engineering proceedings

Proceeding Paper

Image Classification to Identify Style Composition Ratios in Crossover Cars †

Hung-Hsiang Wang and Hung-Jui Su *

Department of Industrial Design, National Taipei University of Technology, Taipei 10608, Taiwan; wanghh@mail.ntut.edu.tw

* Correspondence: howard9155@gmail.com

† Presented at the 2024 IEEE 7th International Conference on Knowledge Innovation and Invention, Nagoya, Japan, 16–18 August 2024.

Abstract: As the global demand for multifunctional and high-performance vehicles increases, automotive manufacturers face significant challenges in designing new crossover models. Consumers expect vehicles to blend features from various car models, which pushes the industry to adopt innovative design tools and methods. We explored the use of Waikato Environment for Knowledge Analysis (WEKA) image classification to predict the style composition ratios of sedans, hatchbacks, multi-purpose vehicles (MPVs), and sport utility vehicles (SUVs) as crossover vehicles. We collected 240 high-resolution side-view images of luxury vehicles from brands including Mercedes-Benz, BMW, and Lexus, and preprocessed the data using format unification and feature enhancement. We employed WEKA to extract image features and train a classification model using the edge histogram filter and sequential minimal optimization (SMO) classifier, which achieved an 86% classification accuracy. Subsequently, we used Vizcom, a generative Artificial Intelligence(AI) tool, to simulate realistic designs for new crossover cars and predict their style composition ratios. The proposed designs were evaluated by five experts, who found that the model accurately identified style composition ratios and helped designers create new car styles with market potential. The novel application of image classification can be used for analyzing blended styles in automotive design and enables designers to identify, evaluate, and control styles to meet market demands.

Keywords: car styling; car model; image classification; WEKA

Academic Editors: Teen-Hang Meen, Chun-Yen Chang and Cheng-Fu Yang

Published: 27 February 2025

Citation: Wang, H.-H.; Su, H.-J. Image Classification to Identify Style Composition Ratios in Crossover Cars. *Eng. Proc.* **2025**, *89*, 26. https://doi.org/10.3390/engproc2025089026

1. Introduction

The automotive industry has shifted from a manufacturer-driven market to a consumer-driven market, where consumer needs are prioritized in selecting specific car models [1]. In the contemporary automotive industry, developing innovative vehicle types, especially electric vehicles and hybrid models, has become a trend, following the growing market demand for diversity and environmental protection [2]. Therefore, it is important to develop new vehicles that align with market trends and consumer expectations by applying image recognition technology and machine learning. This promotes design innovation and aligns with the future development direction of the automotive industry.

We explored the application of image recognition technology in automotive design, particularly in the development of new vehicles. With the increasing market demand for innovative designs and environmentally friendly models, artificial intelligence (AI) techniques need to be used for automotive development [3].

2. Related Work

2.1. AI in Industry

The application of AI in the industry has garnered widespread attention. By integrating digital sensors, network technologies, and automation systems [4], AI is redefining the economy and creating a new industrial era. Existing applications of AI are categorized into the following two types: "strong AI", which simulates human behavior and reasoning, and "weak AI", which uses machine learning to perform simple tasks traditionally carried out by humans, such as image recognition or natural language processing [3,4].

The core of AI lies in decision-making, and its greatest contribution to humanity is decision-making efficiency. When applied to business forecasting or industrial production, AI provides data-driven, objective decision-making recommendations. Similarly, AI in design thinking plays a crucial role in implementing core innovative decisions [5]. Therefore, AI is significant in promoting innovation and improving decision-making efficiency.

2.2. AI-Driven Automotive Styling

Applications of AI in automotive-related fields have primarily focused on autonomous driving systems [6], automotive manufacturing processes [7], intelligent traffic management [8], and vehicle recognition [9,10]. Previous studies have demonstrated the application of machine learning tools in car styling classification and consumer preference prediction. Hong et al. used AI to differentiate between fuel and electric vehicle types and product semantics, achieving high accuracy through image classification [11]. Wang et al. utilized deep learning and WEKA to predict consumer preferences for the front view of the BMW M3 series models, accurately explaining consumer preferences for innovative appearances [12]. Additionally, Wang and Chen analyzed the evolution of car styling and brand consistency for Dodge and Jaguar using deep learning methods, which accurately identified brand styles and design features [13]. However, these studies have not explored the application of machine learning in the design of different car types. To fill this gap, we developed an image recognition model to identify and select vehicle designs with market potential, thereby promoting design innovation in the automotive industry.

