1.

a.

Included at the end of the file.

b.

- Proposed ML models and its aim: a new verification system that calculates the similarity of a wheel design and provides the brand model of the car along with the index score indicating the degree of similarity. The model use Mask R-CNN to extract wheels then labelled the wheels with the brand names then use a resnet to check the wheel's similarity.

- Datasets: collected approximately 730,000 automobile images from one of the largest automobile image websites (Hyundai is my guess). These images include brands and detailed models, including their names, years, and countries

c.

- The model is straightforward and straight up not that important, thus bias or in accuracy is not a big issue. It simply benefits those who work in the wheel-related industries
- Dual use: since it allows people to identify the cars, it can also be used by criminals.
- Since the data is collected directly from a big company, the problem regarding consent is solved.
- If this a more serious issue (which is not totally impossible) like police trying to identify which car the criminals are using. Then bias such as some wheel does not exists in the datasets could lead to wrong direction in the capturing.

d.

To avoid being used with bad intentions, adding more security and giving permissions to those related is an option. To avoid bias, in the last point, we can completly remove the label of the data and instead set input to be wheels with the same label as a pair or trio.

2.

a.

Notice that for any points labeled -1, the first element is less than 2 and larger than 2 otherwise thus the idea is to create a vertical line at 2, which is the line $x_1 = 2$, which can be done by setting $w = [1, 0]$ and $b = -2$. Indeed, plugging in we will see that $w \cdot (x_1, x_2) + b = 0 \implies x_1 = -b = 2$ is the line equation. The line correctly identify all points as $+1$ and -1 without any points having value between -1 and 1.

b.

Notice that every point labeled -1 have their elements with absolute value 1 and labeled 1 have their elements with absolute value 2. Thus we can use any form of k-th norm to first transform it, we will use norm 1. Let K be that transformation

$$K : \mathbb{R}^2 \to \mathbb{R}, \qquad (x_1, x_2) \to |x_1| + |x_2|$$

Thus we can rewrite the data points, every data points labeled -1 now have value 2 and labeled 1 now have value 4. Thus we can simply compare that to number 3 which means $w = 1$ and $b = -3$. The equation correctly identify all points as $+1$ and -1 without any points having value between -1 and 1.

3.

a.

Compare the models CNN low-res MNIST, SVM Original MNIST, and SVM low-res MNIST. Using the results from t-test, we can say with 95% confidence that $CNNlow - resMNIST$ is better than $SVMoriginalMNIST$, which is better than $SVMlow - resMNIST$.

b.

Using t-test requires at least 30 samples, which we ignores in this case as it is computationally expensive to do so. However, that impact could be reduced because we know that the results is not by chance due to the permutation test.

4.

a.

The baseline of the code follow the CNN slides from CMPUT 466 and this guide. The summary of the code is as followed for each function:

- load_datasets: load, reshape each image into (W,H,L) where L is the layer (RGB has 3) and one-hot encode Y
- prep_pixels: since each pixels has a value between 0 and 255 we can normalize it between 0 and 1 by dividing by 255
- define_model: define the main CNN model

- evaluate_model: K-fold cross validation and train model on each of them.
- low_resolution: (for low-resolution mnist) reduce the image dimensions.

The parameters are chosen after looking at the results of different models (with different epochs, parameters), some of the graphs were included below:

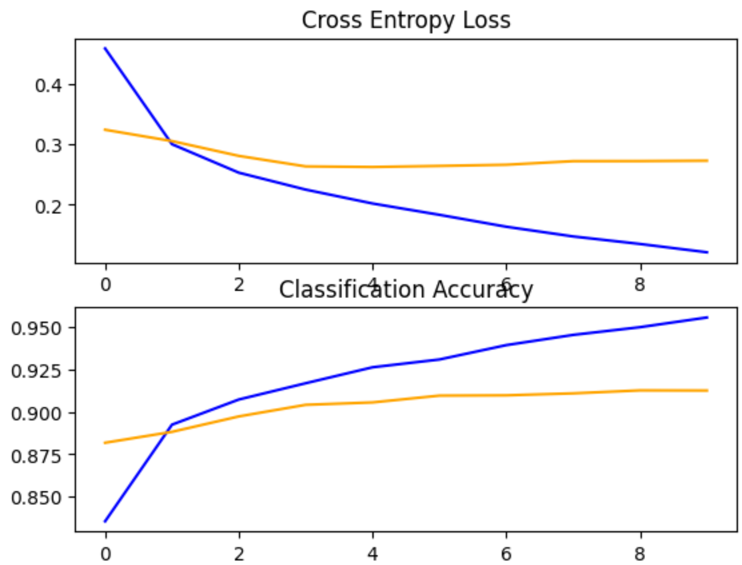


Figure 1: Base model

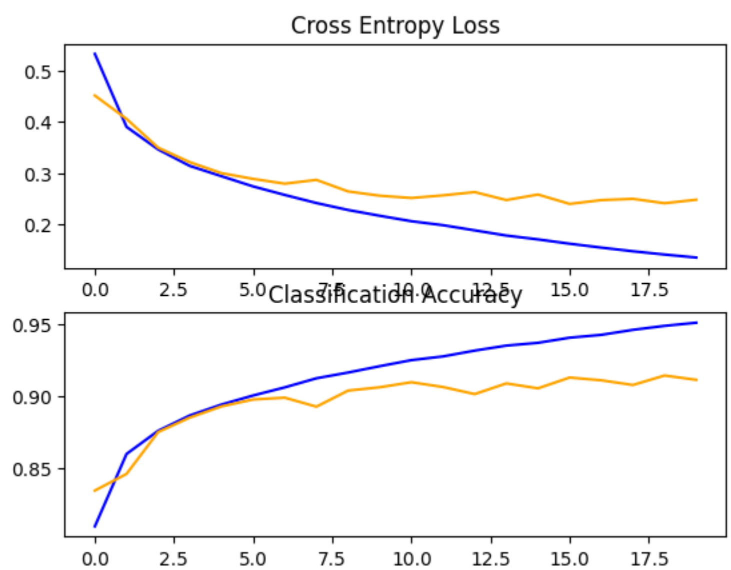


Figure 2: lr = 0.005, momentum = 0.75, extra dropout layer after first layer, padding = 'same' in Conv2D

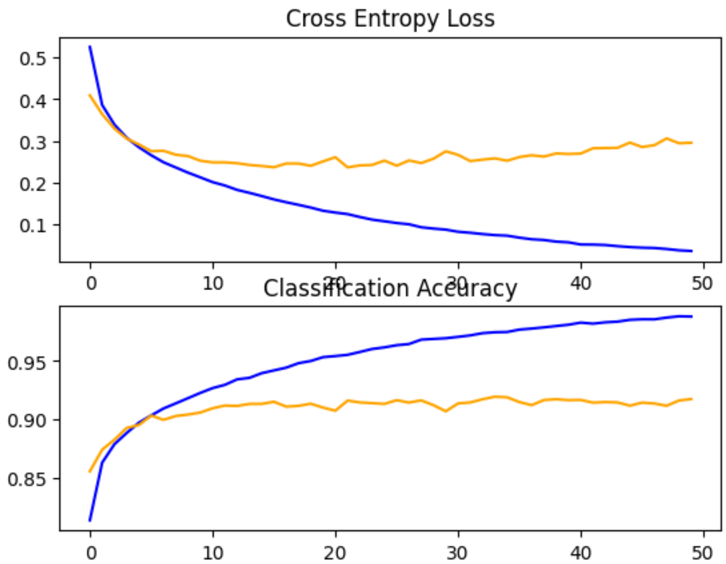


Figure 3: kernel = 'he_normal' in Conv2D, add extra layers, BatchNormalization, Dropout

Decide to stick with the last model and stop at epoch 40 to avoid overfitting too much but at the same time have enough time to extract features. This process I found is quite hard to fix as the model loss start to increase but the accuracy also increase or stay the same, my guess is this happened because the model started to overfit but there is still useful features to extract from the dataset. That is why I tried adding in new layers, decrease learning rate and increase epochs as well as adding in overfitting countermeasure. Early stopping is also an option in preventing overfitting.

b.

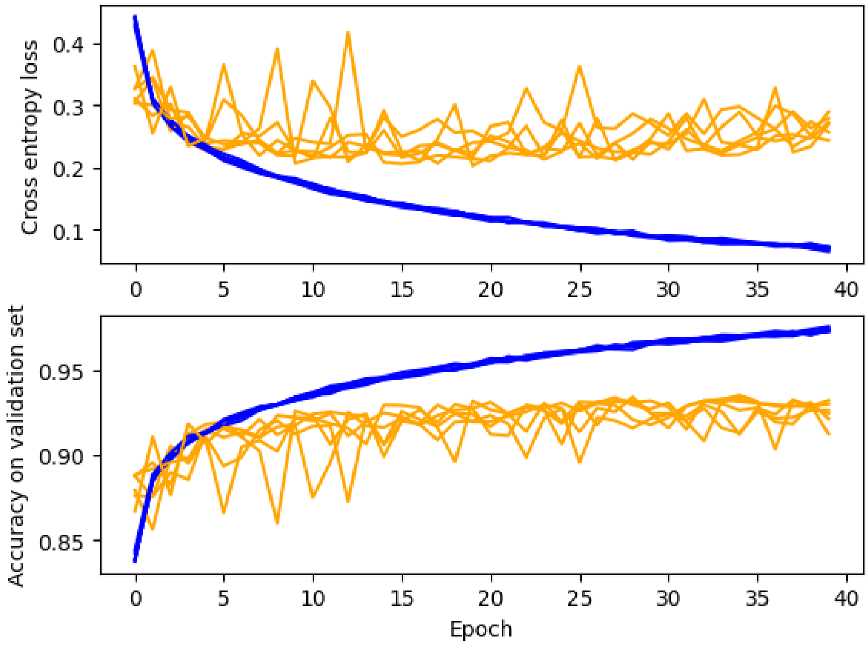


Figure 4: K-fold cross-validation (K=6)

The test accuracy is:
$[93.270469811, 92.990064146, 93.180691335, 92.645498230, 92.640225226, 92.645536653]$.
Applying the t-test, we have that the 95% confidence interval is
$(92.59088736525, 93.19994110175)$
Applying permutation test: I relabeled Y 10000 times and check for its accuracy, the number of relabled datasets having higher accuracy than 92% is 0. Thus the confidence interval of the model not having those accuracy by chance is $(99.5, 100)$ by using $\frac{1}{2\sqrt{k}}$ [1] where k is the number of test as the range.

c.

