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APPLICATION OF IMAGE CLASSIFICATION MODEL TO IMPROVE VISUAL INSPECTION SYSTEMS OF INDUSTRIAL CUTTERS

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Abstract. *Many manufacturing companies are interested in implementing smart factory-related technologies in Industry 4.0 era, and related case studies are also increasing. However, in the case of SMEs, the application of advanced technologies is slow and not applied properly. In this study, an image classification model was applied to improving the task of operators viewing the screen and checking the image. This study is to address issues such as increased inspection time and increased operator fatigue. After labeling those images, transformed images were generated to compensate for data imbalances. We use AlexNet and ResNet models to classify a total of 20,171 blade images and 17,648 wheel cutter images. For blades, ResNet34 showed the highest accuracy with 99.73%, and for wheel cutters, ResNet34 and ResNet50 showed the highest accuracy with 99.60%. Increasing the number of inspected objects and continuing research to improve accuracy will improve the fieldwork environment.*

Keywords: Smart factory, Inspection process, Image classification, Deep learning

1. **Introduction.** As the manufacturing processes of manufacturing companies become digitized, they are rapidly becoming intelligent. Accordingly, core new technologies such as the Internet of Things, artificial intelligence, wireless sensor networks, big data, cloud computing, and cyber-physical systems are introduced into the manufacturing environment, leading to the 4th industrial revolution [1].

With the start of Germany's Industry 4.0 strategy, the smart factory concept was in full swing. The Korean government is promoting a project to construct smart factories for small and medium-sized enterprises (SMEs) [2]. The introduction of the smart factory is a means of enhancing new competitiveness in the manufacturing sector, and by converging the company's professional capabilities with the latest new technologies, it is possible to discover values that can create new values such as productivity improvement, quality improvement, cost reduction, defect rate reduction, and delivery improvement [3]. In Korea, a policy aimed at constructing 30,000 smart factories by 2025 is in progress. In the case of SMEs, since they are linked with domestic large companies and global companies through the supply chain, the smartization of SMEs is essential for the fundamental development of industrial competitiveness; it can be said that the importance is further emphasized [4]. However, the introduction of the advanced smart factory system is centered on large enterprises, so it is often not possible to reflect the situation of SMEs. SMEs are experiencing many financial difficulties, and the government is promoting infrastructure construction projects such as financial and professional manpower to compensate for this. However, it is still difficult to secure professional manpower [2].

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This paper is the result of a study that analyzed the image data of an SME. The company in question is a company that produces industrial cutters. During the current product inspection, operators visually classify the inspection images while looking at the computer screen. However, this type of work greatly affects the work speed and results according to the operator's personal experience, and there can be deviations depending on the operator, which may make the product inspection result unstable. To prevent this, it is necessary to design an image classification system so that operators can only check the classification results. Therefore, this study aims to improve the efficiency of the inspection process by automating the classification of defective images.

2. **Related Works.** The deep learning technique was used in the manufacturing site to improve the accuracy of the industrial pellet classification system and to extract the characteristics of the product, contributing to increasing the reliability of the grade evaluation [5]. Image classification is based on the existing field classifier in use in the field, PLS-DA (partial least squares discriminant analysis), a standard chemical measurement technique for discriminant analysis, and RF (random forests), a well-established machine learning method based on an ensemble of classification trees, and deep neural network (DNN) and VGG-16 model with transfer learning. Two types of labels were specified. The first was to determine whether the shape of the pellet was round or not. The second was to determine whether the pellet had a tail or not. The two types were classified in consideration of product characteristics. As for classification accuracy, VGG-16 showed the best results with an accuracy of 96% or more.

Xia et al. [6] defined some anomalies such as humping, spattering, robot suspend, pores, and cracking that can occur in wire-arc additive manufacturing, and classification performance was compared using ResNet, EfficientNet, VGG-16, and GoogLeNet. The results showed that ResNet performed best at 97.62%, 97.45%, 97.15%, and 97.25%, making it effective for laminate manufacturing or arc welding techniques.

