Developing the Wheel Image Similarity Application with Deep Metric Learning: Hyundai Motor Company Case

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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 application that performs a similarity verification task of wheel designs using an AI model and cloud computing technology. At Jan 2022, we successfully implemented the application to the wheel design process of Hyundai Motor Company's design team and shortened the similarity verification time by 90% to a maximum of 10 minutes. We believe that this study is the first to build a wheel image database and empirically prove that the cross-entropy loss does similar tasks as the pairwise losses do in the embedding space. As a result, we successfully automated Hyundai Motor's verification task of wheel design similarity. With a few clicks, the end-users in Hyundai Motor could take advantage of our application.

Introduction

Automobile manufacturers around the world strive to make novel designs as the market demands for car designs change rapidly. In particular, the faster the customers' needs change, the greater the manufacturers put efforts to shorten the design period for new cars, which usually takes more than a year (Koricanac 2021). Recently, manufacturers apply new technologies (e.g. artificial intelligence) to bring a creative design to market faster than before. Among the overall appearance of an automobile, the manufacturers often focus on the wheel design, which can easily represent the novelty of automobile brands (i.e. interview from the design team in Hyundai Motor). However, the whole process of designing the wheel (until the mass production) often takes too much time and effort, and sometimes fails to[1] design the unique wheel (e.g., found similar wheel images later). Aware of the importance of wheel design, the digital design team of Hyundai Motor Company (hereafter, Hyundai Motor), one of the global leading automobile companies, tries to apply new technologies to make the process of wheel design effective.

Hyundai Motor now tries to shorten the process of wheel design by checking how its wheel design is similar with existing ones. Once designers finish making the draft of a wheel (e.g., initial rendering images), they should check out whether the blueprint is similar to any designs of competitors' wheel. In the interview, the design team of Hyundai Motor addressed the importance of the task that a failure of the task could lead to the mass-production of the design infringed wheel, which might cause the sunk costs over 3,000,000 US dollars. The previous verification task in Hyundai Motor relied on a manual. That is, the designers searched for similar designs through the Internet and a motor show, then performed the verification task with their own experience. However, such handwork can undermine the design process and increase the likelihood of failure in the verification procedure. Hence, we suggest a novel breakthrough to improve the verification process of wheel design similarity, and we show how our application improves the time efficiency of Hyundai Motor's wheel design process. Specifically, we aim to study (1) *how to build a wheel database for the verification application*, (2) *how to efficiently calculate the wheel image similarity*, and (3) *how to develop a delicate AI model*. Furthermore, from the applicative point of view, we investigate (4) *how much our verification application could reduce the design time comparing with the previous one*.

We develop a new application that verifies the similarity of a wheel design and returns the brand model of the car with the index score of the similarity. The application works as the following steps. First, once we put a query image (draft design of a wheel), an AI model extracts the feature vector from the query image. The model is based on the ResNet50 network structure, trained through Deep Metric Learning (DML) using the cross-entropy loss (Boudiaf et al. 2020).

Second, the verification application searches for similar feature vectors from the database containing more than 500,000 wheel images, then returns similar feature vectors. The searching procedure works with approximate search method through k-nearest neighbor graph algorithm (Sugawara et al.

