mouse because the cost is reduced. The size of the two circuit boards, wireless and wired, is almost the same. Another reason was that miniature wired mouse devices were popular at the time, so the average length of the overall wired mouse was lowered. But in more time, the miniature wireless mouse will always give users the feeling of a more delicate design. Since this approach based on time series to classify the mouse devices by volume is not as good as expected, we will present the classification using PCA in the next section.

4.2 Classifying with PCA

The study used PCA [42] to analyze the dataset of fifty Genius mouse devices produced by the KYE System Corp. between 1986 and 2020. The design features used for dimension reduction include the length, width, height, and year to market. In addition, the Genius mice had more design features: styles of the scrolling function, control of cursor function (ball or optical sensor), multifunction, and signal transmission types (wired or wireless). These features will be represented in eigenvectors, which provide a basis for transforming the original feature space into a new space defined by the principal components (PCs).

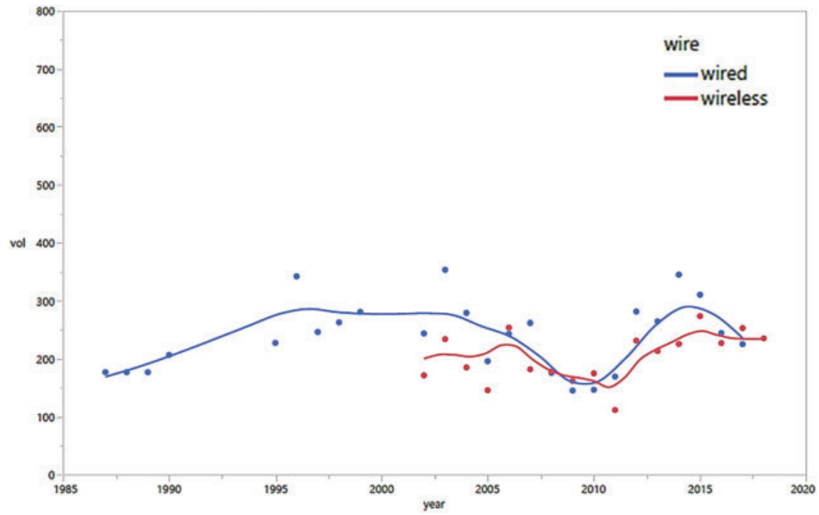

Figure 7: Evolution of wired and wireless mouse volumes according to time series

Results show that these mouse devices can be roughly divided into two categories: wired mouse devices (group A) and wireless mouse devices (group B), as shown in Fig. 8. The eigenvector of height, represented by the sub-axis of height, has the largest magnitude and the most parallel direction to the horizontal axis, represented the first principal component (PC1). The largest magnitude indicates that the height eigenvector has the most importance in explaining the variance in the data, whereas the most horizontal direction indicates the direction of maximum variance in the original feature space. In this sense, the PC1 might correspond to product appearance variation in length or body size of mouse devices and could be named "volume" or "magnitude." In contrast, what variation the second principal component (PC2) represents is unclear. However, PC1 accounts for 33.1% of the variation, and PC2 accounts for 22.0% of the variation. Together, they explain 55.1% of the total variation in the dataset, which is a moderate amount of variance explained. In this case, the PCA provides limited dimensionality reduction.