Kwon [7] defined the types of defective products that can occur on the top and bottom of a screw during the thread inspection process. Hough Circles and PCA were applied for image processing, and a model was built based on VGG for image classification. It showed an accuracy of 98.54% (±1.34%) for the top-binary classification and 99.43% (±0.83%) for the bottom-binary classification. In the defect classification, the accuracies of 91.50% on the upper surface and 89.26% on the lower surface were shown, the calculation time was confirmed to be about 0.07 sec in all cases, and an automatic screw quality inspection system was constructed.

Dheir and Abu Naser [8] refer to a method and mechanism for image identification by conducting a study on multi-disease computer-assisted detection of the stomach using deep learning technology and aim to improve the medical system by reducing cost and time. For image data, the Kvasir dataset was used for Paper with Code. Eight categories including anatomical landmarks (pylorus, z-line, cecum) were classified using the state-of-the-art neural network architectures, VGG16, ResNet, MobileNet, Inception-v3, and Xception. The accuracies were 98.3%, 92.3%, 97.6%, 90%, and 98.2%, respectively. The best performing VGG-16 and Xception achieved over 98% accuracy through retraining.

Krizhevsky et al. [9] had a total of 8 layers: 5 convolution layers and 3 fully connected layers. It consists of 5 convolutional layers, a neural network with 60 million parameters, and 650,000 neurons. Convolutional layers use the ReLU activation function to increase the learning rate by up to 6x compared to the traditional tanh function. They also used local response normalization (LRN) to promote brightness normalization, suppress adjacent pixels in the image, and emphasize features. In this case, they used saturable neurons and GPUs to speed up the implementation. In the fully connected layer, 'dropout' was used to reduce overfitting. Each layer has the feature of learning a filter by extracting features independently of one image and adjusting the weights.

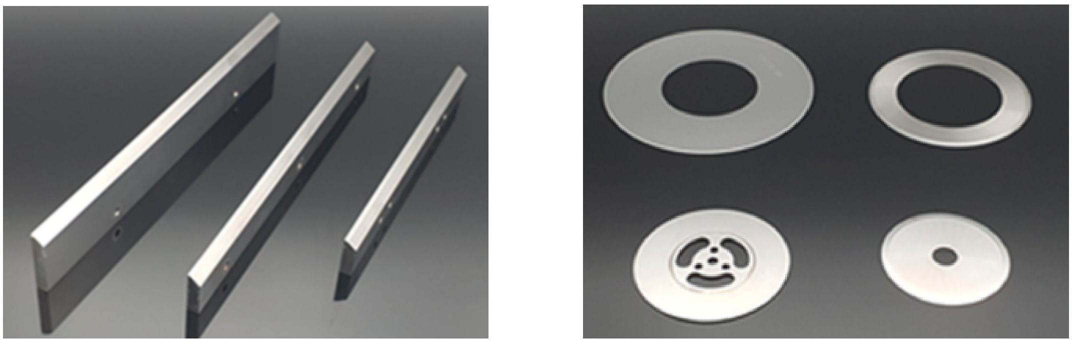
To solve the problem that DNN has difficulty in learning, the rest of the learning methods were presented [10]. Looking at the results of the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) competition, the depth has a great effect on the performance of the model. However, as the depth increases, problems such as overfitting, weight loss, and computational increase occur. Because of these problems, deep neural network training is quite difficult. We proposed a method to solve the gradient loss problem related to layer deepening through residual learning using skip linkage. Residual learning was used to reuse the results of previous layers. In other words, by using a residual function that reuses layers, easier optimization and improved accuracy in deep networks are possible. We applied this method to the model.

This study identified the problems with the company's current system. After labeling the images, additional images were generated in case of insufficient image type. Then, by applying AlexNet and ResNet to the areas where image classification is required, the most accurate classification method can be applied to reducing the deviation between operators and presenting a plan to improve the inspection process system.