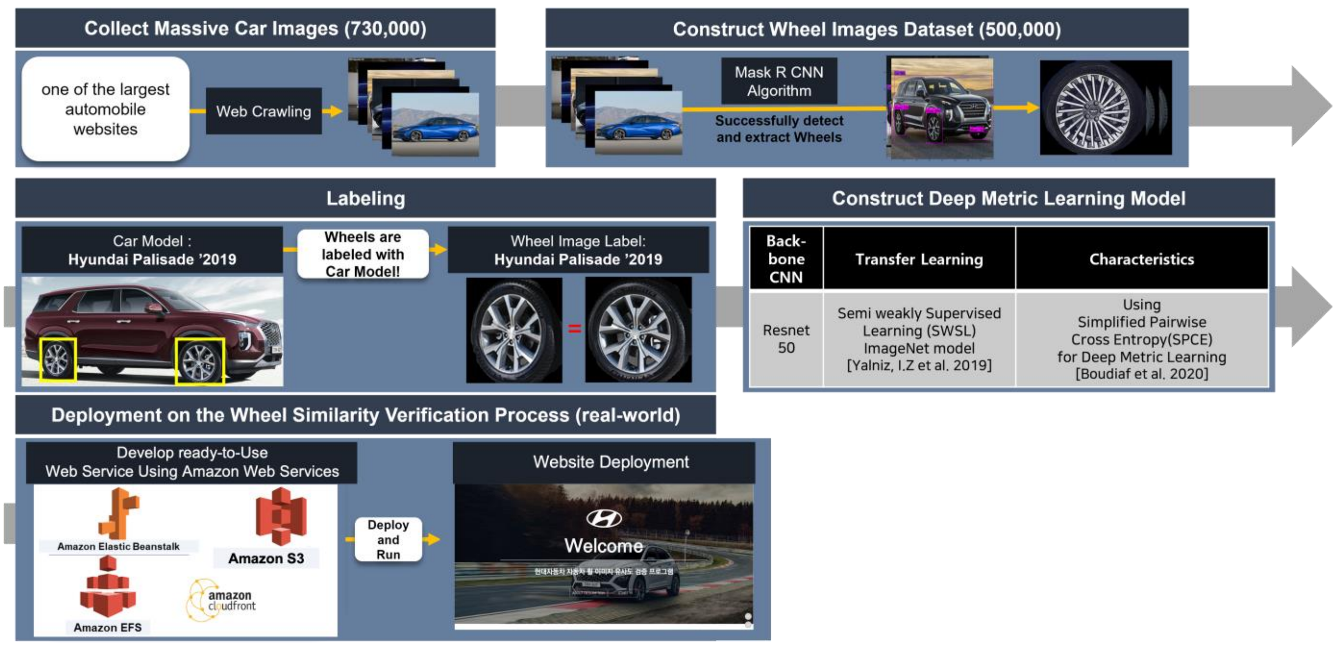


Figure 1: A working process of our research

2016), which searches similar images by calculating the angular distance between the feature vectors - one from the query image and others from the images in the database. Last, the application shows the top 6 similar wheel images to end-users together with the brand model and the index score of the similarity within one or three seconds. Specifically, we describe each stage of our research in Figure 1.

Our research provides several contributions to the industry of automobile design. We are the first to construct the wheel image database containing worldwide brands. Furthermore, we develop an AI model which efficiently extracts the feature vector from a wheel image. Instead of using labels based on the features of wheel images, we used a brand model of a car as a label for a wheel. The relative labels allowed us to train our DML model and the Recall @ 1 of the model was around 88.93%. Last, we show how our AI similarity algorithm has been applied to the working environment. The time required for the task of similarity verification, which previously took around 120 minutes, was reduced by 90% to a maximum of 10 minutes. This shows the possibility of improving the existing process to AI-based-process other than the design process in the industry of automobiles.

Prior Process of Similarity Verification

The task of wheel similarity verification involves two stages - searching and judging. In the stage of searching, designers search for wheel designs that are similar to the draft designs they sketched. Next, the designers determine whether the draft design has infringed on other competitors' designs or not. The process is performed manually and depends mainly on the designers' subjective opinions. For example, designers use automobile websites or Google image searches in searching for similar designs. In addition, the judgment of the similarities relies fully on the designers' subjective opinions. The subjective judgments may be accurate because the designers are experts in the domain. Nevertheless, designers can't verify all the wheels' similarity manually. Also, the verification process takes too much time and human resources.

Problems in Methodology

In this section, we demonstrate how we overcome for solving real-world problems (improving the verification task of Hyundai Motor's wheel image similarity).