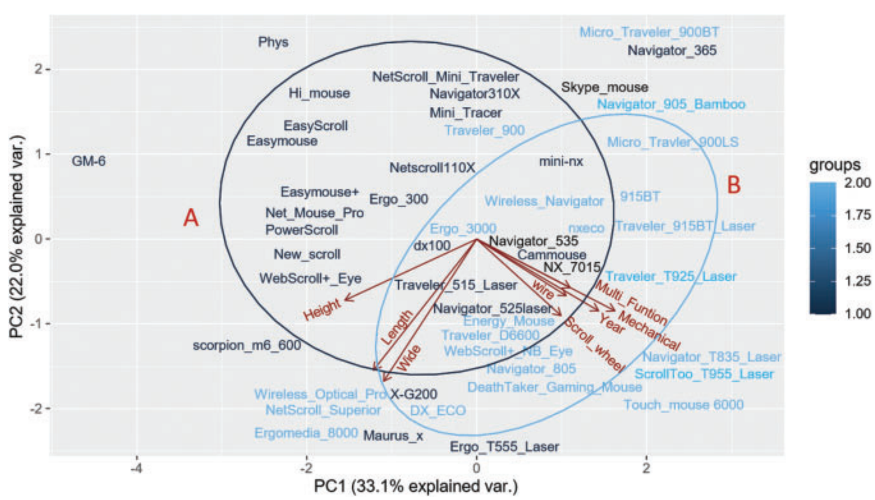

Figure 8: Analysis of 50 Genius wired and wireless mouse devices applying PCA

4.3 Feature Extraction with PCA

Results show that the mouse devices are divided into four groups, namely (A) without scroll wheel design, (B) traditional scroll wheel design, (C) optical scrolling design, and (D) the scroll wheel-like design features of the transitional period, displayed in Fig. 9. Interestingly, the mouse devices of the transitional period only occupied a small area, as shown in the red ova area D in Fig. 9. As the explained variance percentages of PC1 (33.1%) and PC2 (22.0%) of PCA are not as high, it indicates that the principal components do not explain the variance in the data enough of the system. However, it is still possible to plot a cluster plot with four groups from PCA results.

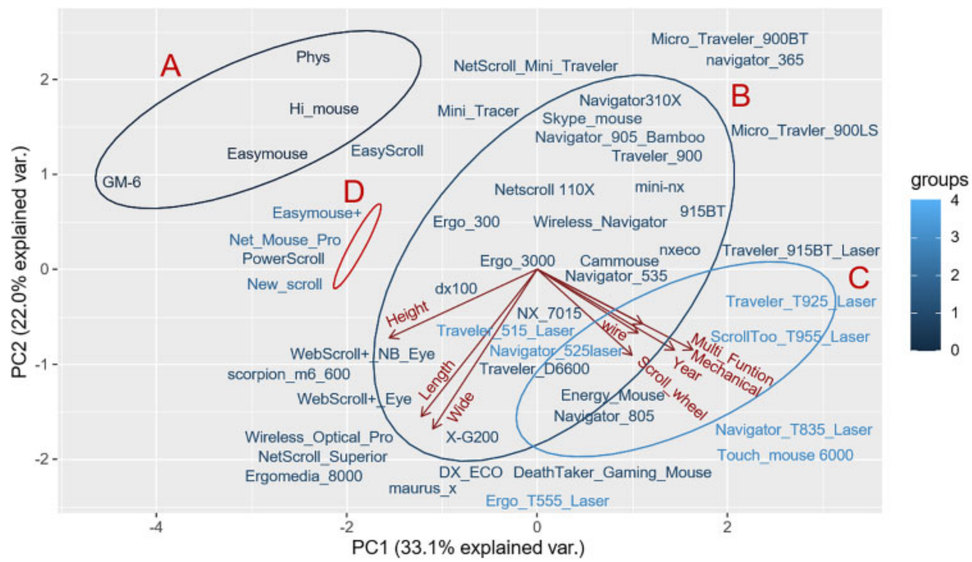

Figure 9: Classifying 50 Genius brand mouse devices with PCA; the red area D represents the Genius mouse devices with other types of scrolling (the transitional period)

4.4 Classifying with Deep Learning

The study used the attribute "period" as the label of each image of mouse devices for supervised learning with CNN. The value of the label is either the Early Stage or the Late Stage. The mouse devices of the Early Stage contain the Genius mouse from 1986 to 2008, and those of the Late Stage contain the Genius mouse from 2008 to 2018. In the training phase, there were 2140 computer mouse images in the Early Stage and 2272 computer mouse images in the Late Stage. In the verification phase, there were 664 computer mouse images in the Early Stage and 966 computer mouse images in the Late Stage. Training is performed with a batch size of 32 and epochs of 100. It takes one hour on an AMD notebook computer, and the graphics card uses the RTX 3060 series. The accuracy is shown on the left of Fig. 10, which is the percentage indicating the correct prediction of the CNN model, which is also a concept that can only be applied to classification tasks. The loss value is shown on the right, representing the sum of errors in the CNN model in the database. The result is that the accuracy of the training and validation phase converges to 81.4%. In addition, in the CNN model loss graph, training and validation are decreasing steadily, with every epoch converging to 0.47.

