

A Defect Detection Model for Casting Product using Wavelet Transform Denoise and Xception

Juyong Park*, Seokju Oh*, Jongpil Jeong*

*Department of Smart Factory Convergence, Sungkyunkwan University, Suwon, Republic of Korea

jypark9740@g.skku.edu, kas7189@g.skku.edu, jpjeong@skku.edu

Abstract— In the Fourth Industrial Revolution, Smart convergence of manufacturing including information and knowledge is rapidly taking place. Inspecting the quality to produce a complete product is a very important factor. Casting is the basic process of manufacturing. Casting products are completely melted and made into a liquid state, then poured into a mold to solidify and solidify. These casting products are being used in various fields such as automobile industry, shipbuilding industry, and machinery industry. In order to make a casting product, the quality inspection must be carried out strictly according to the specification standard. Therefore, it is important to accurately check the presence or absence of defects in the casting, identify the cause, and take corrective measures. Methods for quality inspection include visual inspection and vision inspection. In this paper, we propose to improve defect detection using Wavelet Transform denoise and Deep Learning for cast images used to quality inspection to accurately detect defects in cast products. The purpose of this study is to apply a Gaussian noise filter to a general image using a data set and apply the Wavelet Transform Denoise algorithm. Finally, We improved the noise data and evaluate the classification performance, and the improved performance was obtained through the experiment.

Keywords—Casting, Manufacturing, Surface defect, Deep Learning, Xception, Wavelet Transform

I. INTRODUCTION

Since the advent of the 4th industrial revolution, the smart manufacturing industry is continuously growing due to digital transformation, and smart convergence technology is expanding in line with the era of change and speed. In the manufacturing industry, the quality of manufacturing is one of the important processes to meet the needs of consumers, and quality improvement through quality control is a very important factor.

Casting is the basic process of manufacturing. Casting products are products that are completely melted and made into a liquid state, then poured into a mold to solidify and solidify. Casting feature is that it is easier to create a detailed and three-dimensional shape than forging, which is produced by applying pressure to the metal surface. Therefore, it has been widely applied to the production of handicrafts and parts with complex shapes. Recently, the heat resistance of casting has increased and the structure control technology has been developed a lot. In the case of small products, casting is often produced in large quantities. A representative example is die casting. These casting products are being used in various fields such as automobile industry, shipbuilding industry, and machinery

industry. In order to make a casting product, the quality inspection must be carried out strictly according to the specification standard. Defects or defects in the casting that occur during casting affect the performance and quality of the cast product. Therefore, it is important to accurately check the presence or absence of defects in the casting, identify the cause, and take corrective measures.

In order to conduct an accurate quality inspection, it is important to accurately identify and classify defects and minimize errors. However, depending on the factory environment and Aging equipment, low-quality data may be extracted and inaccurate results may be obtained. Therefore, in this paper, the noise of the image is removed to detect defects in cast products, and Xception, a CNN model, is presented to check the performance of defect detection. Many researchers have proposed various methods and models for detecting image defects in products. Xiaojun Wu et al. [1] introduced a CNN (Convolutional Neural Network) algorithm to detect defects for the purpose of detecting surface defects. Haodong Zhang et al. [2] Kazunori Imoto et al. [3] proposed for defect detection using deep learning technology to detect the location of defects in products in the manufacturing industry.

Therefore, a deep learning-based vision inspection system is important to detect various defects without being affected by manual operation errors according to the skill level of the operator. and Efficient vision system through accurate quality inspection is required in the industrial field. In this paper, to solve the above-mentioned problem, we propose to improve defect detection by removing noise extracted from industrial sites through Wavelet Transform. To verify the performance of the proposed system, the casting dataset was used, and a Gaussian noise filter was applied to the image to assume that it was trained on unclear data.

This paper is structured as follows. Section 2 describes the related work, and Section 3 proposes a method and model for detecting defects in cast products. Chapter 4 describes the evaluation indicators and results of experiments to evaluate the proposed method. And finally, Section 5 describes the conclusion.