2.3. Image Recognition Technology

2.3.1. Applications of Machine Learning

Machine learning technology has been widely applied in the classification of automotive styling. Methods such as support vector machines (SVMs) and convolutional neural networks (CNNs) have shown excellent performance in image classification. These technologies are used in design and commercial trend forecasting. For instance, Wang and Chen used CNNs and heatmap analysis to classify and compare the styles of the Dodge and Jaguar brands. They demonstrated that deep learning is highly effective in identifying automotive design features and brand consistency [13]. Hong et al. used WEKA, a machine learning tool, to distinguish between the types and product semantics of fuel and electric vehicles. By analyzing 100 vehicle images, they showed that even small datasets can be used to train high-accuracy models, effectively distinguishing different vehicle types and semantics [11].

2.3.2. Image Feature Extraction Techniques

In automotive design, image feature extraction is a crucial step. The edge histogram, as a feature extractor, can effectively identify edge variations in vehicles, which is particularly important for distinguishing different vehicle models [14]. Analyzing edge histogram features in images allows machine learning models to accurately classify vehicle models. This technology enhances vehicle identification, which is crucial for intelligent transportation applications, and thereby improves classification performance.

3. Methods

We used the WEKA toolkit for image recognition to analyze styling components of sedans, hatchbacks, MPVs, and SUVs from brands including Mercedes-Benz, BMW, and Lexus and explore their application in designing new models. The research process consisted of the following three stages: data collection and preprocessing, model training, and application development.

3.1. Procedure

3.1.1. Data Collection and Preprocessing

We collected 60 high-resolution side-view images for each vehicle type from Mercedes-Benz, BMW, and Lexus, totaling 240 images. These images were standardized in format, resized for uniform resolution and dimensions, and enhanced using contrast and brightness adjustments and noise reduction to improve quality and subsequent analysis accuracy.

3.1.2. Feature Extraction and Model Training

Using WEKA's image processing tools, we extracted key features from vehicle images, including edge detection, texture analysis, and color histograms (specifically edge histogram). These features were used to train machine learning models. Based on preliminary trials, the best-performing classifiers, including SVM, random forest (RF), deep learning models, and optimized SVM, were selected. Cross-validation was employed to evaluate the models' generalization ability and accuracy, ensuring their effective application in practical styling recognition.

3.1.3. Application and Expert Evaluation

We proposed new hybrid vehicle designs based on model analysis results. We used AI technology to generate and optimize design sketches to determine market trends and consumer preferences. Using 2023 European preferences for mini cars (A-Segment) and crossovers, we employed generative AI (specifically Vizcom) to simulate designs of the Fiat 500e and Dacia Spring [2]. We developed a robust image recognition model to identify and select marketable vehicle designs, promoting innovation in the automotive industry.

We trained the WEKA classification model to analyze AI-generated design proposals and submit the results to industry experts for evaluation. We selected five experts with extensive automotive exterior design experience to provide comprehensive feedback, offering a wide range of professional insights. In the evaluation, each expert spent 20 min in a one-on-one assessment session and compared the AI analysis with their intuitive judgments to assess consistency and application value.

3.2. Data Collection

We applied image recognition technology in automotive design for the development of innovative models. To conduct in-depth image and text analysis, we collected a total of 240 images of sedans, hatchbacks, MPVs, and SUVs from the official sales websites of Mercedes-Benz, BMW, and Lexus between 2009 and 2024, as shown in Figure 1. Semantic terms related to "style" were selected. These curated data served as the primary data source for the study, supporting subsequent analyses, especially in image recognition and styling composition analysis.