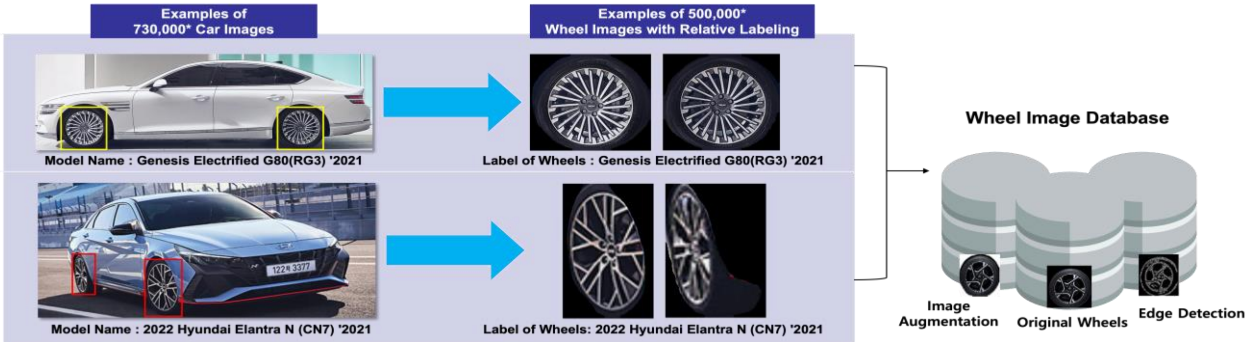


Figure 2: We extracted the wheel images from 730,000 car images using the Mask R CNN algorithm. Filtering images with bad qualities (marked with the red box), we composed a database with around 500,000 wheel images.

The Absence of Dataset

The verification application of wheel similarity requires a wheel image dataset. However, there was no wheel images dataset containing worldwide brands of automobiles. To construct the wheel database, we collected around 730,000 automobile images from one of the largest automobile image websites. The website provides more than 1.4 million images of automobiles released in the world with brands, models, and detail models (year, country, etc.). We then extracted only the wheel part from the car images using the Mask R CNN algorithm (He et al. 2017). After filtering inappropriate images for learning, we obtained more than 500,000 wheel images and constructed a database containing wheel images released in the global markets. Figure 2 describes the process of building the wheel images database.

Moreover, we performed several updates to enhance the performance of our application. First, we performed a simple image augmentation (e.g., rotation, flip, etc.) to make our database contain various wheel designs. Second, we conducted an edge detection with the wheel images in our database. Edge detection is one of the important processes in image processing because it allows us to capture the outline of the target image (Rong et al. 2014). After detecting the edge of images, we reflected the results to our database so that our verification application could verify the similarity of the sketched images as well as the rendered query images. The examples of augmented and edge-detected images are shown in Figure 3.

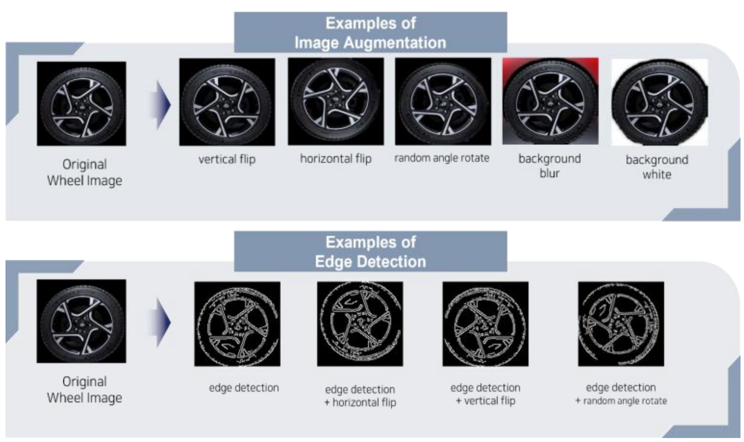


Figure 3: We performed image augmentation to make our database contain various wheel designs. Furthermore, we conducted edge detection using a canny edge detection algorithm to improve the performance of verification for the sketched and rendered query images.