II. RELATED WORK

A. Product Quality Inspection

Quality control (QC) is to maintain and improve quality by finding the cause of defective products through statistical

methods in production control and removing defects and defects. Accurate quality inspection is necessary to manage good quality. The following inspections are carried out in the quality inspection process. The inspection process consists of import inspection, purchase inspection, process inspection, final inspection, and shipment inspection. At this time, a visual inspection of the machine vision system or the operator is performed. In particular, the quality of precision casting products requires accurate quality inspection because quality errors occur due to micrometer units. Visual inspection is limited in precise inspection, and quality cannot be guaranteed by the subjective standards of the operator, and it is heavily dependent on experience. And when performing quality inspection, working for a long time under bright lighting is harmful to the human body of the worker. Therefore, in order to automatically inspect defects, it is important factor by inspecting quality through vision technology [4].

In the casting process, quality inspection is carried out through warehousing inspection, dimensional inspection, hardness inspection, and tissue inspection. At this time, the surface is verified for appearance defects such as stains, foreign substances, and scratches, and the surface inspection is performed with a vision system and a visual inspection. Recently, machine vision technology based on artificial intelligence a very important factor in detecting defects and defects of parts in manufacturing production lines. In this regard, vision systems are being studied in various fields by combining image processing technology and artificial intelligence. In particular, Yu Jiang et al. [5] studied the deep learning-based real-time anomaly detection technique to verify the balance and imbalance in actual industrial production scenarios. Kudrov Maksim et al. [6] proposed a method for data augmentation using a convolutional neural network to detect wafer defect patterns and a convolutional autoencoder. As such, extensive research on surface defect detection is being conducted in the manufacturing industry.

B. Wavelet Transform

The wavelet transform consists of a set of special signals of signals, systems, and process models, and is similar to Fourier transforms with different performance functions. The Fourier transform is a function that transforms point data to facilitate frequency analysis, and as a Fourier function containing only information about a single frequency, it was difficult to apply it to various fields. Wavelet can analyse signals in all aspects in space and frequency, and has excellent performance in continuous control. In particular, it is widely used as a filter for video and image compression, resolution analysis, and noise removal. In general, the wavelet transform is expressed in the following way.

$$F(A, B) = \int_{-\infty}^{\infty} f(x) \Psi_{(A, B)}^*(x) dx \quad (1)$$

Wavelet transforms can actually be viewed as a set of different transforms depending on the performance function used in the

computation. Image denoising applied by the wavelet transform method is mainly performed by the wavelet threshold in the wavelet domain [8]. Through thresholding, image denoising can be considered as an optimal estimate of a noisy input image. The application of the wavelet threshold for noise removal in the image proceeds as follows [9]:

1. Wavelet coefficients are obtained by wavelet decomposition of noisy input data.

$$w = W(X + N) \quad (2)$$

w is the wavelet coefficient, W is the wavelet transform, X is the ideal input data, and N is the noise data.

2. Wavelet Threshold The best estimate is obtained through the wavelet coefficients.

$$W' = \delta_{\lambda}(W) \quad (3)$$

W' is the best estimate of the wavelet coefficients, $\delta_{\lambda}(W)$ is the wavelet threshold function, and λ is the threshold.

3. When the noise filter is removed, the value can be obtained by inverse wavelet transform of the wavelet coefficients.

$$X' = W^{-1}W' \quad (4)$$

C. Deep Learning Model : Xception

In 2017, Francois et al. [10] proposed a CNN model with Inception as its underlying structure. The Inception Module captures the correlation between channels through 1x1 conv, and performs 3x3 conv operation on each output channel separately. Xception went further and wanted to completely separate the search for relationships between channels and the search for local information in the image. Fig.1. It is a structure in which Depthwise Separable Convolution is repeatedly stacked together with Residual.