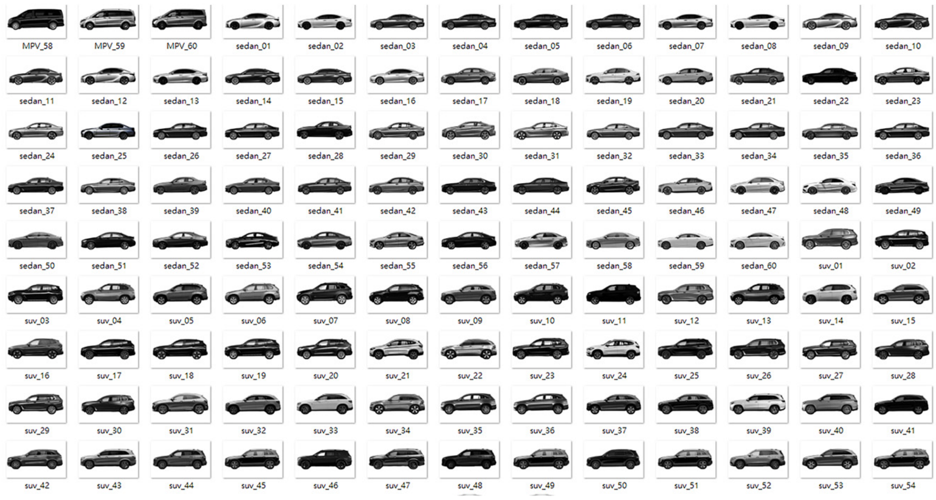

Figure 1. Examples of car design images.

3.3. Data Preprocessing

We standardized images collected from the official websites of Mercedes-Benz, BMW, and Lexus, as well as those acquired through the Copilot assistant integrated within Internet Explorer (IE). This involved unifying image formats and adjusting dimensions to ensure consistent resolution and size. To enhance automation and efficiency, we used Python 3 scripts to traverse images in Portable Network Graphic (PNG) in the designated folders and applied the rembg library for background removal. Using the deep learning-based library, we separated the foreground from the background to highlight the main features of the vehicles. All images were resized to fixed dimensions: 16 cm in width and 10 cm in height. Image enhancement processes, including contrast adjustment, brightness adjustment, and noise reduction, were performed to improve analysis precision. These steps were executed using Photoshop, and the saturation of the photos was adjusted to black and white grayscale using Microsoft tools to ensure consistency in visual analysis.

When the processing was complete, the images were renamed and saved in the output folder, according to WEKA's naming conventions. For this, we used Python 3's counter and string formatting functions, which significantly sped up processing and ensured consistency in the naming format. We enhanced the visual quality of the images effectively, ensuring optimal conditions for subsequent image recognition and feature extraction. This, in turn, supported the training of machine learning models and styling recognition analysis. Through these carefully designed preprocessing steps, the model laid a solid foundation for improving the overall quality and reliability of the research.

3.4. Feature Extraction and Classification Techniques

We used various image processing tools of the WEKA platform to analyze and extract key image features (Figure 2), including edge detection, texture analysis, and color histograms. These features are particularly important for identifying and classifying vehicle styles. Additionally, we utilized the SMO classifier in WEKA to train the SVM model and effectively classify vehicle types by combining different kernel functions and regularization parameters [15]. Extracting features such as edges, textures, and colors was essential for transforming vehicle image data into inputs for machine-learning models. This process captured the stylistic characteristics of different vehicle models for the development of predictive models for automatic vehicle style recognition. By using the filters, the models' predictive capability was enhanced, and a foundation for understanding various vehicle design characteristics was provided. This approach aids in accurately identifying vehicle styles and offers designers valuable insights, supporting new directions and innovations in vehicle design.