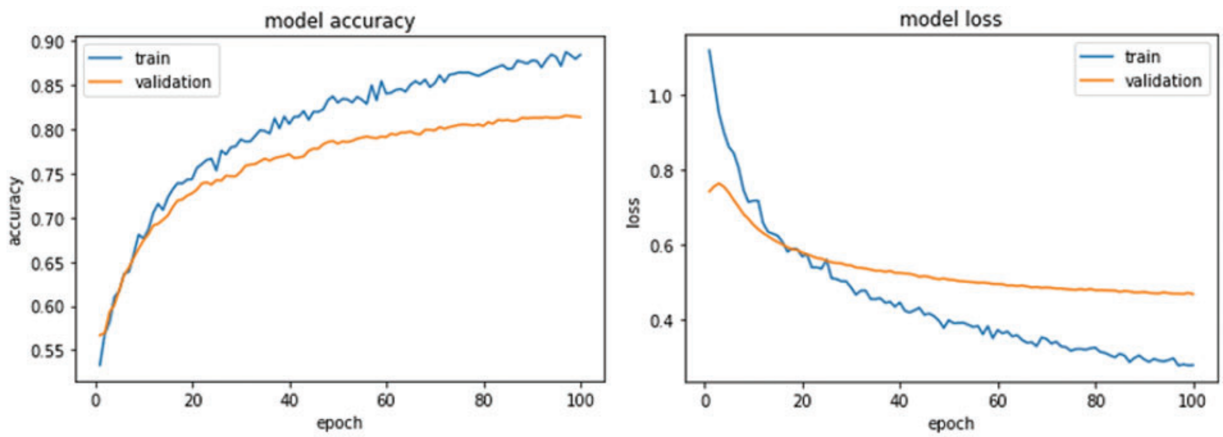

Figure 10: Model accuracy (Left) and loss (Right) in databases' training and validation phase

5 Discussion

5.1 Evolution of Scroll Wheel Functionality

The study investigates the design evolution of a scroll wheel with similar functions. After the scroll wheel function was invented, some products had the same function but different shapes or operations. The initial scrolling design was still not enough to be accepted by the market immediately due to various considerations such as users' behavior, design quality, assembly method, or cost. Thus, companies continued to develop other similar designs, and similar function designs continued to appear in the market. The following is an example of the four mice produced by KYE (see Fig. 11). The design includes an up-and-down button style, a single-button style, a joystick style, and a traditional scroll wheel.

Since the first scroll wheel mouse was introduced in 1996, over four years. There were several different scrolling-like designs during the transition period. Most brand companies felt unsure about future development and market trends. Even though they had already mastered a patent design that could change people's behavior, KYE continued the research & development to increase the possibility of success until the scroll wheel mouse of Microsoft came onto the market in 2000.

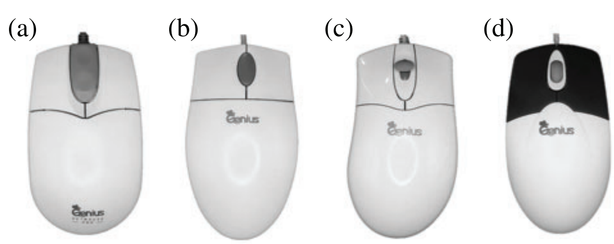

Figure 11: Design evolution comparison of four scroll wheel functions of KYE/Genius mouse during the transition period; (a) Net mouse Pro (1997), (b) Easy Mouse (1998), (c) New Scroll (1999), (d) Power Scroll Mouse (2001) (The mice are from the author's collection)

Furthermore, we could see the curve change between the buttons and the top shell, evolving from the seagull style in 1997 to the straight line style in 1998 and resorting back to the seagull style in 1999 again (see Fig. 11). The design is a complex form of combining one curve on top of another curve.

Also, we observed differences in the location, color, and size of the logo identified by the company in different periods.

The four mice could be viewed as evolving from without a scroll wheel to a traditional scroll wheel design. But in this evolutionary process, few were certain of the outcome for future design. The result is an explosion of creative and innovative ideas at this time. The period would be regarded as the most diversified period with scrolling function types of mice. But with the increasing popularity of the Microsoft Windows operating system, mice with scroll wheels were also gaining support from consumers, and Microsoft even introduced its own design. As a result, these excessive designs that attempt to replace the scroll wheel function faded slowly from the market.

5.2 Product Appearance Variation with Deep Learning

This study uses the heat map method of deep learning to analyze the difference between design features in the Early Stage and the Late Stage. The deep learning-based evaluation of product appearance variation identifies several brand styles in the Early Stage and the Late Stage, see Fig. 12.

The following describes the results of predicting the above four mouse devices:

A. Genius Navigator 535

The serial number of Genius Navigator 535 is GM-050022, which means this mouse was launched in 2005 and belongs to the Early Stage style of the mouse. In this study, the probability of predicting that its style belongs to the Early Stage is 90.3%, and the probability of belonging to the Late Stage is 9.7%, so the prediction is correct. The heat map A reveals green LED light features of the Genius Navigator 535 mouse image, a crucial feature for recognizing the Genius brand's Early Stage.