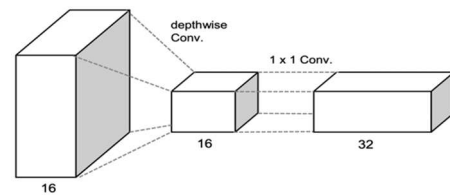


Fig. 1. Depth-wise Separable Convolution

Xception consists of three structures. Entry flow There are Middle flow and Exit flow, and Entry flow has 2 Conv layers and 6 Separable Conv layers. Middle flow consists of 3 Separable Conv layers and repeats 8 times. Exit flow consists of 4 Separable Conv layers. And there is batch normalization at the end of all conv layers and separable conv layers. And Max Pooling and ReLu functions are used.

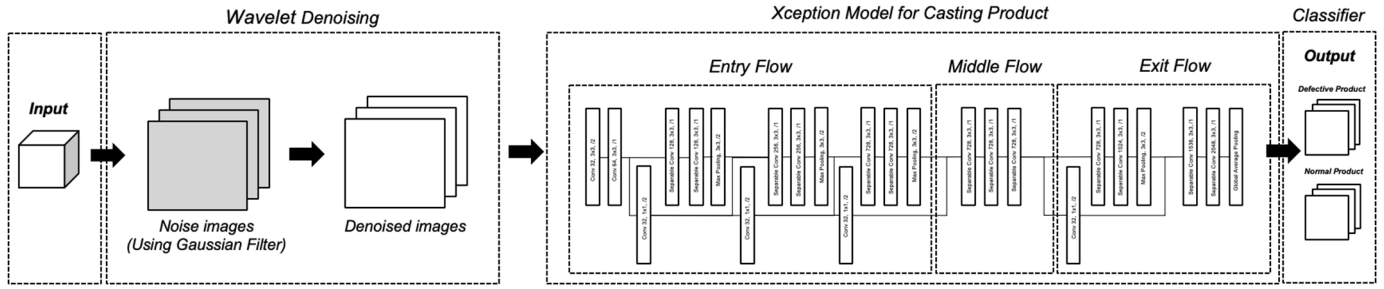


Fig 2. Structure of A Defect Detection Model for Casting Product using Wavelet Transform Denoise and Xception

III. DEFECT DETECTION MODEL FOR CASTING PRODUCT

A. Xception Model for Casting Product

We proposed Defect Detection Model for Casting Product using Wavelet Transform Denoise and Xception. The overall flow of the proposed structure and model to refer the implementation process is shown in Figure. 2.

B. Gaussian Noise Filter

A Gaussian filter is applied to the image data to assume that the noise emitter is collected for quality inspection in the industrial field. The reason image noise occurs is because it has the following Gaussian distribution function.

$$N(x|\mu, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{1/2}} \exp\left\{-\frac{1}{2\sigma^2}(x - \mu)^2\right\} \quad (1)$$

Gaussian noise usually occurs during image compression and transmission. When the image is compressed, the image is reduced, and when it is restored to its original state, a value generated through an error rather than the existing image is entered due to various factors. Similarly, when an image is transmitted, it occurs during the transmission process even if there is no problem in the compression and decompression process. Therefore, in order to proceed with this experiment, a Gaussian noise filter was applied to the dataset.

C. Wavelet Transform Denoise

Gaussian noise tends to be represented by small values in the wavelet domain, and can be removed by setting the coefficients below a given threshold to zero or reducing all coefficients to zero by a specified amount. There are two different methods for wavelet coefficient threshold selection, BayesShrink and VisuShrink. The VisuShrink approach uses a single universal threshold for all wavelet detail coefficients. This threshold is designed to remove additional Gaussian noise with a high probability, so that the image shape tends to be overly smooth. Specifying a sigma that is less than the actual noise standard deviation will result in better visually pleasing results. The second is the BayesShrink algorithm. It is an adaptive approach to the wavelet soft threshold in which a unique threshold is estimated for each wavelet subband. This is usually an improvement over what can be achieved with a single

threshold. In this experiment, the wavelet coefficient thresholds of the two methods were selected and proceeded.