The code is the same for the mnistfashion dataset except for an extra AveragePooling2D outside the model to resize the images while retaining most of the images information, which was also included in part a. The base model has a decent enough accuracy across a K-fold cross-validation (K=6), all have an accuracy of higher than 98% thus I did not modify any parameters of the base model. Though I did run the models on both the original size mnist and low-resolution mnist with K-fold cross validation and obtain an approximate accuracy for both.

d.

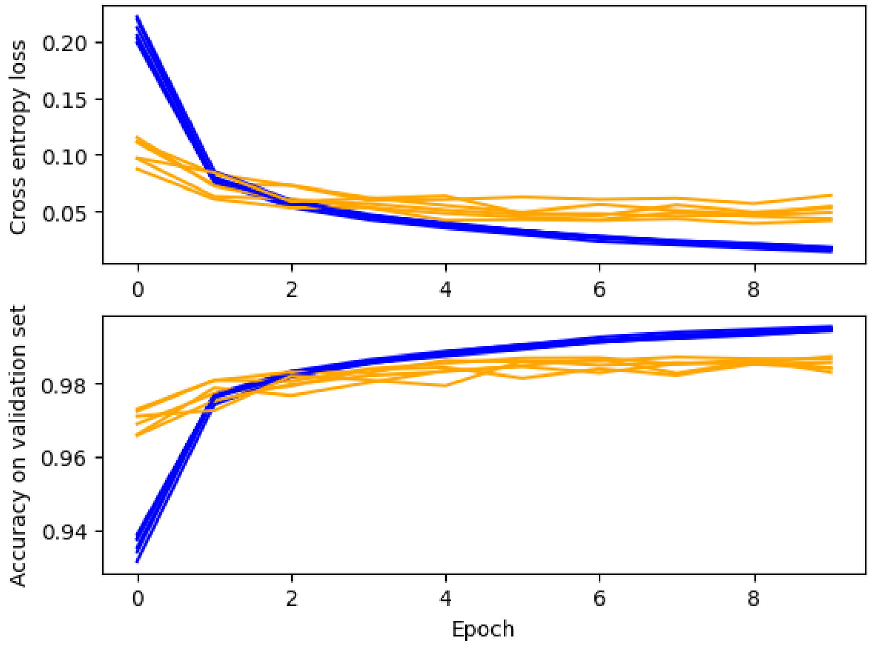


Figure 5: K-fold cross-validation (K=6)

The test accuracy is:
$[98.746262626, 98.278001932, 98.892868030, 98.691421652, 98.994553821, 98.172831632]$.
Applying the t-test, we have that the 95% confidence interval is
$(98.28057206333, 98.97807450101)$
Applying permutation test: I relabeled Y 10000 times and check for its accuracy, the number of relabled datasets having higher accuracy is 0. Thus the confidence interval of the model not having those accuracy by chance is $(99.5, 100)$ by using $\frac{1}{2\sqrt{k}}$ [1] where k is the number of test as the range.

e.

If we are looking at the model on the datasets, there is sufficient evidence to say that the model for the part on mnist low resolution is better as it simply has higher accuracy on the testing sets with a 95% confidence using the results from the t-tests.

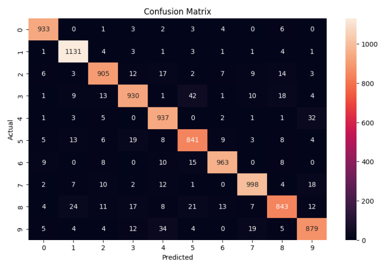
5.

b.

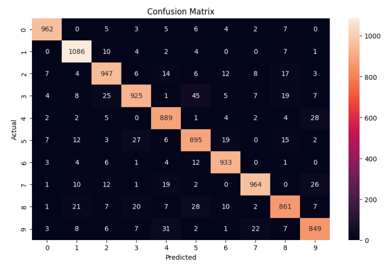
Using K-fold cross validation with $k = 6$, I obtained the following train and test accuracy

- train: $[0.93644, 0.93648, 0.93782, 0.93752, 0.93732, 0.93664]$
- test: $[0.9361, 0.9381, 0.9299, 0.932, 0.9311, 0.936]$

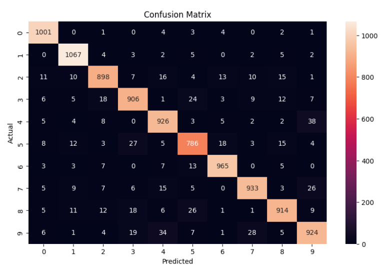
Applying the t-test on the test's accuracy set, we have that the 95% confidence interval is $(0.930407, 0.937326)$.
We also have the following confusion matrix:



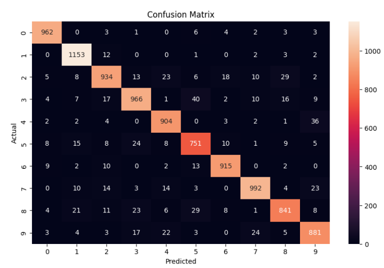
(a) index 1



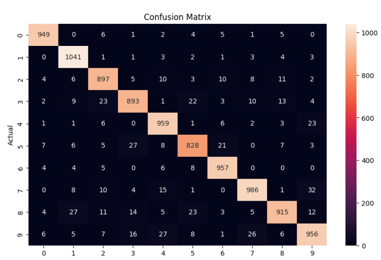
(b) index 2



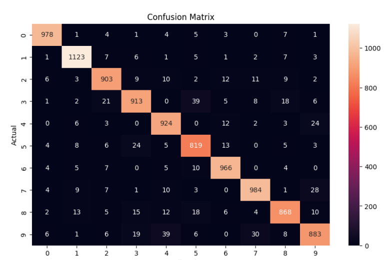
(c) index 1



(d) index 2



(e) index 1



(f) index 2

Figure 6: K-fold cross-validation (K = 6)

We can see that (4,9) and (3,5) are where the model has trouble predicting, which makes sense.

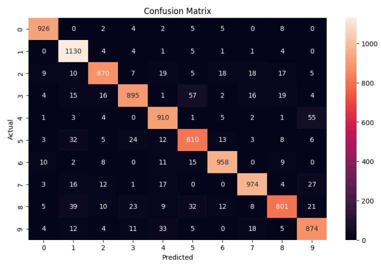
d.

Using K-fold cross validation with $k = 6$, I obtained the following train and test accuracy

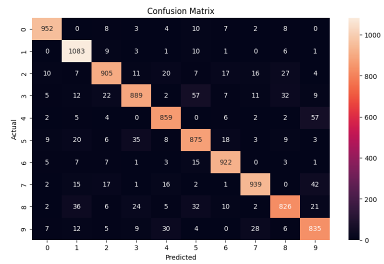
- train: $[0.91304, 0.91366, 0.91368, 0.91436, 0.91236, 0.9126]$

- test: $[0.9137, 0.9184, 0.9073, 0.9105, 0.9085, 0.9148]$

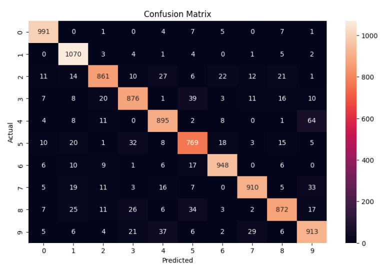
Applying the t-test on the test's accuracy set, we have that the 95% confidence interval is $(0.907796, 0.916604)$
We also have the following confusion matrix:



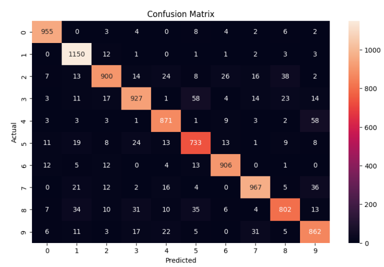
(a) index 1



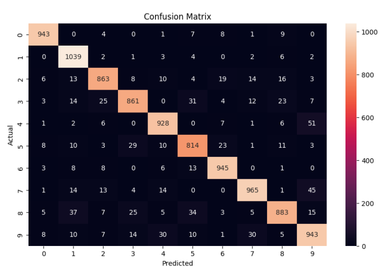
(b) index 2



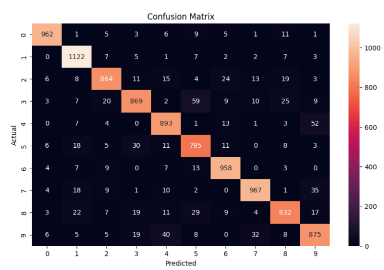
(c) index 1



(d) index 2



(e) index 1



(f) index 2

Figure 7: K-fold cross-validation (K = 6)

We can see that (4,9) and (3,5) are where the model has trouble predicting similar to the other model.

e.