Data Preparation and Relative Labeling

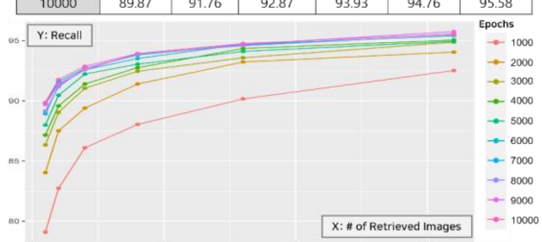
Deep Metric Learning (DML) is a neural-network-based approach to measure the similarities between a given data with an optimal distance metric. DML aims to keep distances of samples from different classes far from one another and samples in the same class close together (Zabihzadeh 2021). Hence, DML needs a label for the given data to determine whether the data is in the same class or not. However, labeling more than 500,000 images manually takes too much time and effort. We solve the issue by labeling the wheel images with the model name of the car. In addition, because wheel images extracted from one car image are very likely to be the same wheel, we granted the same labels to those wheel images. For example, when 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

For learning, we have to choose an optimal loss function that was suitable for our research. Considering the time efficiency and relatively labeled data, we apply a standard cross-entropy loss for DML. While the standard cross-entropy loss is widely used in the community of classification, few research documents the application of the methodology in DML. To the best of our knowledge, no researcher used the cross-entropy loss in the field of DML because it might be irrelevant to the pairwise losses. DML aims to enforce pairwise distance on the embedding space. Hence, the pointwise approach may not be suitable for DML. However, the cross-entropy loss is theoretically relevant to several well-known pairwise losses and even shows the state-of-the-art results (Boudiaf et al. 2020).

The pairwise losses consist of the tightness part and the contrast part. The tightness part makes samples from the same class close together. On the contrary, the contrast part forces samples from different classes to have a large distance from one another. Now, let $\hat{Z}$ denote learned features and let Y denote labels. Then the tightness part of pairwise losses is theoretically relevant to the conditional entropy denoted by $H(\hat{Z}|Y)$ in that we can interpret minimizing the tightness part as minimizing $H(\hat{Z}|Y)$. Likewise, the contrastive part is related to the entropy features denoted by $H(\hat{Z})$. The optimization to find the global minima for each loss is mathematically identical to the maximization of the value of Mutual Information($H\left(\hat{Z}\right) - H(\hat{Z}|Y)$), which is the shared amount of information between two random variables. The cross-entropy loss function also consists of the tightness part and the contrastive part. In addition, the minimization of cross-entropy is mathematically identical to the maximized value of MI. That is, the cross-entropy loss performs the same task as pairwise loss does in DML (Boudiaf et al. 2020).

# Epoch	R@1	R@2	R@4	R@8	R@16	R@32
1000	79.09	82.74	86.10	88.04	90.16	92.52
2000	84.04	87.51	89.40	91.40	93.23	94.05
3000	86.34	89.05	91.05	92.46	93.58	94.88
4000	87.16	89.58	91.40	92.76	94.35	95.05
5000	87.99	90.46	92.23	93.05	94.11	94.94
6000	88.93	91.28	92.58	93.52	94.70	95.41
7000	89.75	91.58	92.70	93.82	94.64	95.47
8000	89.16	91.17	92.70	93.88	94.58	95.47
9000	89.69	91.40	92.58	93.93	94.70	95.76
10000	89.87	91.76	92.87	93.93	94.76	95.58



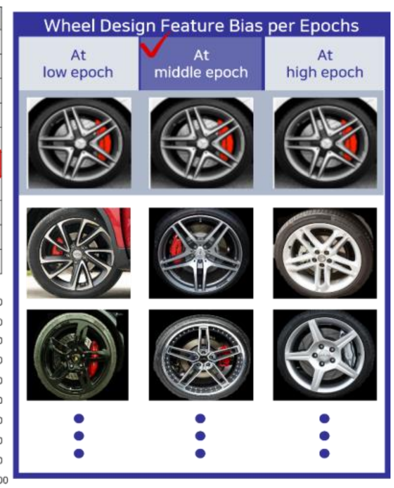


Figure 4: The figure shows the overall performance of our DML model. R@1 of our model already reaches about 84% at epoch 2000. At a low epoch, the model captures the detail of the design (e.g. colors) rather than the overall shape. On the other hand, the model at the high epoch captures the overall shape of the design rather than the details. Finding the balance, we chose a model with epoch 6000.