IV. EXPERIMENTS AND RESULT

A. Dataset

The data set used in the experiment is a submersible pump impeller among casting products. A submersible pump impeller is a pump component that promotes the flow of a fluid. The fluid introduced into the centrifugal pump flows to the center of the impeller, and when the impeller rotates, the fluid is pushed out of the impeller by centrifugal force and the speed increases. Therefore, it can be seen that the submersible pump impeller, a casting product, is important in terms of quality. Most impellers are manufactured by casting. In this paper, the image of the submersible pump impeller manufactured by the casting process is used, and Figure 3 is the data image of the product used.

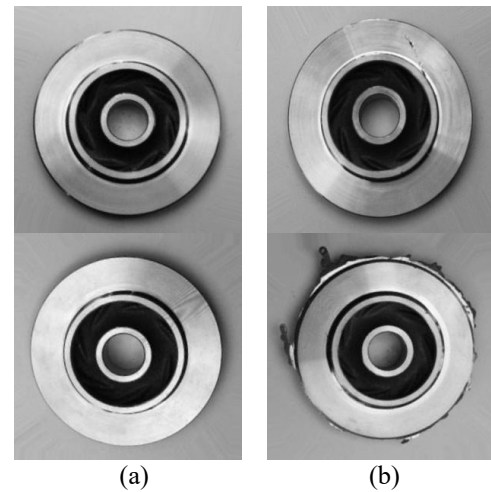


Fig .3. Casting Image : Normal(a) and Fault(b)

B. Experiment and Evaluation Metrics

Accuracy, precision, recall values are calculated to evaluate the performance of casting product surfaces for defect detection

and classification. Next is the precision, which is the ratio of true to what the model classifies as true.

$$Precision = \frac{|TP|}{|TP|+|FP|} \quad (1)$$

Recall is the ratio to the truth that the model will predict. Recall and precision are trade-offs, and the expression is

$$Recall = \frac{|TP|}{|TP|+|FN|} \quad (2)$$

The accuracy of a model is the most intuitive indicator. The formula is expressed as

$$Accuracy = \frac{|TP|+|TN|}{|TP|+|FP|+|FN|+|TN|} \quad (3)$$

In the formula, the mean TP is the predicted value of a true answer as a true answer, FP is the predicted value of an incorrect answer as a true answer, FN is the predicted value of a true answer as a wrong answer, and TN is the predicted value of a wrong answer as an incorrect answer.

C. Result

Fig. 4. is the result of learning Xception, a deep learning model, and Fig. 5. shows the result of applying a Gaussian noise filter, and Fig.6. is the result of applying wavelet denoise. To accurately evaluate the performance of the proposed model, we evaluated the Xception model in the same environment. The evaluation criteria verified the accuracy of the evaluation index presented in Section. E. through experiments. As shown in Fig. 4, it can be seen that when the Xception model is evaluated with normal data, the accuracy is 99.16%. Figure 5 shows an accuracy of 95.78% when tested with Gaussian noise applied. Figure.6. shows that 97.62% of the Xception model was measured as an experimental result by wavelet denoising of the noise data. From the experimental results, it can be seen that the image is improved by wavelet denoising when there is a noise filter. As shown in the figure, Epoch was set to 25 to perform the experiment. In the graph, the red line indicates the accuracy of the test, and the green line indicates the loss value of the test progress.