If we are looking at the model on the datasets, there is sufficient evidence to say that the model for the part on the original mnist is better as it simply has higher accuracy on the testing sets with a 95% confidence using the results from the t-tests.

References

[1] https://ieeexplore.ieee.org/abstract/document/1284395

[2] https://dmkothari.github.io/Machine-Learning-Projects/SVM_with_MNIST.html

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SPECIAL TOPIC ARTICLE

Application of deep metric learning in the verification process of wheel design similarity: Hyundai motor company case

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Funding information
Hyundai Motor Group

Abstract

The global automobile market experiences quick changes in design preferences. In response to the demand shifts, manufacturers now try to apply new technologies to bring a novel design to market faster. In this paper, we introduce a novel AI application that performs a similarity verification task of wheel designs that aims to solve the real-world problem. Through the deep metric learning approach, we empirically prove that the cross-entropy loss does similar tasks as the pairwise losses do in the embedding space. On Jan 2022, we successfully transitioned the verification system to the wheel design process of Hyundai Motor Company's design team and shortened the verification time by 90% to a maximum of 10 min. With a few clicks, the designers at Hyundai Motor could take advantage of our verification system.

INTRODUCTION

Automobile manufacturers around the world strive to create innovative designs to meet rapidly changing customer demands. In particular, manufacturers aim to shorten the design period for new cars, which typically takes more than a year (Koricanac 2021). Manufacturers now apply new technologies, such as artificial intelligence (AI) to speed up the design process. For instance, AI technologies such as GANs (Radhakrishnan et al. 2018) and 3D CAD models (Yoo et al. 2020) can effectively reduce the design process by generating the overall shape of car designs.

In addition to the overall shape of the car, manufacturers often place significant emphasis on the wheel design as it can represent the novelty of automobile brands (i.e., according to an interview with the design team at Hyundai Motor). However, the entire process of designing wheels can be time-consuming, and sometimes result in huge sunk costs when similar wheel designs are discovered later. In the interview, the design team of Hyundai Motor emphasized the importance of similarity verification task, noting that a failure could lead to the mass-production of a design-infringed wheel, resulting in sunk costs of over 3,000,000 US dollars. To address this challenge, the digital design team of Hyundai Motor Company (hereafter, Hyundai Motor), a global leader in the automobile industry, is exploring the use of AI models to make the wheel design process more efficient. This study focuses on the application of AI models in collaboration with Hyundai Motor to shorten the design period.

Specifically, Hyundai Motor now tries to improve the wheel design process by focusing on shortening the design

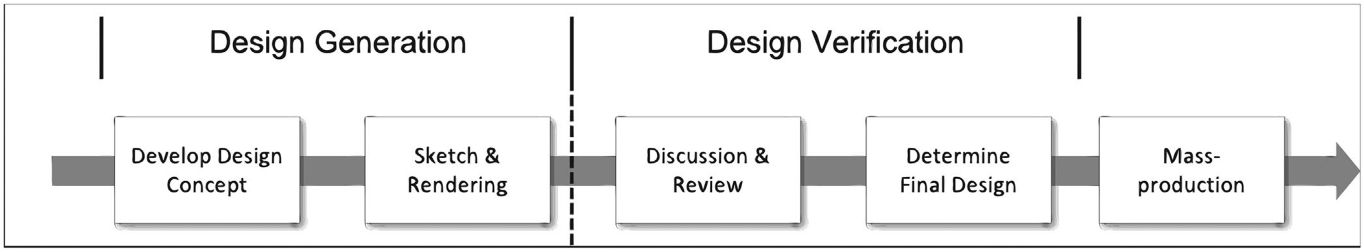


FIGURE 1 The process of creating wheel designs.

verification stage. As depicted in Figure 1, the design process consists of two stages: design generation and design verification. According to Hyundai Motor, the design verification stage involves not only the selection of novel designs, but also the detection of infringed designs. After designers complete the initial rendering of a wheel (i.e., initial designs), they need to verify whether the blueprint bears any resemblance to preexisting wheel designs of competitors. Despite the importance of design verification stage, scant research deals with the application of AI in this particular stage.

The previous verification task in Hyundai Motor relied on a manual process. For instance, the designers searched for similar designs through web surfing and then performed the verification task based on their own experience. However, manual verification can undermine the design process and increase the risk of errors in the verification procedure. Hence, we suggest a novel breakthrough to improve the verification process of wheel design similarity, and we demonstrate how our application enhances the time efficiency of Hyundai Motor's wheel design process. Specifically, our study aims to address the following objectives: *(1) establishing a wheel database for the verification system, (2) efficiently calculating the wheel image similarity, and (3) implementing our AI model into Hyundai Motor's design process. Furthermore, from an applicative perspective, we investigate (4) the extent to which our verification system can reduce design time compared to the previous process.*

We develop a new verification system that calculates the similarity of a wheel design and provides the brand model of the car along with the index score indicating the degree of similarity. The system operates through the following steps. First, designers input a query image (a draft design of a wheel), and an AI model extracts the feature vector from the query image. The model is based on the ResNet50 network structure and has been trained using deep metric learning (DML) with the cross-entropy loss. While DML methods typically employ pairwise losses as the loss function, we empirically demonstrate the outstanding performance of DML with cross-entropy loss in the real-world applications. Second, the verification system searches for similar feature vectors within a database containing over 500,000 wheel images and retrieves the corresponding similar vector embeddings. The searching procedure employs an approximate search method utilizing the k-nearest neighbor graph algorithm (Sugawara, Kobayashi, and Iwasaki 2016). It calculates the angular distance between the feature vectors, comparing the query image's vector with others from the database. Last, the system presents the top six similar wheel images to end-users along with the brand model and the index score indicating the similarity. The process is accomplished within one to three seconds. Figure 2 provides a detailed description of each stage of our research.

Our research has significant contributions to the automobile design industry by providing valuable guidelines for handling potential issues that may arise when applying AI models in real-world scenarios, such as data and budget constraints. To address the data issue, we constructed a wheel image database containing worldwide brands. We also developed an AI model using the DML method with cross-entropy loss, which is less complex and costly than pairwise losses. Instead of using features of wheel images as labels, we used a car's brand model as a label for a wheel, saving development time. In addition, we demonstrate the practical application of our AI model in the working environment, reducing the time required for verification tasks by up to 90%, from 120 to 10 min. We believe that our research can serve as a valuable reference for the industry.

PRIOR PROCESS OF SIMILARITY VERIFICATION

The verification stage of the wheel design process at Hyundai Motors consists of two sub-stages. In the first sub-stage, 15 wheel designs are verified. To create a final wheel design, each designer generates 15 new wheel designs for new cars. To verify these new designs, each designer spends approximately one hour searching for similar wheel designs by googling and visiting motor show websites. The second sub-stage is a regular meeting where designers discuss the newly designed wheels, evaluating their quality and similarity to other wheel designs. In this

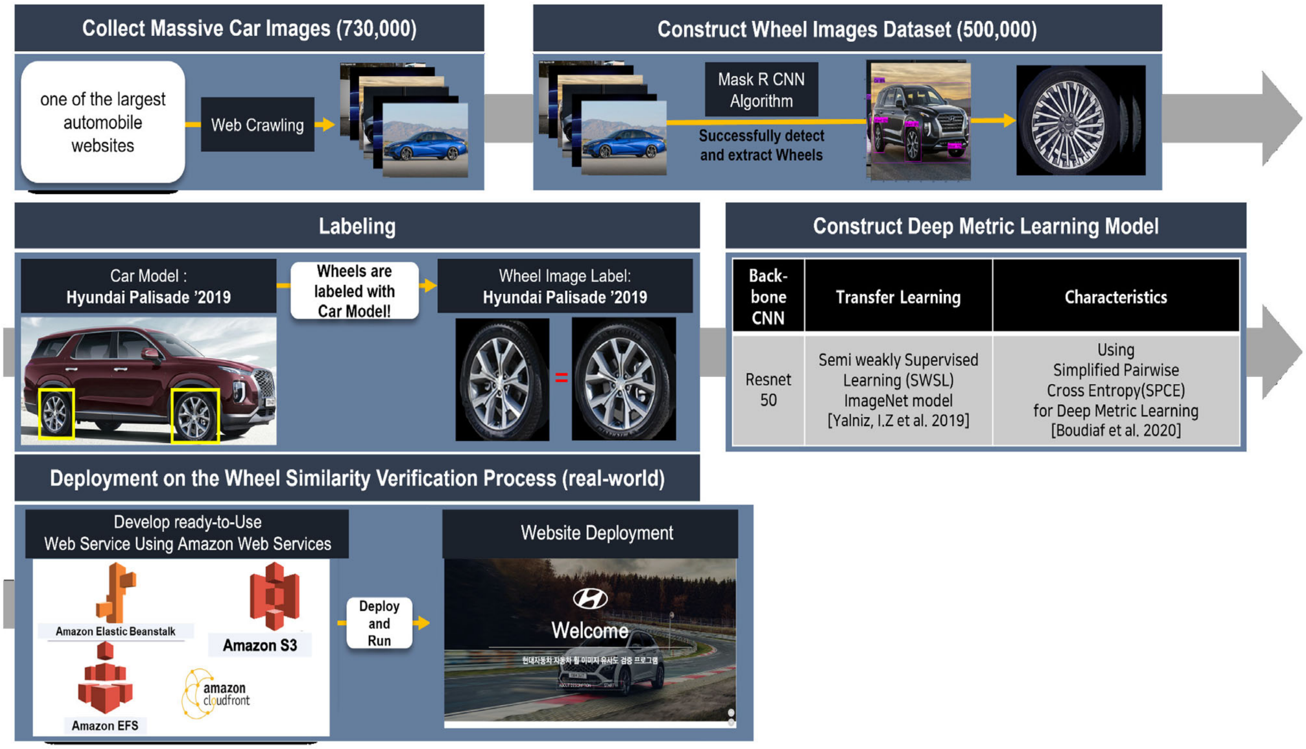


FIGURE 2 A working process of our research.