3. **Research Process.**

3.1. **Data description.**

The research target is a company that produces and supplies industrial cutters. There are two types of cutters: cutting blade and wheel cutter. They are used in automation equipment in the semiconductor industry, automobile industry, and electric and electronic industry. These cutters are utilized to produce cameras, mobile phones, automobiles, TVs, etc. Figure 1 shows images of the cutting blades and wheel cutters for better understanding.



(a) Cutting blades (b) Wheel cutters

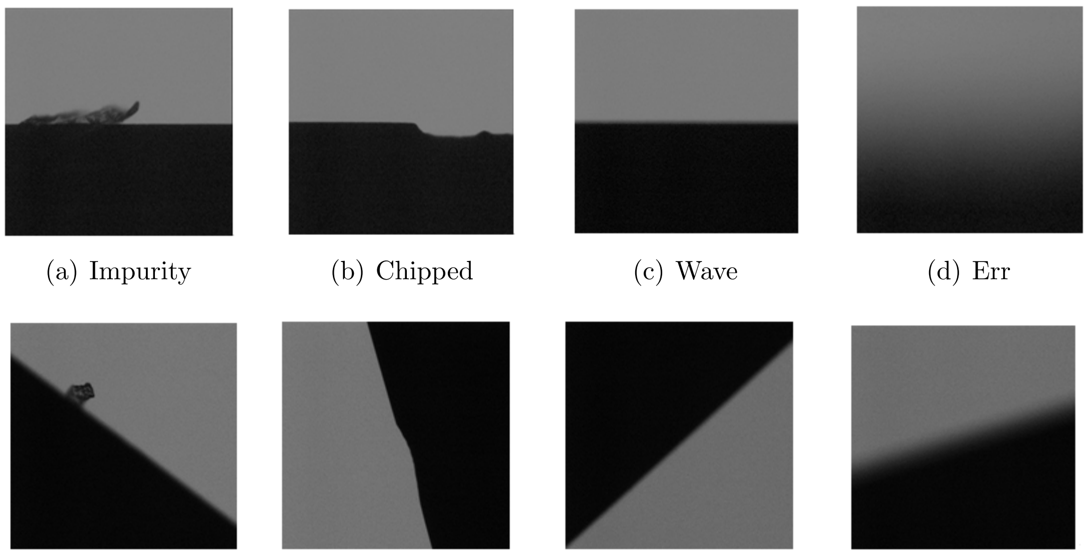
Figure 1. The image of cutting blades and wheel cutters

The current inspection process inspects products that have been subjected to precision processing. The data measured and stored by the equipment during the inspection process includes text and images.

The text data is saved as "product identification number (inspection date and time) _action", and the error value per measurement interval for one product can be checked. The cutting blades can be checked using the average value (comb) by grouping five measured values and can be checked by the straightness of one product. The wheel cutter can be checked by the values of the outer diameter and inner diameter of each product.

As for the image data, it is possible to check a photo when NG (not good) occurs. For the blades, straightness is evaluated through about 2,035 measurements per product. For the wheel cutters, the outer and inner diameters are evaluated through about 1,537 measurements per product. If it exceeds the allowable error per measurement (1.5 μm), it is classified as NG. In addition, a photo of the corresponding NG is printed out, and the image file name is marked as 'measured length (error or ER)'.

3.2. **Current inspections and problems.** The following NG occurs when inspecting the processed blades and cutters: impurity, chipped, wave, and err (out of focus) as shown in Figure 2. NG types of wheel cutters were also defined as an impurity, chipped, wave, and err as shown in Figures 2(e)-2(h). Unlike the cutting blade, it can be seen that the cutter rotates 360°.