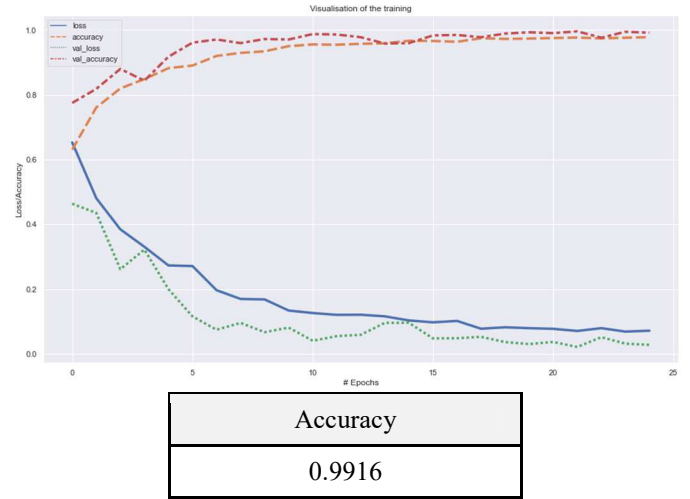


Fig. 4. Training and Test Results using Xception Model

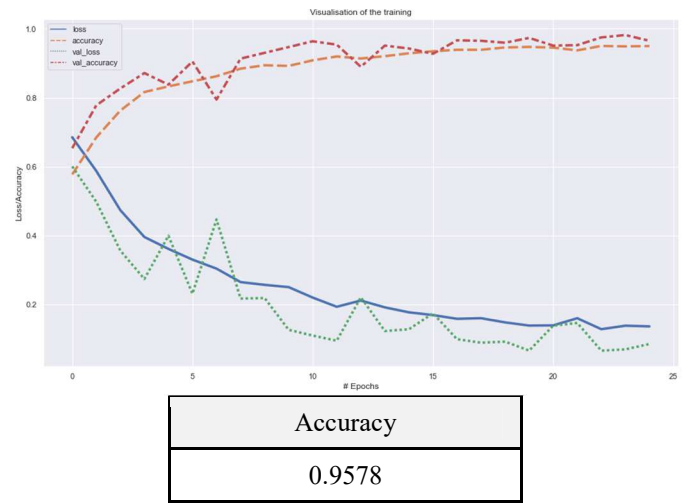


Fig. 5. Training and Test Results using Xception Model + Gaussian Noise

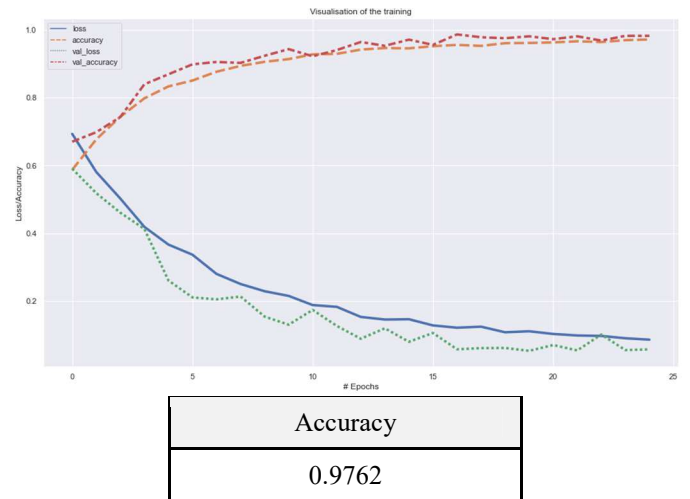


Fig. 6. Training and Test Results using Xception Model + Gaussian Noise + Wavelet Denoising

V. CONCLUSIONS

The quality of the cast product is one of the important manufacturing processes. In this paper, we demonstrate an effective approach to surface defect detection through data from cast products. We proposed the Xception architecture, which solves the data noise problem and is a lightweight model of deep learning. In image detection and classification research, deep learning model is developing with improve performance. Quality inspection is one of the important processes in the manufacturing industry. In this paper, we propose the Xception model for the defect classification of casting data and use the Wavelet algorithm to improve the image and remove the noise. In future research, we will study effective methods for detecting surface defects of products, Improved Deep Learning Models, applying various denoise techniques, and quality inspection.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. 2021R1F1A1060054). Corresponding author: Prof. Jongpil Jeong.