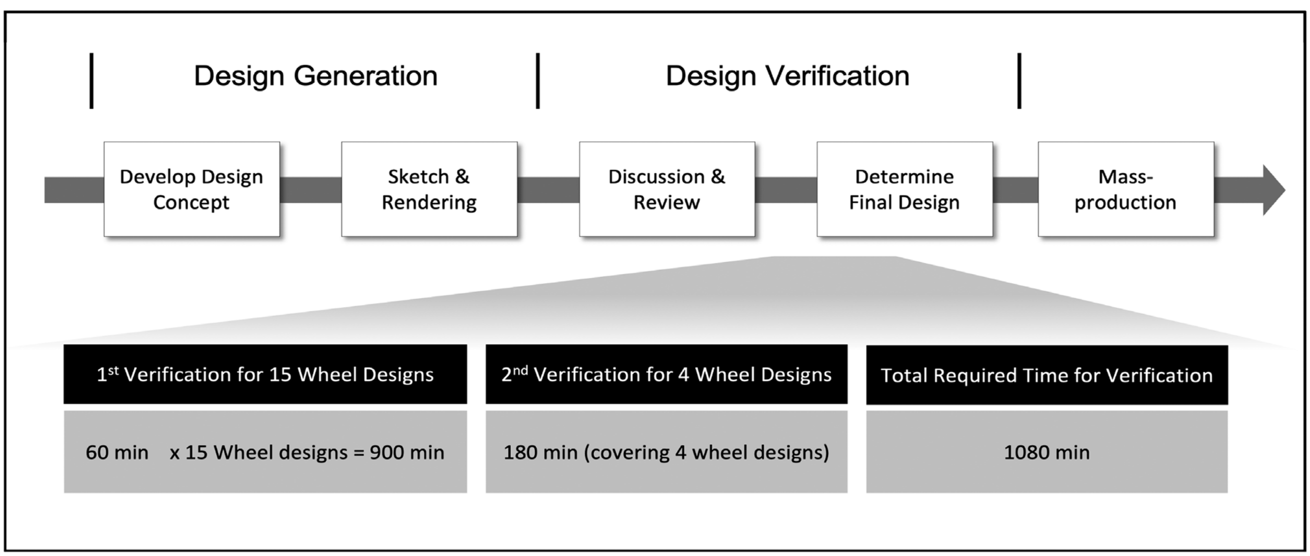


FIGURE 3 The process of design verification stage.

step, designers rely on their subjective opinions based on their personal experiences. The meeting covers four design candidates for one final wheel design and usually takes 180 min. Overall, the entire verification process takes at least 1080 min for one wheel design. Figure 3 provides a more detailed description of this process.

The verification based on the designers' personal experiences may be accurate because the designers are experts in the domain. Nevertheless, designers cannot manually verify the similarity of all the wheels. This manual step not only takes up a significant amount of time but also increases the risk of mass-producing a wheel design that infringes on copyrights, resulting in potential sunk costs. Hence, this study aims to automate the verification stage of wheel designs at Hyundai Motors through the application of an AI model.

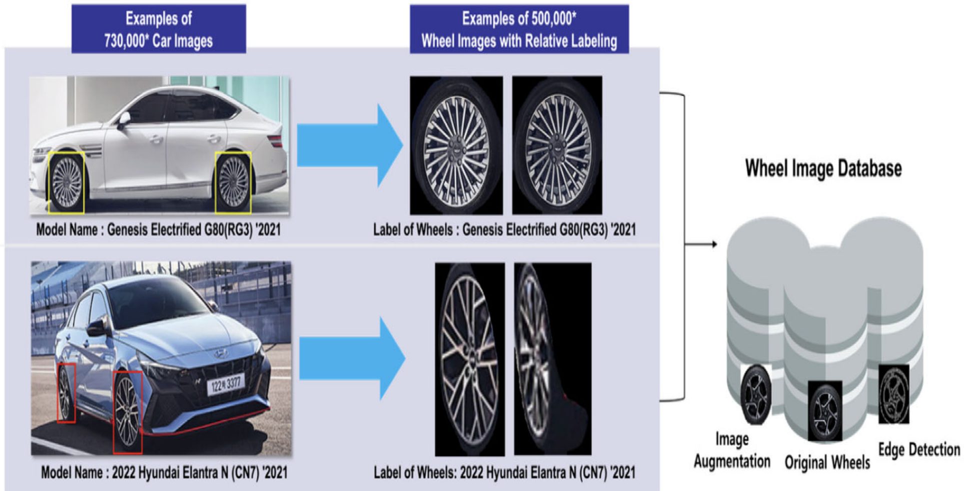


FIGURE 4 The process of building the wheel images database.

METHODOLOGY

In this section, we discuss the methodological challenges that may arise when applying AI models in real-world scenarios, specifically in the context of improving the verification process of Hyundai Motor's wheel image similarity. We also present our approach to addressing these challenges.

Data collection

The wheel similarity verification system requires a wheel image dataset. However, there was no wheel images dataset containing worldwide brands of automobiles. To construct the wheel database, we collected approximately 730,000 automobile images from one of the largest automobile image websites. These images include brands and detailed models, including their names, years, and countries. We then used the Mask R-CNN algorithm to extract only the wheel portion from the car images (He et al. 2017). After removing unsuitable images for training, we obtained over 500,000 wheel images and constructed a database that includes wheel images of automobiles released in the global markets. The process of building the wheel image database is described in Figure 4.

Furthermore, we have made several updates to enhance the performance of our system. First, we applied simple image augmentation techniques (e.g., rotation, flipping, etc.) to ensure that our database contains a variety of wheel designs. Second, we conducted edge detection on the wheel images in our database. Edge detection is an important process in image processing because it allows us to capture the outline of the target image (Rong et al. 2014). Once the edges of images were detected, we added the results to our database. This enabled our verification system to assess the similarity of both sketched and rendered query images. Examples of augmented and edge-detected images are shown in Figure 5.

Data preparation and relative labeling

DML is a neural-network-based approach that utilizes an optimal distance metric to measure the similarities between a given dataset. The goal of DML is to ensure that samples from the same class are close together, while samples from different classes are far apart (Zabihzadeh 2021). Thus, DML requires labels for the given data to determine whether they belong to the same class or not. However, manually labeling over 500,000 images can be a time-consuming and labor-intensive task. We handle this issue by labeling the wheel images with the corresponding car model name. In addition, we assigned the same label to wheel images that were extracted from the same car image. For example, if we obtained two images of wheels from a car with the model name "Hyundai Elantra abroad version 2014," we assigned the label "Hyundai Elantra abroad version 2014" to both images.

Deep metric learning and cross-entropy loss

DML methods typically train image embeddings by focusing on local relationships between pairs (Bell and Bala 2015; Chopra, Hadsell, and LeCun 2005) or triplets (Hoffer and Ailon 2017; Schroff, Kalenichenko, and Philbin

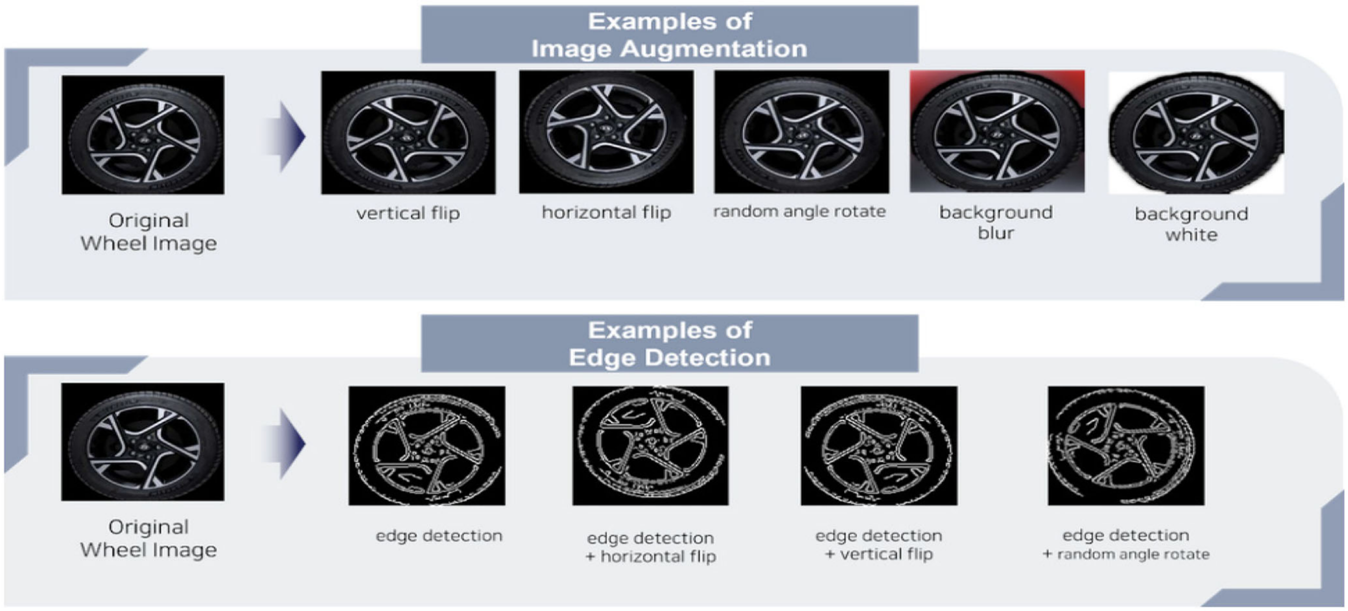


FIGURE 5 Examples of augmented and edge-detected images.