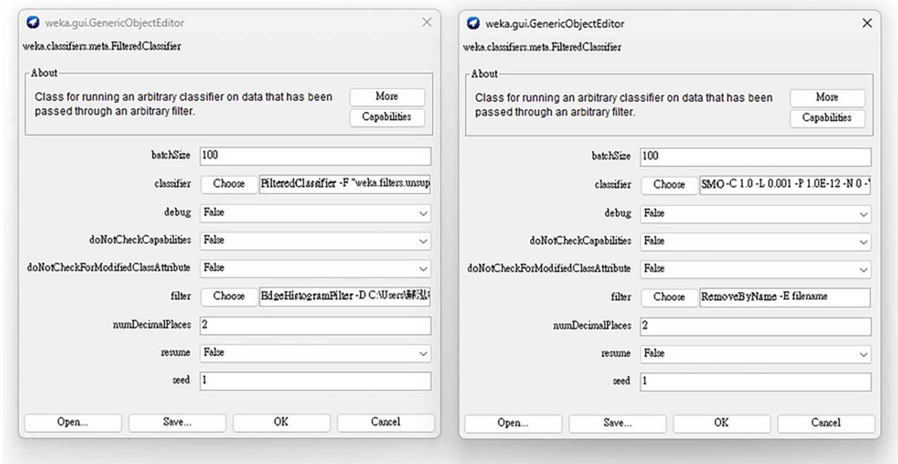

Figure 2. Example of WEKA filters and classifiers.

3.5. Validation and Testing

To verify the usability and accuracy of the database, we experimented with 240 images. Of these, 60% (144 images) were used as the training set, and the remaining 40% (96 images) were used as the testing set. The images included four different vehicle types to evaluate the model's performance in vehicle-type recognition. The experimental results (Figure 3) indicated that the model achieved an accuracy of 86.1% on the test set. To confirm reliability, we manually compared the classifications of the 96 images in the test set. After careful examination, 15 images were incorrectly classified, resulting in an actual accuracy of 84.4%. Although the accuracy was lower than the initial automatic accuracy, the model remained reliable and effective.

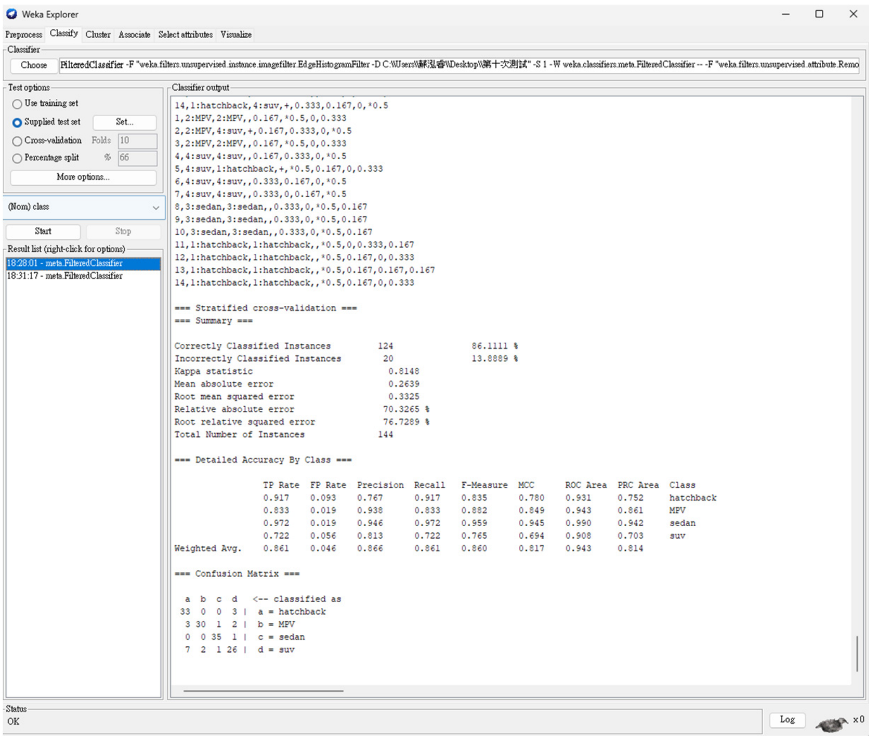

Figure 3. Accuracy of model on the testing set was up to 86.1%.

We expanded the training dataset from 144 to 240 images to improve the model's generalization ability and accuracy. After training, the model's accuracy increased to 86.6%, improving its performance with the increased data volume. To verify the model's effectiveness in recognizing complex vehicle styles, we tested two different crossover models from different manufacturers (Figures 4 and 5). When classifying models from the same series of the same manufacturer, the model accurately identified style compositions and proportions. The style compositions and proportions of the same model types were similar, indicating that the model could identify the style composition of different vehicles (Tables 1 and 2).

Figure 4. Six test samples of crossover designs from BMW.

Figure 5. Three test samples of crossover designs from Lexus.