B. Genius Traveler 9000LS

The serial number of Genius Traveler 9000LS is GM-120018/T, which means this mouse was launched in 2012 and belongs to the Late Stage style of the mouse. In this study, the probability of predicting that its style belongs to the Early Stage is 14.7%, and the probability of belonging to the Late Stage is 85.3%, so the prediction is correct. For the Genius brand, the rubber design element with a pattern is highlighted in heat map B, giving an important visual representation for recognizing the Late Stage.

C. Genius Netscroll 310

The serial number of Genius Netscroll 310 is GM-050017, which means this mouse was launched in 2005 and belongs to the Early Stage style of the mouse. In this study, the probability of predicting that its style belongs to the Early Stage is 92.7%, and the probability of belonging to the Late Stage is 7.3%, so the prediction is correct. By analyzing the heat map C, the feature of the smile curve between the key and up cover can infer the importance of specific features on the Genius Netscroll 310 model to recognize the Early Stage.

D. Genius Ergo R815

The serial number of Genius Ergo R815 is GM-05004U/T, which means this mouse was launched in 2005 and belongs to the Early Stage style of the mouse. In this study, the probability of predicting that its style belongs to the Early Stage is 41.4%, and the probability of belonging to the Late Stage is 58.6%, so the prediction is incorrect. The spray painting region in the key button in heat map D causes the Genius Ergo R815 to make incorrect predictions. Another reason may be that the appearance design of human factor design was innovative at that time, so the recognition based on deep learning could not be identified correctly.