(a) Impurity (b) Chipped (c) Wave (d) Err

(e) Impurity (f) Chipped (g) Wave (h) Err

FIGURE 2. Type of NGs of the cutting blades and the wheel cutters

If the camera is out of focus during the inspection process, it is difficult to check the measurement results, so the product must be re-inspected. Therefore, if the camera is out of focus, the operator classifies it separately and proceeds with re-inspection. The operator classifies the type of NG by checking the remaining image files except for cases of 2(d) and 2(h) that are out of focus. Currently, in the case of 2(a) and 2(e), the impurities are wiped off and the inspection is performed again. In the case of 2(b), 2(f), 2(c), and 2(g), the product must be reprocessed because it is a product that has been processed incorrectly beyond the tolerance.

In the process of classifying the images displayed on the computer screen, the eye fatigue of the operator may increase, and misclassification may exist due to the deviation between the operators. In addition, it was identified that there is a risk that can lead to the bottleneck process given the overall process due to the delay in working time.

3.3. **Systems design for image classification.** Based on the current inspection process, the design of the system to classify images can be summarized as shown in Figure 3.

When the inspection is completed, the NG files are saved in the form of 'measured location (ER: this means measurement error)'. For example, a file with an error that the camera does not focus on, such as Figures 2(d) and 2(h), at the location of 440 mm is saved as '440 (ER)'. In such a case, classification proceeds by the file name. Then, check the acceptable standard values if there are no errors out of focus on the camera. If it does not exceed the allowable error, it is treated as a good product. If it exceeds the allowable error, the image classification model is applied. Because 2(b), 2(c), 2(f), and 2(g) are cases beyond the allowable error, they are sent back to the re-manufacturing process. In

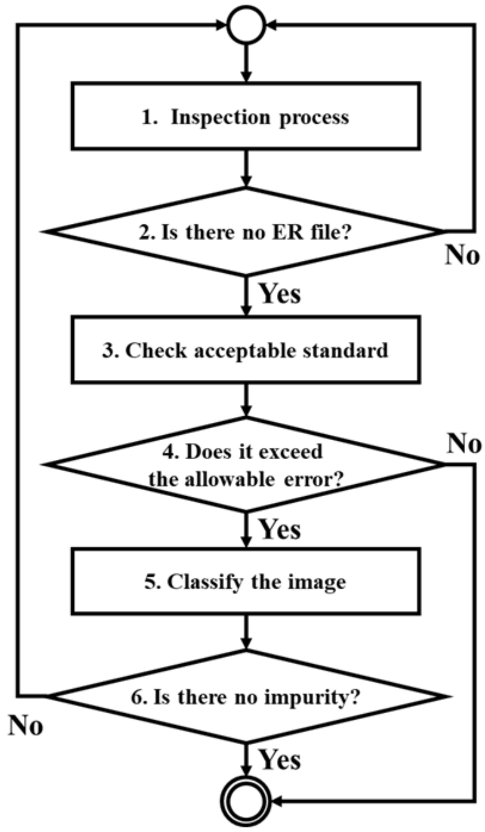


FIGURE 3. Flowchart of system progress

the case of 2(a) and 2(e), the impurities are wiped off and the inspection is performed again.

The system proceeds in the same way as above, and the computer classifies the NG items. It is possible to inform the operator what kind of NG has occurred for the classification result. Then, the operator only needs to check the results that the computer has classified. Therefore, product inspection time can be shortened. It can also reduce operator fatigue.

3.4. **Data preprocessing.** Among the image data received from the company, 17,707 images of cutting blades and 16,068 images of wheel cutters were labeled excluding 2(d) and 2(h). Since there are cases where the number of images by product or type is insufficient, additional images were created to balance the data. The number of images by error types is shown in Table 1.