2015) of images. However, these methods often rely on heuristics and involve increased complexity and additional hyper-parameters, limiting their potential for real-world applications (Boudiaf et al. 2020). Considering the time and cost efficiency, alternative loss functions are needed for practical DML application. In this regard, we address the application of DML using a standard cross-entropy loss as our solution to the real-world problem.

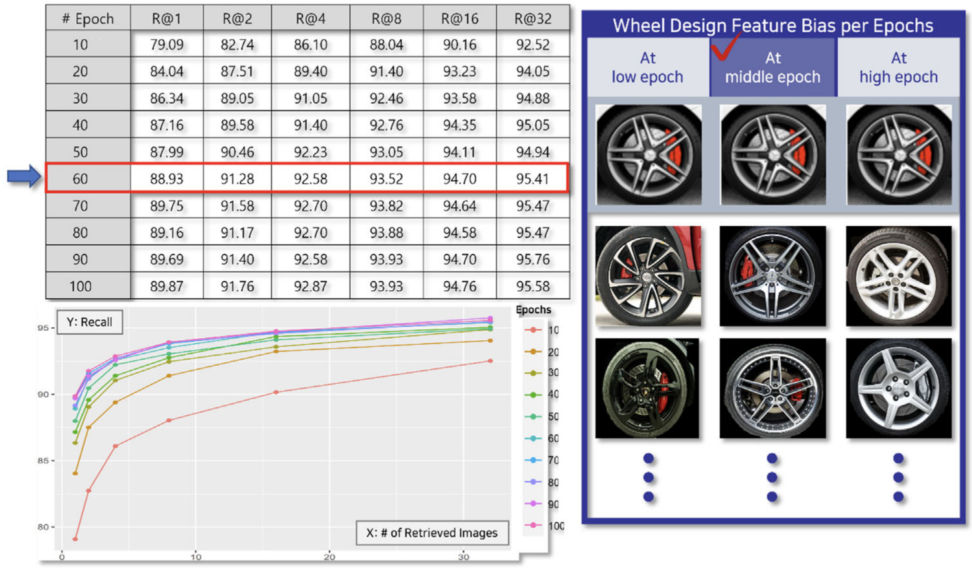
While previous research has empirically explored the performance of a cross-entropy loss in DML (Zhai and Wu 2018), the study did not provide sufficient theoretical insights to support the results. To address this issue, other research provides theoretical justifications that establish a direct connection between cross-entropy and well-known pairwise losses (Boudiaf et al. 2020). Despite these findings, the application of the cross-entropy loss in DML, specifically in the context of solving the real-world problems, has not been fully explored.

Apart from well-organized and commonly used image retrieval datasets, this study is the first to empirically demonstrate the outstanding performance of DML with cross-entropy loss in a real-world application, specifically in the development of the verification system for wheel design similarity. We utilized a Semi weakly Supervised Learning (SWSL) ImageNet model from Facebook for transfer learning. This approach has previously demonstrated state-of-the-art results in classifying ImageNet data using 1 billion web-scale data for semi-supervised learning. By combining the use of cross-entropy loss and transfer learning, we provide a practical and efficient solution for DML in real-world applications. The performance of our DML model, including recalls per epoch, is described in Figure 6.

The figure demonstrates the overall performance of our DML model. By epoch 20, our model already reached an R@1 of approximately 84%. However, it is interesting to note that higher epochs do not necessarily lead to better performance for our model. In our case, at lower epochs, the model focuses more on capturing design details (e.g., colors) rather than the overall shape. Conversely, at higher epochs, the model captures the overall shape but misses out on the details. We had to align our model with the designers viewpoint and consider their feedback. Eventually, by incorporating the designers' feedback, we selected a model with epoch 60.

DEPLOYMENT AND THE RESULTS

Companies today are increasingly leveraging low-code platforms for implementing digital solutions (Rui and Bruno 2020). Theses platforms offer rich functionalities (e.g., machine learning, and AI-based-analysis) through a simple drag-and-drop interface. In this research, we also utilized a low-code platform to deploy our wheel similarity verification system. By doing so, end-users could use our service through a web interface with a simple click. Specifically, we used Amazon Web Services (AWS) as our low-code platform. We developed an innovative service that combines various AWS services, including computing power (EC2), data storage (EFS and S3), application deployment service (Elastic Beanstalk), and content



# Epoch	R@1	R@2	R@4	R@8	R@16	R@32
10	79.09	82.74	86.10	88.04	90.16	92.52
20	84.04	87.51	89.40	91.40	93.23	94.05
30	86.34	89.05	91.05	92.46	93.58	94.88
40	87.16	89.58	91.40	92.76	94.35	95.05
50	87.99	90.46	92.23	93.05	94.11	94.94
60	88.93	91.28	92.58	93.52	94.70	95.41
70	89.75	91.58	92.70	93.82	94.64	95.47
80	89.16	91.17	92.70	93.88	94.58	95.47
90	89.69	91.40	92.58	93.93	94.70	95.76
100	89.87	91.76	92.87	93.93	94.76	95.58

FIGURE 6 The overall performance of our DML model. By incorporating the designers' feedback, we selected a model with epoch 60.

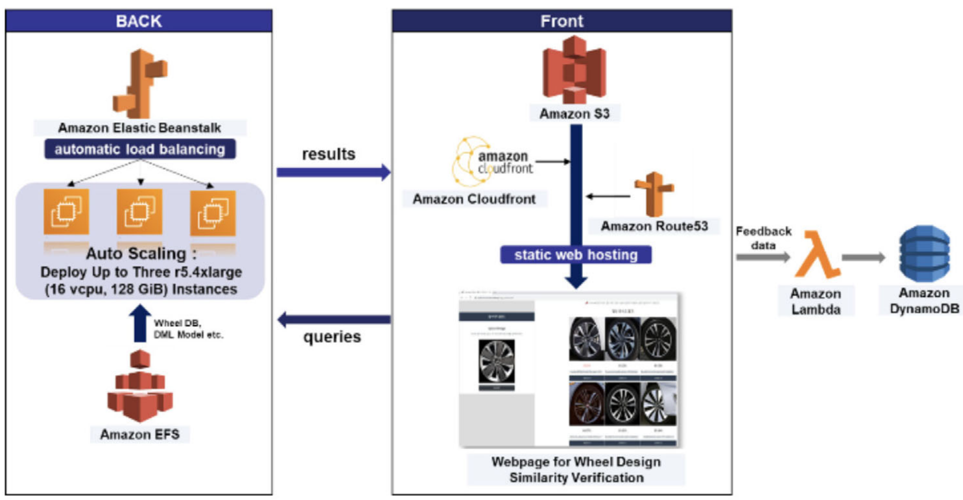


FIGURE 7 The workflow of our deployed system.

delivery network service (CloudFront), and so on. Figure 7 describes the workflow of our deployed application.

We successfully deployed our innovative wheel design similarity verification system in January 2022 (see Appendix A). The technical team at Hyundai Motor is currently responsible for its maintenance, continuously updating both our model and the database to ensure the optimal performance. The system we developed is a user-friendly service that allows end-users to identify the verification results with just a few simple clicks in three seconds. Our system has reduced the time required for similarity verification by 90% compared to the previous process. The examples with respect to scenarios of a wheel design similarity verification task are described in Figure 8. With the implementation of our system, designers at Hyundai Motor no longer need to manually search for similar wheel images. Hence, we expect that designers at Hyundai Motor might focus on other important aspects of the design process and bring new products to market faster.