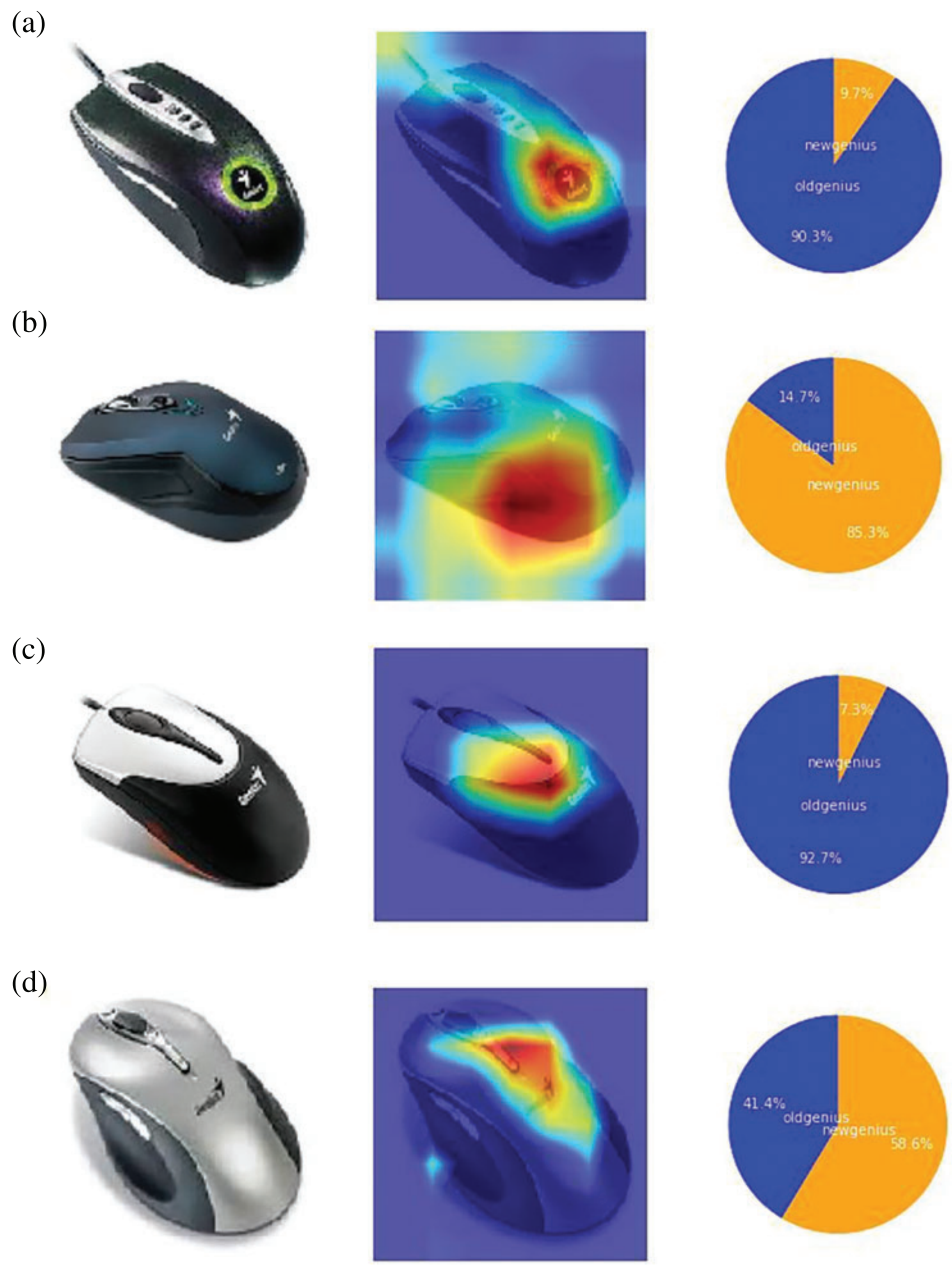

Figure 12: Applying heat map analysis of the convolutional neural network model for recognizing case: (a) Genius navigator 535; (b) Genius traveler 9000LS; (c) Genius netscroll 310; (d) Genius Ergo R815

As previously mentioned, the recognition accuracy rate of the CNN is low (81.4%). It suggests that the model is struggling to accurately capture and generalize the underlying patterns or discriminate between different classes in the dataset. The main cause of the low accuracy can include such factors as imbalanced data or noisy data. Although the accuracy rate of a CNN model cannot be directly used to assess the degree to which the difference between data samples is low, yet we can reflect on the possible implications of it.

Imagine that one assigns two different labels to a set of identical images. This creates a mislabeled dataset, introducing a significant source of inconsistency and confusion during model training and evaluation. The model will encounter conflicting training signals because it will receive contradictory label information for the same images. This can lead to poor convergence during training, as the model attempts to reconcile the conflicting information. Consequently, the accuracy rate of the model will likely be low, as it struggles to classify the images correctly.

We argue that the "periods" of the Genius mouse devices are not consistent labeling by nature, because Genius might not strategically maintain the evolution of product appearance in a long time. Instead of ensuring the accuracy and consistency of labels in the dataset during model training to achieve accurate classification performance, we attempt to use the accuracy rate of the model to abductively inference the degree to which the product appearance variation. If the accuracy rate is low, then the consistency between data samples is plausibly high, and vice versa. The inference could obtain a plausible explanation rather than a certain conclusion.

The boundaries between Early and Late styles are therefore not clear, and the intersection zone between the two stages is also blurry. The mouse device located in the crossover area not only retains the uniqueness of its style stage, but also has a certain brand style consistency. This explains why the accuracy of deep learning is not more than 85%. In addition, unique styles can also emerge at certain moments in the style of the time, such as the design features of the scrolling functions in the transitional period. Regarding the insights as follows:

Insight 1. It can help us understand which regions of the input image contribute more to the network's decision-making process.

Insight 2. In a future study, comparing heat maps by CNN and eye-tracking can examine how CNN focuses on regions of the image that align with human visual attention. And explain why.

Insight 3. Understanding a CNN's heat map requires domain knowledge, model architecture understanding, and empirical analysis. Integrating these requirements helps provide meaningful insights from the heat map into the model's decision-making.

The study finally uses an evaluation database of 99 samples as the tested model. The samples are not the same shape as the mouse used in the training and verification folders. The tests showed about 82.8% accuracy, which means that out of 99 test cases, 82 cases were correctly predicted, and 17 cases were placed in the wrong stage. Among them, the accuracy rate of 49 test cases in the Early Stage was 81.6%. The accuracy rate of 50 test cases in the Late Stage is 84%, see Fig. 13. This result indicates that the Late Stage style of the mouse is more accessible to recognize than the Early Stage. The reason may be that the Early Stage style models sometimes have diversified styles (the company needs to develop more styles in Early Stage, thus making them more difficult to recognize).

Confusion matrices are typically used to evaluate the performance of a classification model. However, the classification of brand style in the present study is not the case. The boundaries between the brand styles between the Early (A period) and Late Stage (B period) are significantly unclear; the confusion matrix may not effectively capture the complexity of the classification challenges. Another reason is that the division of more categories is not based on some criteria of appearance differentiation. Instead, it is based on the functions.

The model's performance on the new test data set (82.8%) is close to the verification accuracy (81.4%). The reasons for the Early Stage being misclassified to Late Stage include adding retractable cable design, spray painting region in the key button, and polishing design of the mouse middle part. The reasons for the Late Stage misclassified to the Early Stage include plating decorative design, retro style (replan color the old components), side rubber material design, and wedge shape at the front of the button. Meanwhile, the issues also include the following three reasons in this study. 1. Insufficient samples can hinder the model's ability to identify intricate patterns, resulting in suboptimal performance. 2. Limited dataset size may inadequately capture the data's variability through available features. 3. Fine-tuning hyperparameters is challenging with a small dataset.