Table 1. Analysis results of six crossover models from BMW.

	Hatchback	MPV	Sedan	SUV
Unknown01	16.7%	33.3%	0%	50%
Unknown02	33.3%	16.7%	0%	50%
Unknown03	33.3%	16.7%	0%	50%
Unknown04	33.3%	0%	16.7%	50%
Unknown05	33.3%	0%	16.7%	50%
Unknown06	33.3%	0%	16.7%	50%

Table 2. Analysis results of three crossover models from Lexus.

	Hatchback	MPV	Sedan	SUV
Unknown01	33.3%	0%	33.3%	33.3%
Unknown02	33.3%	0%	33.3%	33.3%
Unknown03	50%	0%	16.7%	33.3%

The model performed satisfactorily in basic vehicle type recognition and in analyzing complex style combinations. The model's effectiveness was also verified in basic vehicle type recognition and complex style combinations, providing a solid foundation for future research. Additionally, they offer information on automotive design and market analysis, helping the industry understand and predict consumer preferences for various vehicle styles.

Considering European consumer preferences for mini cars (Segment A) and crossovers from 2023 to the present, Fiat 500e and Dacia Spring models were analyzed by the invited experts [2]. Generative AI technology (Vizcom) was used to create these proposals (Figure 6). The model analysis results of the simulated proposals were compiled into a detailed chart, presenting the style composition data for each vehicle model (Table 3). The experts were able to make well-informed evaluations and provide valuable feedback for improving the model and its application in vehicle design.

Figure 6. Two test samples of crossover designs generated using Vizcom.

Table 3. Analysis results of two crossover models generated using Vizcom.

	Hatchback	MPV	Sedan	SUV
Unknown01	16.7%	33.3%	0%	50%
Unknown02	33.3%	0%	33.3%	33.3%

We collected and analyzed expert opinions and suggestions on the style results, focusing on areas where the insights of the experts differed from the model's output. After the meeting, we integrated their feedback to assess the AI model's accuracy and reliability. Based on the experts' feedback, we made necessary adjustments to enhance the model's performance and practical value.

We invited five experts, including two women and three men, with more than 4 years of industrial design experience to participate in the validation via an interview. From the interview, the reasonableness of the analyzed vehicle style proportions was evaluated (Table 4), and the model's value in predicting sales trends and designing new vehicle models was estimated (Table 5). In the 20 min interview, data presentation, initial insights, discrepancies, and potential improvement measures were discussed.

Table 4. Five experts' answers to Q1.

Answer	Reasons and Suggestions
Expert A (agree)	Car model one has the highest proportion of SUVs, which aligns with my understanding. The proportion of hatchbacks and MPVs is also appropriate. Car model two appears to be evenly split among hatchbacks, sedans, and SUVs. In reality, it combines the front of an SUV, the chassis of a sedan, and the rear of a hatchback, making it highly valuable for reference.
Expert B (agree)	In model one, SUVs have the highest proportion, matching technical and design logic. The proportions of hatchbacks and MPVs are also appropriate. Model two seems to be evenly split among hatchbacks, sedans, and SUVs. In reality, it combines the front of an SUV, the chassis of a sedan, and the rear of a hatchback. This innovative design shows the potential of technical fusion and is valuable for reference.

Table 4. *Cont.*

Answer	Reasons and Suggestions
Expert C (agree)	Model one shows SUVs as the highest proportion, matching my judgment. Hatchbacks and MPVs are also reasonable. This composition combines an SUV front, sedan chassis, and hatchback rear. The analysis matches my observations and is valuable for reference.
Expert D (agree)	The model for car one shows the highest proportion of SUVs, slightly lower for MPVs, and an appropriate proportion of hatchbacks, reflecting actual hatchback features. For car two, the analysis shows an even split among hatchbacks, sedans, and SUVs, but I believe the hatchback proportion should be higher and the SUV and sedan proportions lower. Despite this discrepancy, the analysis method is still valuable for reference.
Expert E (agree)	The model for car one shows the actual car is composed of various car features. For car two, the analysis results show an even split among hatchbacks, sedans, and SUVs. However, I believe hatchbacks should be 60% and sedans close to 0%. Despite the model fitting proportions from a features perspective, it has blind spots in length and wheelbase. This analysis method is still valuable for reference.