TABLE 1. Number of images by error types

Type	Cutting blade		Wheel cutter	
	Initial	After balancing	Initial	After balancing
Impurity	**404**	**2,868**	1,045	1,045
Chipped	3,507	3,507	**675**	**2,255**
Wave	13,796	13,796	14,348	14,348
Total	17,707	20,171	16,068	17,648

In the case of impurity of the cutting blade, the initial number of images was 404, which was insufficient compared to other types. For the wheel cutter, the initial number of chipped cutter images was 675. Using Keras image preprocessing libraries, we generated additional images from the existing image through methods such as right horizontal movement, left horizontal movement, left and right inversion, and right horizontal movement after left and right inversion. If an impurity is located at the end of the image, the impurity may become invisible when generating another one while moving the image. Images without impurities were deleted, and a total of 2,464 images were generated. It was the same in the case of image conversion for the chipped type of wheel cutter, a total of 1,580 images were generated.

4. **Models Application and Results.** The image dataset was divided into Train : Validation : Test = 7 : 1 : 2. The model for image classification was trained using four algorithms of AlexNet, ResNet18, ResNet34, and ResNet50, and the performance was compared. Based on Python, the model was built using the PyTorch framework and trained using the GPU (RTX 3090) for fast learning. In most cases, it took 48 seconds per 1 epoch.

The original data were black and white images. Therefore, the input value from the first convolution layer is modified to 1 channel. And all models used Adam as the optimizer whose step size is not affected by gradient rescaling, and the learning rate was set to 0.001. However, in the case of the AlexNet algorithm, the loss value did not decrease and stayed at the local optimum. To find the global optimum, the learning rate was set to 0.0001, and then the rate was gradually reduced through the learning rate scheduler.

The learning rate scheduler uses LambdaLR to calculate the learning rate and multiplies the initial learning rate by the value of the Lambda function. In this study, the learning rate was reduced by multiplying by 0.95 from the Lambda function. Each model has trained 150 epochs, and the test was conducted using the model of the epoch with the highest validation accuracy among them. The cutting blade had the highest accuracy at 89, 5, 4, and 7 epochs of AlexNet, ResNet18, ResNet34, and ResNet50, respectively. The wheel cutter had the highest accuracy at 56, 15, 16, and 9 epochs, respectively. The comparison of the performance results of the models is shown in Table 2. ResNet34 performed best for the cutting blade with an accuracy of 99.73%. For the wheel cutter, ResNet34 and ResNet50 showed an accuracy of 99.60%. Since ResNet algorithms showed higher performance even with fewer epochs, it is expected to increase time efficiency by further reducing epochs when applied to the field. Applying the classification model, the classification result can be confirmed to the operator in less than 0.65 seconds.

Table 2. Comparison of performance results of the application models (Test accuracy)

	AlexNet	ResNet18	ResNet34	ResNet50
Cutting blade	99.48%	99.58%	**99.73%**	99.33%
Wheel cutter	98.98%	99.32%	**99.60%**	**99.60%**

5. **Conclusions.** In the era of Industry 4.0, many companies hope to introduce smart factory-related technologies. However, in the case of SMEs, indeed, the application is still slow. This study analyzed the data of an SME, which produce cutting tools, and identify the problems of the current system, to improve the inspection process efficiency. Deep learning-based image classification models were created, and the system was redesigned so that the operator could visually see and judge the image files. As a result of applying the models, we obtained the classification accuracy of 99.73% for the cutting blade and 99.60% for the wheel cutter, showing an average error of less than 0.4%.

It takes about 3.5 minutes for the existing inspection equipment to take images of a single product and inspect them. And it takes 3 minutes for the operator to classify the images. However, when classifying them with a computer, it was confirmed that it took about 0.69 seconds based on 24 files, which took less than 1 second. Therefore, it is possible to shorten the manufacturing lead time per product and increase work efficiency. By applying a classification model, the operator only needs to check the results classified by computer. Applying this classification model can eliminate the hassle of opening folders and checking image files for product inspection. In addition, the time spent looking at the monitor is greatly reduced, which is expected to reduce eye fatigue.

We have a plan to research to improve the performance of model accuracy by applying more image data in the future. Also, we plan to build an information system that can be introduced into the workplace through GUI design.

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