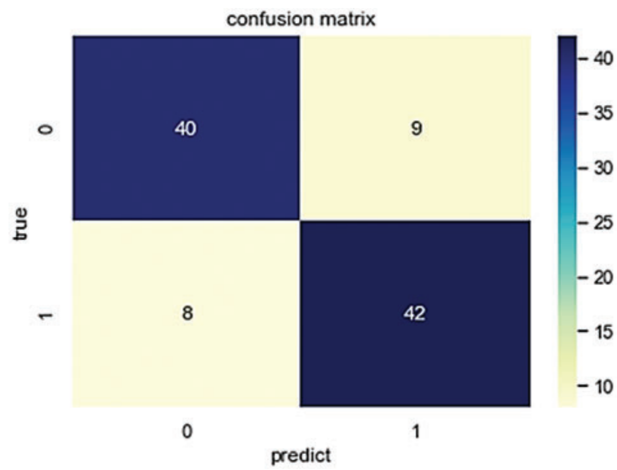

Figure 13: Confusion matrix to evaluate product appearance variation and brand style consistency

5.3 Brand Consistency Based on Product Appearance Variation

The database of the study is KYE mouse and uses deep learning as an evaluation tool to explore brand style. This model includes two evaluation elements, product appearance variation and brand style consistency. Simply put, if the brand product has been continuously changing over time but has no same design features to connect it, it is impossible to find the consistency of its brand. On the contrary, if the brand product has always maintained its brand design features and finds its consistency over time, it is not easy to find the element of product appearance variation. Therefore, a good brand style must have certain elements of product appearance variation, but it can also find the consistency of the brand style.

This study changes the problem of the consistency and consistency of the mouse style to a classification problem of Early Stage and Later Stages. If it is assumed that there is no continuation from the Early Stage to the Late Stage. If it is assumed that there is no continuation from the Early Stage to the Late Stage style, the brand styles between the early and Late Stage should not be consistent. The accuracy rate of recognition should be very high based on deep learning. However, if it is assumed that the Late Stage style has a continuation from the Early Stage style, it is not easy to distinguish between the styles of the Early Stage and the Late Stage. This study reconstructed the data set of another brand, Mad Catz, and compared it with the Genius brand.

From the results of this investigation in Fig. 14, it seems that there is indeed consistency, and overlap in styles between the Early (A period) and Late Stage (B period). Therefore, the recognition accuracy rate of the two stages using deep learning on the Genius mouse is only 81.4%. It shows the product differentiation presented by the CNN accuracy rate is not always perfect in brand products. Moreover, the appearance of the Late Stage products is very different from that of the Early Stage products, and there is only some brand consistency. Another possibility is the mouse evolution of the

KYE Systems like the “amoeba” change or application of retro design, which affects the brand style consistency.

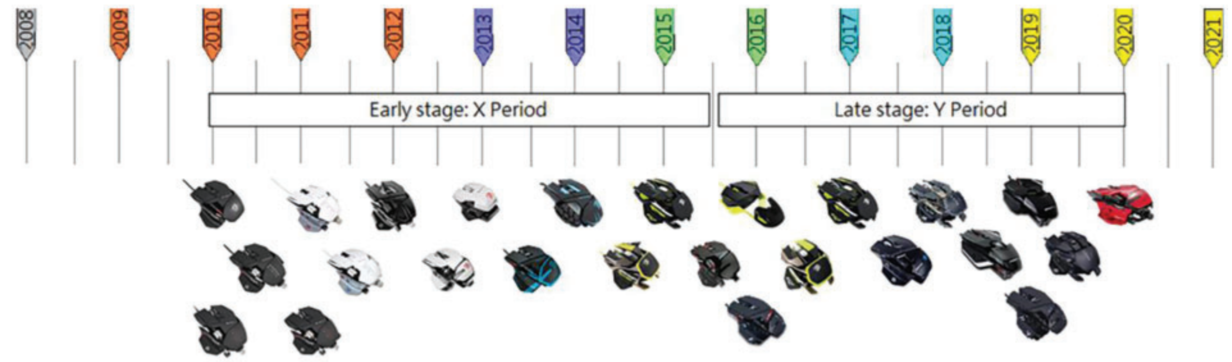

Figure 14: The research collects Mad Catz mouse devices to compare the brand style consistency of Genius and Mad Catz mouse devices

The Genius mouse belongs to type 3 and is based on product appearance variation (see Fig. 15). From the results of deep learning in this study, it can be known that the accuracy of the style of the Genius mouse is 81.4%. Hence, the evaluation score of product appearance variation is 0.64. The evaluation score of brand style consistency is 0.36. The Genius mouse has a brand style with certain elements of product appearance variation, which can be used to measure the consistency of the brand style.