CONCLUSION

In this study, we present a novel application of AI models that verifies the similarity of wheel designs, in collaboration with Hyundai Motor. This study is the first to use the cross-entropy loss in DML, which focuses on a

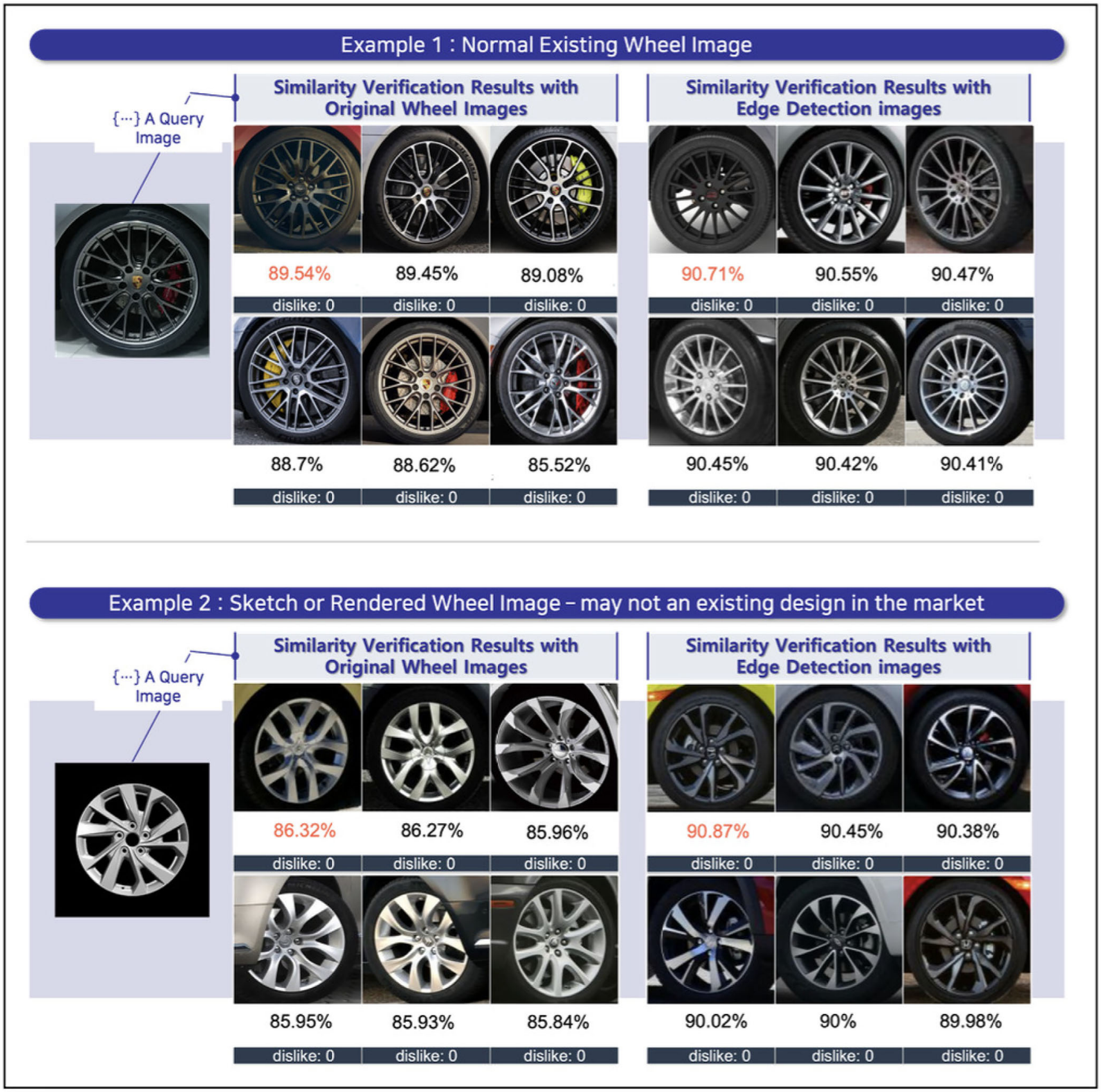


FIGURE 8 Each example is a scenario of a wheel design similarity verification task. The examples show us that our innovative service works well on both normal wheel images and sketch/rendered images. For more scenarios, see Appendix B.

real-world problem. As a result, we successfully implemented the verification system in Hyundai Motor's design process in January 2022. With a few simple clicks, approximately 75 designers at Hyundai Motor now take advantage of our system, shortening the verification task by up to 90%, as described in Figure 9.

Our research provides rich insights for the automobile design industry regarding the effective application of AI models in practical settings. To address the data issue, we constructed a wheel image database containing worldwide brands. We also developed an AI model using DML method with cross-entropy loss, which is meaningful as it addresses real-world problems. Our findings not only demonstrate the effectiveness of the cross-entropy loss in the context of DML but also empirical evidence for its application, which was previously documented only theoretically (Boudiaf et al. 2020).

Moreover, we believe our study can inspire future research on applying AI models in the design process of other automobile components. For example, our AI-based

	Time Required per New Design	1st Verification for 10 New Design	2nd Verification for 4 New Design	Time Total
Previous Process	120 min	120 min x 10 = 1200 min	120 min x 4 = 480 min	1680 min 3.5 days
Current Process with Our Innovative Application	10 min	10 min x 10 = 100 min	10 min x 4 = 40 min	140 min 0.3 days

FIGURE 9 Our innovative AI application reduced the time required in the verification process up to 90%.

verification system can be expanded to verify the designs of other automobile parts, including bumpers, headlights, or radiator grilles. The results of our study provide valuable insights for global automobile manufacturers. We hope that our research can inspire further advancements in the application of AI models in the automobile design process (see Figures A1–B3).

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CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict.

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REFERENCES

Bell, S., and K. Bala. 2015. "Learning Visual Similarity for Product Design With Convolutional Neural Networks." *ACM Transactions on Graphics (TOG)* 34(4): 1–10.

Boudiaf, M., J. Rony, I. Ziko, E. Granger, M. Pedersoli, P. Piantanida, and I. Ayed. 2020. "A Unifying Mutual Information View of Metric Learning: Cross-Entropy vs. Pairwise Losses." In *ECCV*, https://doi.org/10.1007/978-3-030-58539-6_33.

Chopra, S., R. Hadsell, and Y. LeCun. 2005. "Learning a Similarity Metric Discriminatively, With Application to Face Verification." In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 1, 539–46, IEEE.

He, K., G. Gkioxari, P. Dollár, and R. Girshick. 2017. "Mask R-CNN." In *2017 IEEE International Conference on Computer Vision*. https://doi.org/10.1109/ICCV.2017.322.

Hoffer, E., and N. Ailon. 2017. "Deep Metric Learning Using Triplet Network." In *Similarity-Based Pattern Recognition: Third International Workshop, SIMBAD 2015, Copenhagen, Denmark, October 12–14, 2015. Proceedings 3*, 84–92, Springer International Publishing.

Koricanac, I. 2021. "Impact of AI on the Automobile Industry in the US." Available at SSRN 3841426. https://doi.org/10.2139/ssrn.3841426.

Radhakrishnan, S., V. Bharadwaj, V. Manjunath, and R. Srinath. 2018. "Creative Intelligence-Automating Car Design Studio With Generative Adversarial Networks (GAN)." In *Machine Learning and Knowledge Extraction: Second IFIP TC 5, TC 8/WG 8.4, 8.9, TC 12/WG 12.9 International Cross-Domain Conference, CD-MAKE 2018, Hamburg, Germany, August 27–30, 2018, Proceedings 2*, 160–75, Springer International Publishing.

Rong, W., Z. Li, W. Zhang, and L. Sun. 2014. "An Improved Canny Edge Detection Algorithm." In *2014 IEEE International Conference on Mechatronics and Automation*. https://doi.org/10.1109/ICMA.2014.6885761.

Rui, G., and M. Bruno. 2020. "Low-code Platforms Deliver High Rewards." Available at: https://assets.kpmg.com/content/dam/kpmg/ch/pdf/low-code-platforms-deliver-high-rewards.pdf. Accessed 2022-08-01.

Schroff, F., D. Kalenichenko, and J. Philbin. 2015. "Facenet: A Unified Embedding for Face Recognition and Clustering." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 815–23.

Sugawara, K., H. Kobayashi, and M. Iwasaki. 2016. "On Approximately Searching for Similar Word Embeddings." In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics*. https://doi.org/10.18653/v1/P16-1214.

Yoo, S., S. Lee, S. Kim, K. H. Hwang, J. H. Park, and N. Kang. 2020. "Integrating Deep Learning into CAD/CAE System: Case Study on Road Wheel Design Automation." *arXiv preprint arXiv:2006.02138*. https://doi.org/10.18653/v1/P16-1214.

Zabihzadeh, D. 2021. "Ensemble of Loss Functions to Improve Generalizability of Deep Metric Learning Methods." *arXiv: 2107.01130*.

Zhai, A., and H. Y. Wu. 2018. "Classification is a Strong Baseline for Deep Metric Learning." *arXiv preprint arXiv:1811.12649*.