Still, even though the cross-entropy loss is theoretically relevant to the pairwise losses in DML, the application of the cross-entropy loss in DML has not been addressed yet. Apart from well-organized and commonly used datasets for DML, this paper is the first study to empirically show the outstanding performance of cross-entropy loss in the field of DML. Figure 4 shows the performance of our DML model with recalls per epoch. In addition, we used a Semi weakly Supervised Learning (SWSL) ImageNet model from Facebook for the transfer learning. The Facebook AI Research (FAIR) obtained state-of-the-art results in classifying ImageNet data by using 1 billion web-scale data for semi-supervised learning.

Deployment and the Results

Companies today focus on taking advantage of the low-code platform when implementing digital solutions (KPMG 2020). The low-code platform provides rich functions (e.g. machine learning, and AI-based-analysis) with a simple drag-and-drop interface. In this research, we also utilized the low-code platform for our verification application of wheel similarity. We can deploy the application in the form of a web so that the end-users can easily use it with a simple click. Specifically, we used Amazon Web Services (AWS) as a low-code platform. We developed a serverless service by combining computing power (EC2), data storage (EFS and S3), application deployment service (Elastic Beanstalk), and content delivery network service (CloudFront), etc. Figure 5 and describes the workflow of our deployed application.

The similarity verification solution is an innovative service that enables practical end-users without technical understanding to identify the result of verification with a few simple clicks. The AI-based solution is immediately applicable to the actual similarity verification task. The solution reduced 90% of the time required for the previous similarity verification task for a single-wheel design. The examples with respect to scenarios of a wheel design similarity verification task are described in Figure 6.

In detail, the previous similarity verification task in Hyundai Motor proceeds with the following steps (Hyundai Motor Company 2021). First, a single designer initially performs the verification task, searching for wheel images that are similar to the draft design of a wheel (e.g., sketch or initial rendering image). This step takes around 120 minutes because the search procedure relies fully on a manual by searching for websites or visiting a motor show. After a new design wheel successfully gets through the first step, several designers gather and determine whether the design infringes on other competitors' designs or not. This step also takes around 120 minutes. However, our application automated the manually handled verification tasks. From Jan 2022, the design team at Hyundai Motor has started to use our AI similarity application to check their wheel design. Also, designers now do not need to search for similar wheel images through websites nor do they need to visit a motor show. The design team at Hyundai Motor reported that this shortened time consumed for the prior verification task to a maximum of around 10 minutes by 90% this August.

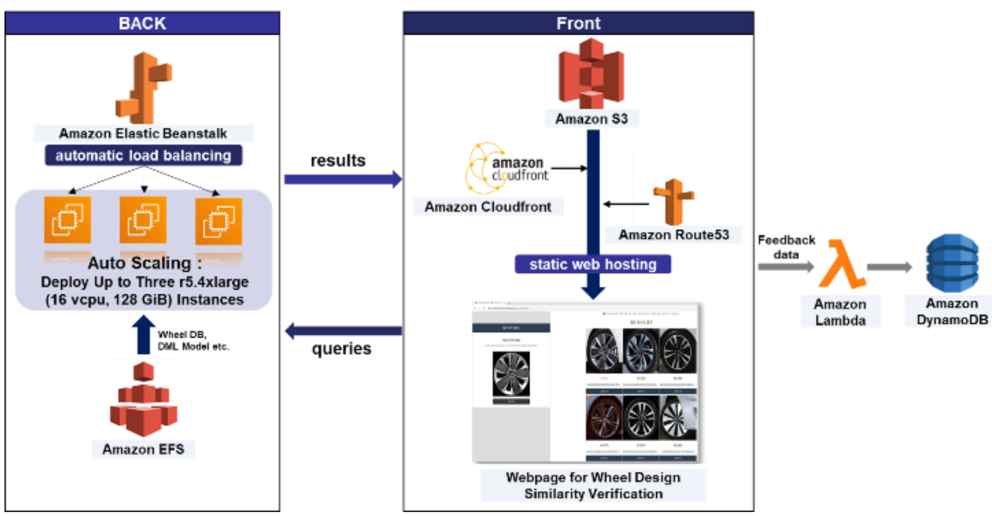


Figure 5: We deployed our innovative verification application of wheel design similarity by combining services from Amazon Web Services (AWS). Especially, Elastic Beanstalk is a service performing load-balancing and auto-scaling based on the level of loads. Users(designers) can give feedback by clicking the "dislike" button per each result image. DynamoDB saves the feedback information for future improvement of our model.