Table 5. Five experts' answers to Q2.

Answer	Reasons and Suggestions
Expert A (valuable)	The classification model, through analyzing sales data, can accurately predict market reactions to new car models and develop effective strategies. It is expected to help designers create more popular models, increasing the success rate.
Expert B (valuable)	Using the classification model to analyze sales data of best-selling car models helps designers understand market demands, improving the acceptance and sales success rate of new car models.
Expert C (valuable)	From a product development perspective, the classification model can refine design directions, reduce risks, improve efficiency, and ensure that new car models better meet market demands, increasing their chances of success.
Expert D (valuable)	The application of the classification model can provide designers with market insights, assisting in the creation of more popular car models. If applied in design education, it can help educational institutions adjust their curriculum to train competitive design talent, promoting the development of the automotive industry.
Expert E (valuable)	I believe the application of the classification model is very helpful. It demonstrates the potential of data analysis in business decisions and provides valuable market insights, helping me better understand consumer needs.

These discussions leveraged the experts' knowledge to optimize the research model and advance the project. Integrating expert feedback was crucial for refining the model and ensuring its practical application in vehicle design and market analysis.

3.5.1. Reasonableness of Analyzed Car Model

We asked the experts two questions: Q1: "Do you agree with the analyzed car model proportions?" and Q2: "Please explain your reasons and discuss whether you think these proportions are reasonable". Table 4 presents the answers of five experts to these questions. All experts agreed with the analysis results and provided detailed reasons and suggestions. Experts A and B noted that the proportion of SUVs in car model one was the highest, aligning with technical and design logic, and they considered the hybrid design of car model two to be highly valuable. Experts C and D believed that the proportion of hatchbacks in car model 2 should be higher, but they still found the analysis valuable. Expert E suggested that the proportion of hatchbacks had to reach 60%. These opinions indicated that the analysis in this study gained expert recognition and provided a reference for the improvement of our analysis methods, supporting designers in the decision-making process for innovative hybrid car models.

3.5.2. Use of the Classification Model in Predicting Car Sales Trends and New Car Model Design

We explored the possibility of the application of the classification model in predicting car sales trends and designing new car models. The experts answered the following question: "How do you assess the practical application value of the classification model in these areas? Please explain your reasoning". We analyzed the sales data of best-selling car models to predict whether new design proposals align with market trends, helping designers understand market demands. The results assist car manufacturers in conducting competitive analysis by providing data on competitors' car model compositions to improve or emulate them. Table 5 presents the responses of five experts, all of whom found the method valuable and provided detailed reasons and suggestions. They emphasized that the classification model helps to optimize design directions, reduce risks, improve efficiency, and develop the automotive industry. These opinions indicate that the analysis method can be used for predicting car sales trends and designing new car models, providing information for further improvement.

In summary, the experts found the model's classification to be reasonable and valuable. The high proportion of SUVs in model one was evaluated to be appropriate, while model two demonstrated innovative design with the potential for technical integration. All experts agreed that the classification model has significant potential in predicting car sales trends and designing new car models. By analyzing sales data, designers can better understand market demands, creating more consumer-friendly models and increasing the success rate of new designs. Additionally, the classification model refines design directions early in the development process to reduce risks, improve design efficiency, and enhance market competitiveness.

The experts' feedback highlights the importance of the classification model in car design and market analysis, confirming its effectiveness and reliability in practical applications.

4. Conclusions

We explored the use of the WEKA toolkit and image recognition technology by analyzing the styling compositions of sedans, hatchbacks, MPVs, and SUVs sold by Mercedes-Benz, BMW, and Lexus. We developed machine learning models to classify stylistic features of these vehicle types and applied generative AI to design new vehicle models. The usefulness of the developed model was validated by the invited experts and demonstrated its effectiveness in automotive design and development. The classification model helps designers better understand market demands by aligning vehicle designs with consumer preferences and focusing on design directions to effectively shorten development time and reduce risks. Suggestions were made for how the automotive industry and design education can use AI tools more effectively. Future research is needed to develop advanced techniques for and apply them to style composition.