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APPENDIX A: THE WEBSITE OF DEPLOYED VERIFICATION SYSTEM

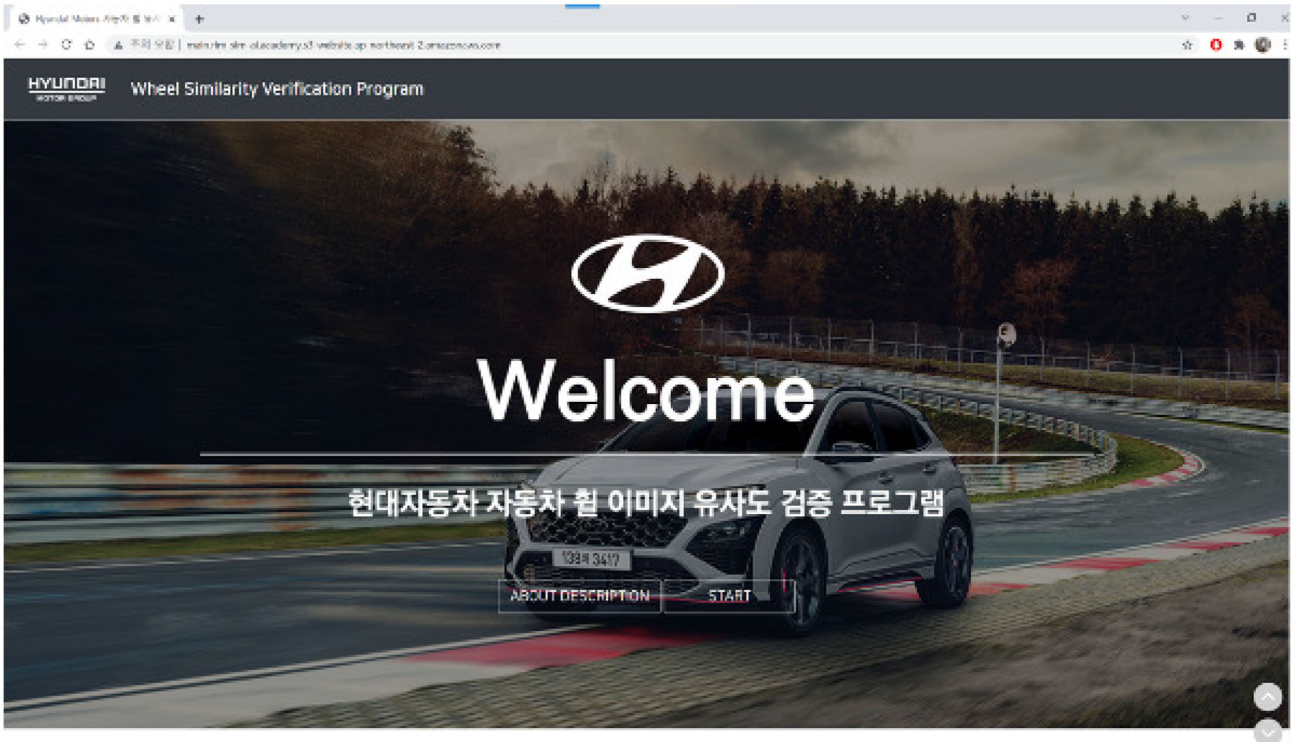

FIGURE A1 The main index page of website. In the main index page, you can see the description of this application. The website is not publicly accessible now since it has been built in the intranet of Hyundai Motors. The web application starts with the start button. Then you can move to the next page.

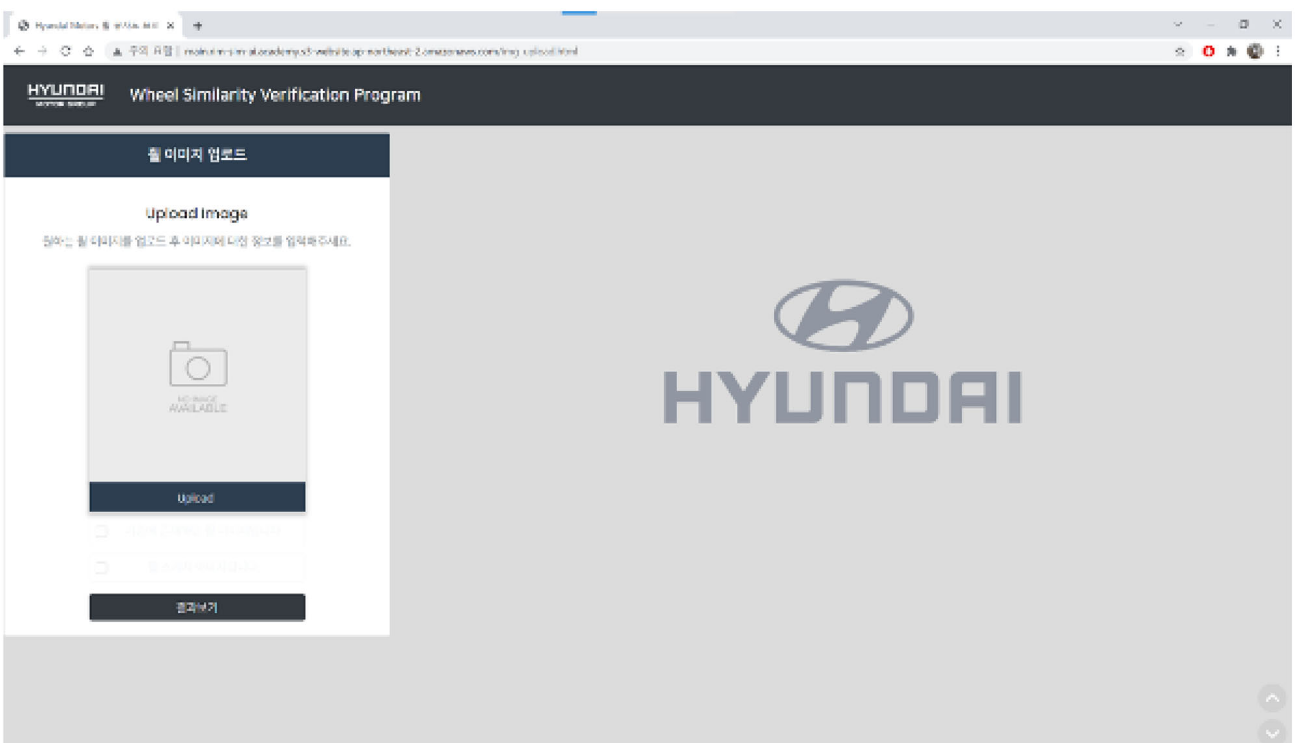

FIGURE A2 The similarity verification page of website. By clicking the "Upload" button, designers can upload their wheel image from local desktop. Once designers upload their wheel image, they can see the result by clicking the result button.

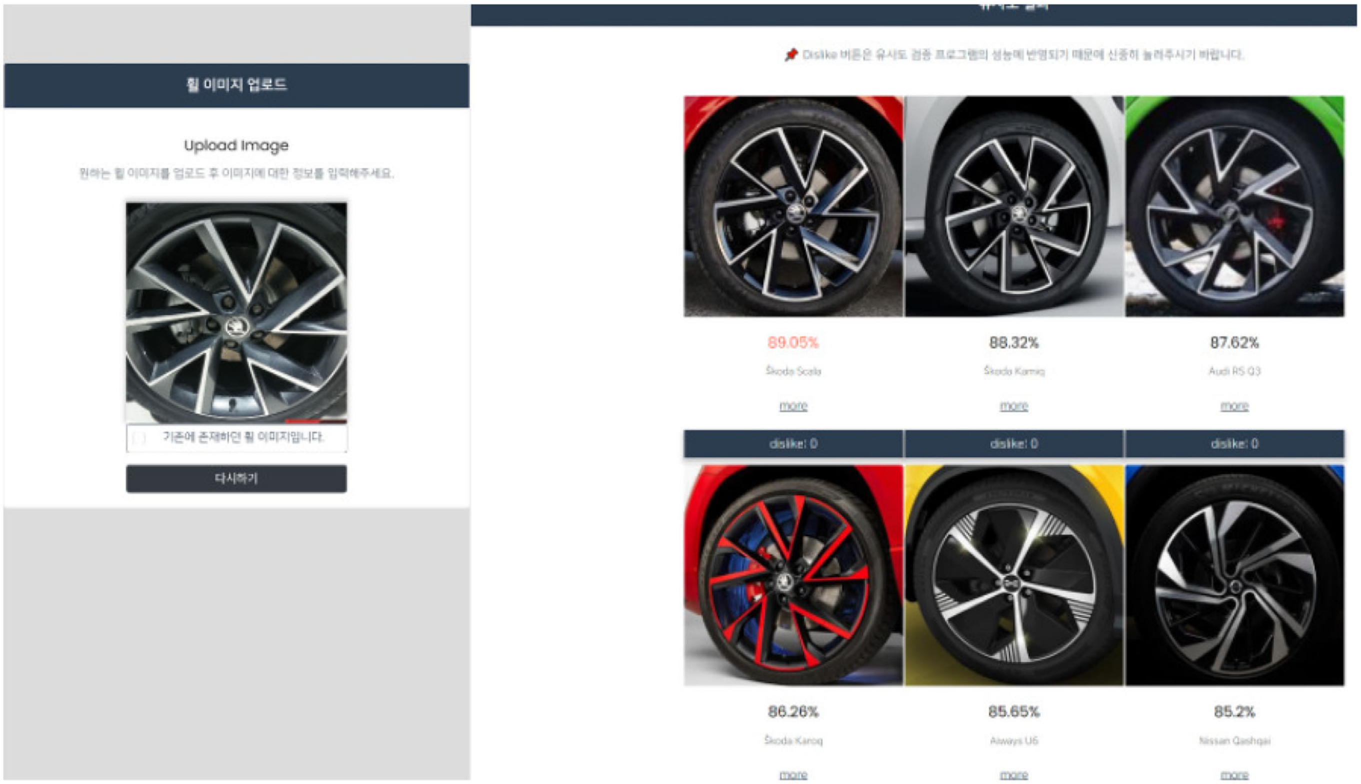

FIGURE A3 The result page of website. In the result page, designers can find top six wheel images that are similar to the uploaded image with the similarity scores. The first one's similarity score is 89.05, which indicates these two wheels are very similar to one another. Sometimes, the viewpoint of our model sometimes may not match the designers' viewpoint. Then, designers can click "dislike" button, which then reflected to next training.