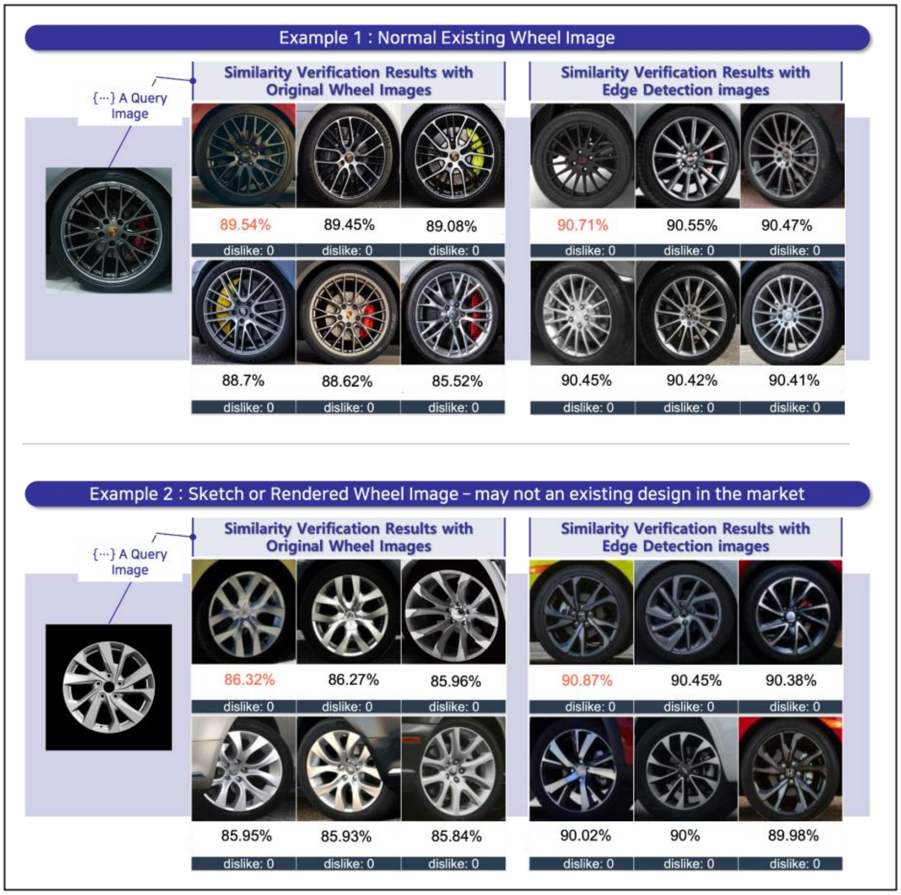


Figure 6: Each example is a scenario of a wheel design similarity verification task. The examples show us that our innovative service works well on both normal wheel images and sketch/rendered images.

	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 7: Our innovative AI application reduced the time required in the verification process up to 90%

Conclusion

One of the global leading automobile manufacturers has successfully implemented new technologies in the design process. Among the process, this paper focuses on the wheel design process. We present a novel application that verifies wheel design similarity. Our research is the first to build a database containing images of wheels released around the world. Moreover, we empirically prove that the cross-entropy loss does similar tasks as the pairwise losses do in the embedding space, which was theoretically documented by prior research only (Boudiaf et al. 2020). Our study is the first to use the cross-entropy loss in Deep Metric Learning (DML) using the wheel images data, other than well-organized and commonly used data for DML. This is meaningful because our research focuses on solving a real-world problem. As a result, we successfully automated Hyundai Motor's verification task of wheel design similarity in Jan 2022. With a few clicks, the designer at Hyundai Motor could take advantage of our application, shortening the verification task up to 90% as described in Figure 7.

Acknowledgements

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