REFERENCES

- [1] Xiaojun Wu, authorKai, CaoXiaodong Gu, "A Surface Defect Detection Based on Convolutional Neural Network", ICVS 2017: Computer Vision Systems pp 185-194, 2017
- [2] Haodong Zhang, Zuzhi Chen, Chaoqun Zhang, Juntong Xi, Xinyi Le, "Weld Defect Detection Based on Deep Learning Method, 2019 IEEE 15th International CASE, 2019
- [3] Kazunori Imoto, Tomohiro Nakai; Tsukasa Ike; Kosuke Haruki; Yoshiyuki Sato, "A CNN-based Transfer Learning Method for Defect Classification in Semiconductor Manufacturing", 2018 International Symposium on Semiconductor Manufacturing (ISSM), 2018
- [4] Hao Shen, ShuxiaoLi, Duoyu Gu, Hongxing Chang, "Bearing defect inspection based on machine vision", ScienceDirect Measurement, Volume 45, Issue 4, May 2012, Pages 719-733
- [5] Yu Jiang, Wei Wang, Chunhui Zhao, "A Machine Vision-based Realtime Anomaly Detection Method for Industrial Products Using Deep Learning", 2019 Chinese Automation Congress (CAC), Nov 2019
- [6] K. Maksim, B. Kirill, Z. Eduard, G. Nikita, B. Aleksandr, L. Arina, S. Vladislav, M. Daniil, and K. Nikolay, "Classification of wafer maps defect based on deep learning methods with small amount of data," in 2019 International Conference on Engineering and Telecommunication (EnT). IEEE, 2019, pp. 1-5.
- [7] Sifuzzaman, M, Islam, M R, Ali, M Z, "Application of Wavelet Transform and its Advantages Compared to Fourier Transform", DSPee, Journal of Physical Science;Vol 13 [2009]
- [8] Yan-lei Xu, Ji-yin Zhao, Yu-bin Jiao. Gray-scale Image Edge Detection Based on Order Morphology Transformation. Proceedings of the 7th world Congress on Intelligent Control and Automation. 5970-5975, June 25 - 27, 2008. (WCICA08)
- [9] D.L.Donono, I.M.Johnstone. Adaptive to unknown smoothness via wavelet shrinkage [J]. Journal of the American Statistical Association. Vol.90, No.432, pp.1200-1224, 1995.
- [10] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp.1251-1258, 2017



JUYONG PARK received the B.S. degree in Electronics and Communications Engineering from Kwangwoon University, Korea. He is currently pursuing the master's degree in the Department of Smartfactory Convergence, Sungkyunkwan University, Suwon, Korea. His research interests include semiconductor manufacturing, deep learning, machine learning and smartfactory.



SEOKJU OH received the B.S. degree in Mechatronics Engineering from Korea Polytechnic University. He is currently pursuing the master's degree in the Department of Smartfactory Convergence, Sungkyunkwan University, Suwon, Korea. His research interests include IIoT, deep learning, machine learning and smartfactory.



JONGPIL JEONG received his B.S. degree in engineering from Sungkyunkwan University and the M.S. and Ph.D. degrees in computer engineering from Sungkyunkwan University, Suwon, Korea, in 2003 and 2008, respectively. He was a Research Professor with Sungkyunkwan University in 2008-2009 and 2011, and a visiting professor with the Department of Interaction Science (WCU Program) in Sungkyunkwan University in 2009-2010. He started his academic profession at the Research & Business Foundation of Sungkyunkwan University, Korea in 2012 as an assistant professor. And now he is a PI and Professor of Department of Smart Factory Convergence. He received twice Excellent Research Awards from Department of Electrical and Computer Engineering, Sungkyunkwan University, Korea (2007), from KSII (Korea Society for Internet Information), Korea (2011), from IIBC (2013, 2014, 2016, 2017), from KIPS (2014, 2017), and from others. His research interests include 4th Industrial Revolution, Smart Factory, Smart Manufacturing, Digital Twin, AI, 5G, Mobile Computing, Mobility Management for IoT Applications and Networks, Interaction Science, Sensor Networking, Protocol Operation based Performance Analysis, Internet Security, MIPv6 and Ubiquitous Computing. He is the 4 patents and 200 international publications in refereed journals and conferences. He is a member of ACM, IEEE, KIPS, IIBC, and member of many international program committees. He has organized many conferences, chaired several technical sessions and gave tutorials at major international conferences. Recently, he is the workshop chair of SFC 2018-2019 (Smart Factory Convergence), and SMSM 2018-2019 (Smart Manufacturing and Smart Mobility).