APPENDIX B: SCENARIOS OF WHEEL DESIGN SIMILARITY VERIFICATION TASKS

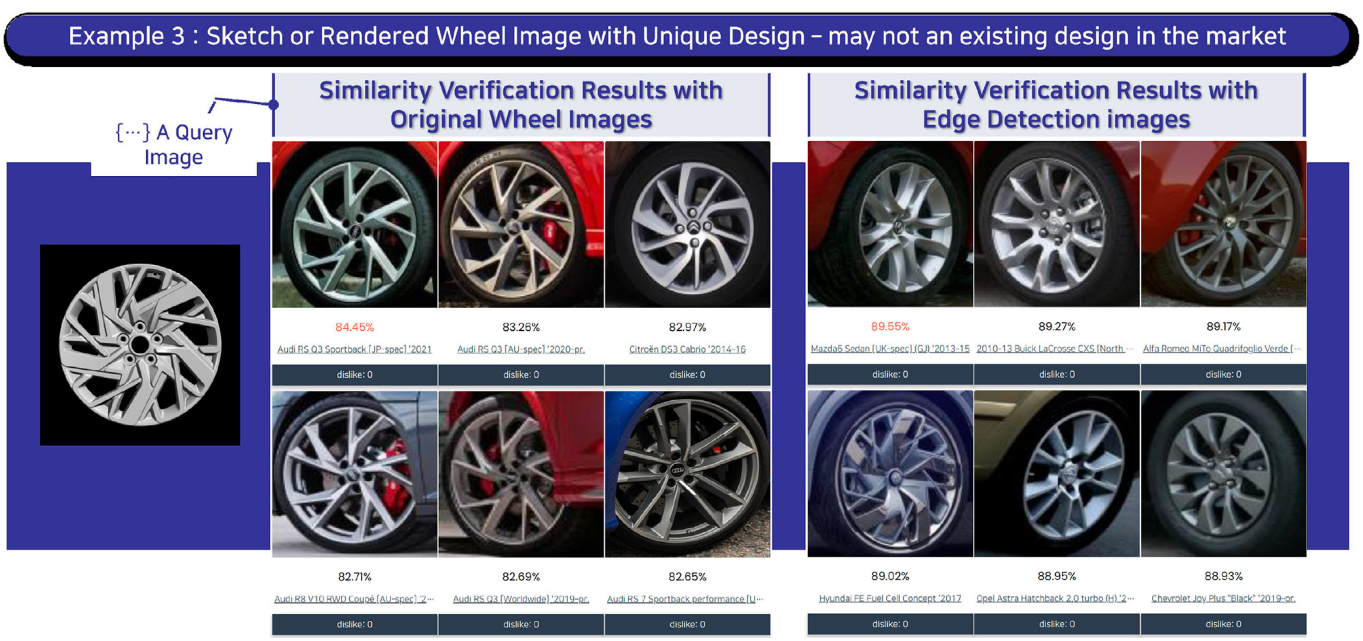

FIGURE B1 Example 4. The verification system works well on both normal wheel images and sketch/rendered images.

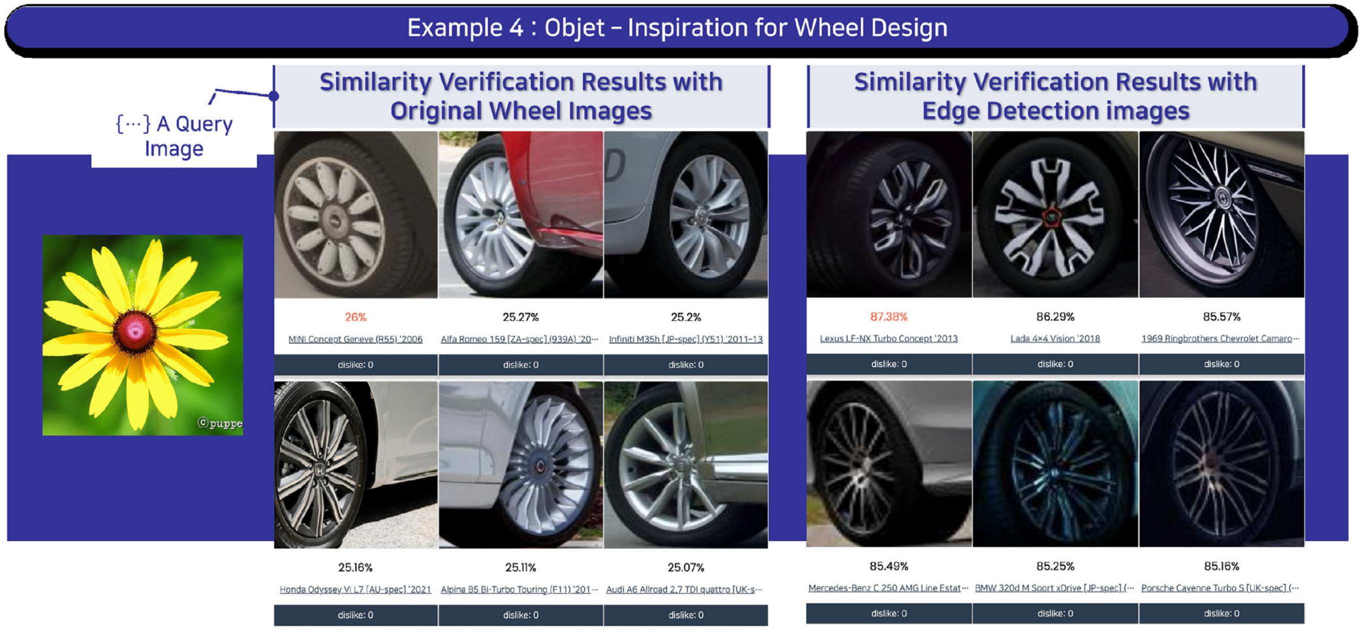

FIGURE B2 Example 5. The verification system not only works well on the rendered image but also on natural objects such as flower.

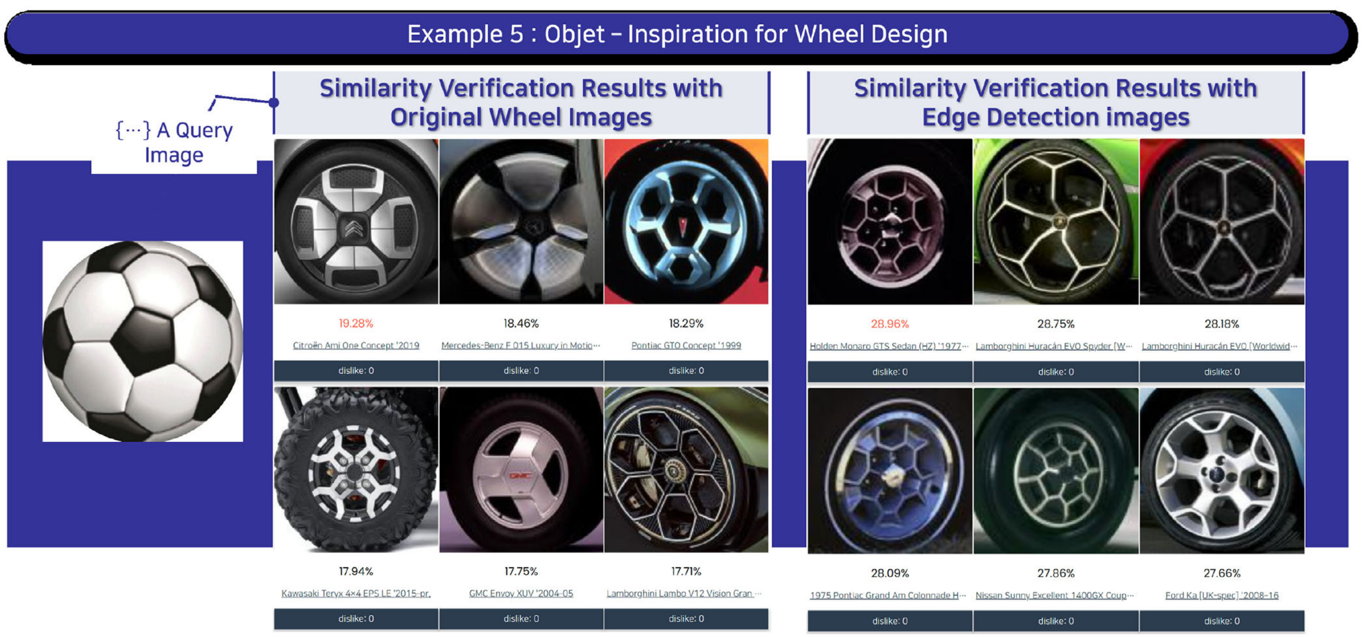

FIGURE B3 Example 6. The verification system not only works well on the rendered image but also on any artificial objects such as soccer ball.

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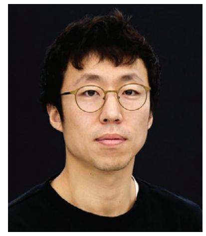

Soon Beom Kwon is the team leader of the Hyundai Digital Design Team at Hyundai Motor Company. His major is transportation design and he earned his master's degree in industrial design from the Hongik University. He has participated in various Hyundai Motors design projects, including the currently mass-produced Ioniq 5 and the Concept car SEVEN,. He is in charge of digital design for all Hyundai Motors currently under development. Additionally, he is conducting various research on design development utilizing AI.

Jae Hong Park is a professor at the School of Management and Big Data Management at Kyung Hee University. His research interests include deep learning, generative AI, business analytics, social media analysis, online word-of-mouth effect, IT investment evaluation, and others. He earned his master's degree from Stanford University, and his PhD degree from the University of Texas at Austin. His works have been published at various journals and conference proceedings such as Information Systems Research, Electronic Commerce Research and Applications, IAAI, and International Conference on Information Systems.