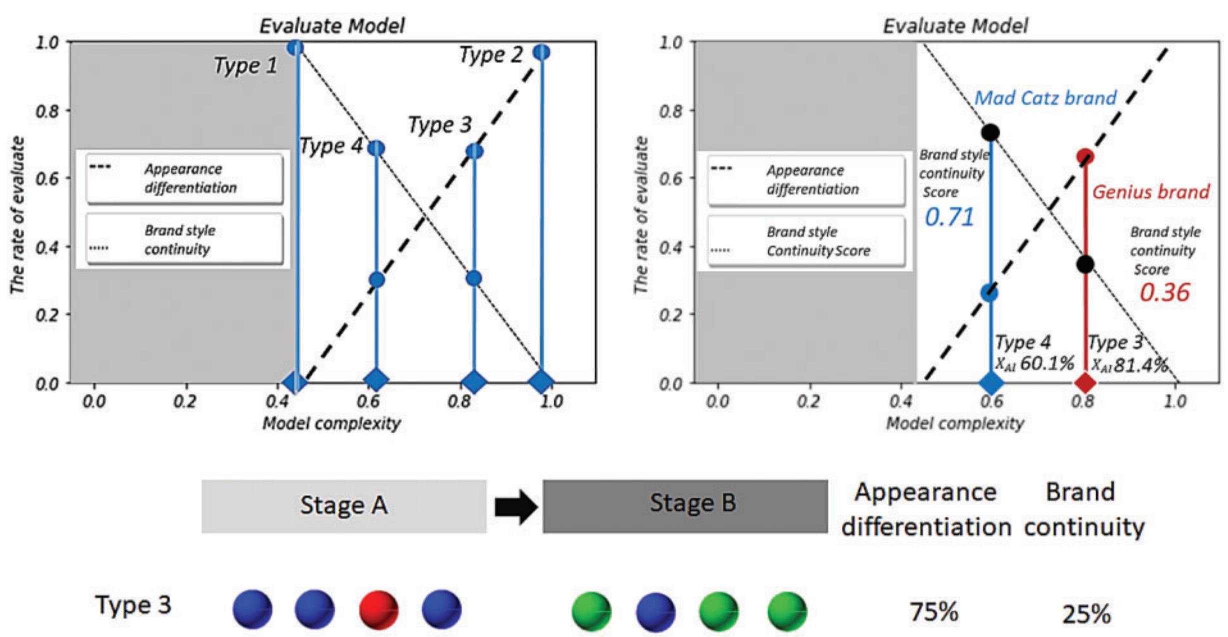

Figure 15: The relationship among product appearance variation, brand style consistency, and evaluation score

We investigated the mouse of another brand, Mad Catz, and found that its validated accuracy rate was 60.1%, and the evaluation score of brand style consistency was 0.71, see Fig. 16. Therefore, we can compare the Genius brand and the Mad Catz brand. The Genius brand has more significant changes than the Mad Catz brand in appearance between the Early Stage and the Late Stage. The Mad Catz brand has better consistency before and after the Genius brand.

The evaluation score of Genius brand style consistency is 0.36 based on the accuracy of CNN 81.4%. Thus, Genius has preserved as much consistency as possible while evolving and innovating through the years. In addition, this method can be extended to determine the change of anything over some time. Its applications include environmental monitoring, medical Imaging, and cultural heritage period style evaluation. It also can be applied in predicting new product styles and future product style roadmaps. Then evaluate whether the planning of future product style roadmap deviates from the original brand style.