Author Contributions: Conceptualization, H.-H.W.; method, H.-H.W.; resources, H.-J.S.; data curation, H.-J.S.; validation, H.-H.W.; writing—original draft preparation, H.-J.S.; writing—review and editing, H.-H.W.; experiments, H.-J.S.; supervision, H.-H.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by NSTC, Taiwan, through grant 111-2410-H-027-019-MY2.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are unavailable due to privacy reasons.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Agarwal, T.; Saroha, N.; Kumar, G. Consumer Behaviour Analysis for Purchasing a Passenger Car in Indian Context. In Proceedings of the Mathematical Analysis II: Optimisation, Differential Equations and Graph Theory: ICRAPAM 2018, New Delhi, India, 23–25 October 2020; pp. 165–177.
2. Guan-Chun, Z. 2023 Global Electric Vehicle Sales Ranking: PHEVs and Mini Cars Become Market Favorites. Available online: https://www.artc.org.tw/tw/knowledge/articles/13733 (accessed on 10 July 2024).
3. Verganti, R.; Vendraminelli, L.; Iansiti, M. Innovation and Design in the Age of Artificial Intelligence. *J. Prod. Innov. Manag.* **2020**, *37*, 212–227. [CrossRef]
4. Iansiti, M.; Lakhani, K.R. From Disruption to Collision: The New Competitive Dynamics. *MIT Sloan Manag. Rev.* **2020**, *61*, 34–39.
5. Liedtka, J. Perspective: Linking Design Thinking with Innovation Outcomes through Cognitive Bias Reduction. *J. Prod. Innov. Manag.* **2014**, *32*, 925–938. [CrossRef]
6. Bayyou, D. Artificially intelligent self-driving vehicle technologies, benefits and challenges. *Int. J. Emerg. Technol. Comput. Sci. Electron.* **2019**, *26*, 5–13.
7. Wang, J.; Ma, Y.; Zhang, L.; Gao, R.X.; Wu, D. Deep learning for smart manufacturing: Methods and applications. *J. Manuf. Syst.* **2018**, *48*, 144–156. [CrossRef]
8. Dhingra, S.; Madda, R.B.; Patan, R.; Jiao, P.; Barri, K.; Alavi, A.H. Internet of things-based fog and cloud computing technology for smart traffic monitoring. *Internet Things* **2021**, *14*, 100175. [CrossRef]
9. Kamencay, P.; Markovic, M.; Dubovan, J.; Dado, M.; Benedikovic, D. Neural-Network-Optimized Vehicle Classification Using Clustered Image and Fiber-Sensor Datasets. *IEEE Access* **2023**, *11*, 41315–41324. [CrossRef]
10. Hicham, B.; Ahmed, A.; Mohammed, M. Vehicle Type Classification Using Convolutional Neural Network. In Proceedings of the 2018 IEEE 5th International Congress on Information Science and Technology (CiSt), Marrakech, Morocco, 21–27 October 2018; pp. 313–316.
11. Wang, H.-H.; Shen, Y.-Y.; Hung, Y.-Y. Car Types and Semantics Classification Using Weka. In Proceedings of the 2022 5th Artificial Intelligence and Cloud Computing Conference, Osaka, Japan, 17–19 December 2022; pp. 34–41.
12. Wang, H.-H.; Liu, C.-K.; Yu, S.-B. Predicting Consumer Preferences by the Deformation Threshold of Product Appearance. In Proceedings of the 2023 IEEE 5th Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability, Tainan, Taiwan, 2–4 June 2023.
13. Wang, H.-H.; Chen, C.-P. A case study on evolution of car styling and brand consistency using deep learning. *Symmetry* **2020**, *12*, 2074. [CrossRef]
14. Tan, S.H.; Chuah, J.H.; Chow, C.-O.; Kanesan, J.; Leong, H.Y. Artificial intelligent systems for vehicle classification: A survey. *Eng. Appl. Artif. Intell.* **2024**, *129*, 107497. [CrossRef]
15. Asry, N.I.M.; Mustapha, A.; Mostafa, S.A. Comparative Analysis of Machine Learning Algorithms in Vehicle Image Classification. In *Methods and Applications for Modeling and Simulation of Complex Systems*; Communications in Computer and Information Science; Springer: Singapore, 2024; pp. 426–436.