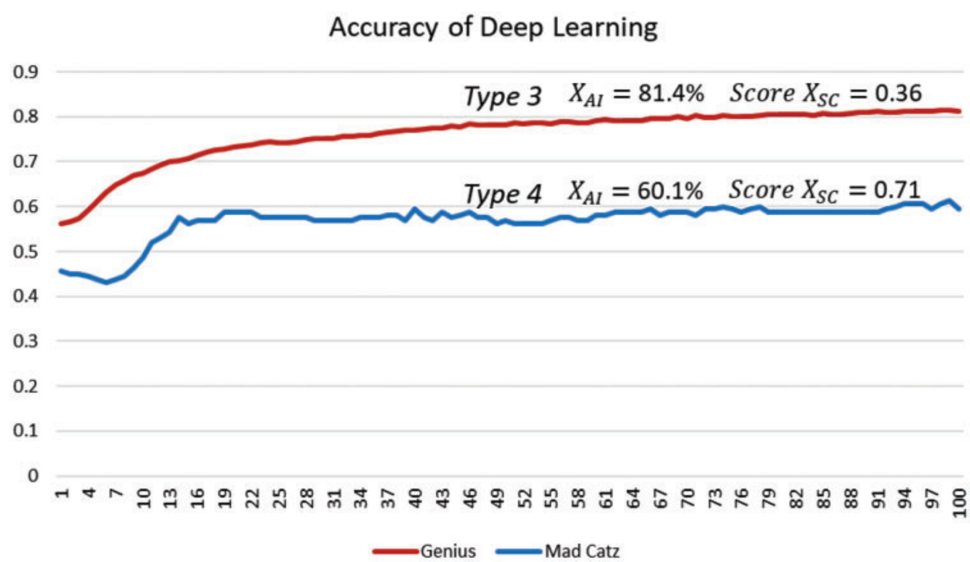

Figure 16: The comparison of different brands of product appearance differentiation and brand style continuity by deep learning accuracy

At the end of this section, we summarize some limitations and potential for the application of PCA and CNN in this study. The limitations are three-fold. First of all, since the number of mouse design features is not large enough, PCA does not fully exercise its dimensional reduction effect. Secondly, this study is limited by the quantity and quality of image data, making it difficult to achieve accuracy in CNN training. Worse, style itself is, by definition, an imprecise categorical concept. Nevertheless, this study has taken a step towards product style research, showcasing an acceptable performance compared to style classification in architecture (e.g., [12]), fashion design (e.g., [9]), and art (e.g., [43]) as well. Furthermore, since style classification is holistic, the application of CNN allows us to automatically and holistically capture the interplay of style elements. However, this study suggests PCA and CNN can complement each other to reduce the above three limitations to some extent. For example, when applying PCA for classification, optical wheel mouse devices were classified into a certain area. On the other hand, we used CNN heat maps to visualize the activations of different parts of the mouse devices classified into the period style of Creative and Diverse Mouse. The heat maps showed that the warmer colors (indicate higher activations) are concentrated in the optical scroll wheel of these mouse devices. This approach sheds light on a new direction for further exploring how the attention patterns align with human intuition and whether the model is capturing semantically meaningful features.

6 Conclusion

This investigation presented several promising methods to investigate branded mouse devices and found some unique and creative mouse devices from the dataset. Experiment 1 used principal component analysis to explore scroll wheel design features in the transitional period. In addition, Experiment 2 aimed to recognize mouse design styles in different stages by the CNN model of deep learning. The recognition accuracy rate of the CNN model is 81.4% for the various stages of the Genius mouse devices. As mentioned previously, design style classification is not a standard classification problem. Many reasons can interfere with the accuracy of the model. First, although human experts can distinguish design styles by their representative product components, yet product features of similar periods will have some similarities. This is a tremendously serious challenge for the CNN model to classify similar periods, for example, “creative and diverse mouse” and “multifunction and affordable mouse.” Second, there were technical limitations in this study, including the uneven number of learned image data by style and the data preprocessing of design style images with different visual quality. Consequently, misjudgment of design styles includes innovative cases of the Early Stage style and retro cases of the Late Stage style. We argued that the Genius mouse has innovative elements in various stages and tries to maintain the consistency of brand style. In this sense, the accuracy rate can be used to abductively inference the degree to which the appearance of products is different.

The study discovered the evolutionary trend of branded mouse styles through machine learning and deep learning techniques, which could objectively learn some unique but tiny designs. From this study, we can also draw some evidence regarding the brand style consistency in the Early Stage and the Late Stage. In addition, the deep learning heat map method can highlight the critical areas of the two stages’ design features. In this sense, machine learning and deep learning are promising approaches to explore unique design features in product history and evaluate the brand mouse’s style consistency. However, from the AI viewpoint, we still cannot answer why consumers eventually prefer the scroll wheel design instead of many other alternatives. It will be a worthy topic for follow-up research. The main contribution and practical value of the study lie in several aspects, including providing design evolution insights for predicting future design directions, objective evaluation of brand style consistency for corporation branding management, application of machine learning and deep learning to more than mouse design, identification of critical design areas for guiding designers to focus on, and abductive inference on the degree of product appearance differences using accuracy rates.

In summary, the study provides actionable insights for designers, manufacturers, and marketers in the field of product design. It not only contributes to the academic understanding of design evolution but also offers practical tools and methodologies for industry professionals to enhance their design processes and maintain brand consistency.

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Availability of Data and Materials: The data supporting this study's findings are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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