Development of a Vision-Image-Based Quality Prediction Neural-Network Algorithm for an Injection Molding Machine Considering Cavity Sensor and Vibration Data

Jun Kim (junkim@kitech.re.kr)
Korea Institute of Industrial Technology https://orcid.org/0000-0002-6574-9245
Ju Yeon Lee

Research Article

Keywords: Quality prediction, Depp learning, Injection molding, Vision image, Cavity sensor

Posted Date: July 14th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1775881/v1

Abstract

This research develops a neural-network-based algorithm for predicting the quality levels of injection molding products to handle quality regarding problems caused by occurrences of low-quality products. With an assumption that vibration data and temperature and pressure data of the cavities in mold generated from the injection molding machine would be different according to the products' quality, main objective of this research is to predict the quality grade for each product utilizing the vibration data of the machine and temperature and pressure data of each cavity collected during a product is processed. Among diverse features that can represent quality of injection molding products, we especially focus on the features that could be driven from vision images of the products. We firstly explain how the infrastructure is constructed for collecting the vibration data, cavity sensor data, and vision-image data. Then, for the vibration and cavity sensor data, statistical features that stand for specific patterns of each data utilized as independent variables are derived. Quality grades of each product are also distinguished by two indicators: flection of the product's housing and alignment of pinholes derived from the vision images of products utilizing the Canny-Edge algorithm. Finally, utilizing statistical features of the vibration and cavity sensor data as independent variables and distinguished quality grades of each product as dependent variables, a neural-network-based quality prediction algorithm is developed, and the performance of the algorithm is evaluated.

1. Introduction

1.1. Background

Manufacturing systems of the injection molding industry often have quality regarding problems caused by the absence of the quality inspection process that eventually leads to considering all manufactured products as non-defective. Since products manufactured in injection molding manufacturing systems are usually small and have low prices, the cost of inspecting the quality of all the products could take charge of a relatively high proportion of the total cost when the total inspection process is conducted. Thus, quality inspection process is often omitted, and only sampling-based quality investigation is carried out occasionally in the real field of the injection molding industry. In fact, several injection molding machines provide a function of discarding products manufactured in certain conditions that exceed lower and upper limits of processing data (e.g., injection pressure, switch over position, switch over pressure, etc.); however, filtering out defective products only utilizing simple logic has high limits. Therefore, this can lead to several problems as follows: 1) Service level of customer can be decreased by delivering defective products, 2) Total cost can be eventually increased by penalty of defective product delivery and urgent production or change of production plan to reproduce the faulty products, 3) Machines of the following process of the injection molding such as assembly process can be broken by processing defective products, and 4) Waste of plastic might occur by producing more quantities of products than the required quantities because of unawareness of quantities of defective products. So far, the quality acceptance range of injection molding products has been broad, since the products are usually utilized as small parts of huge end items such as automobiles. However, as safety becomes the most important issue in the

automobile industry, which consumes a vast number of injection molding products, the quality requested for the injection molding industry begins to narrow. Moreover, as the shapes of injection molding products are designed in more complicated forms compared with the past, low-quality products cause a worse influence on machines of the following process of the injection molding process. Besides, as responsibility of companies for protecting the environment increases, wastes of plastic generated by over-production should be managed. Accordingly, four chronic problems that we stated are being magnified as important issues that should be addressed by predicting the quality of the injection molding products.

1.2 Related works

To address the problems that we mentioned, research on analyzing the quality of the injection molding products have been conducted actively. Sadeghi [1] developed a neural-network model to predict the soundness of the injected plastic parts utilizing melt flow rate, injection pressure, mold temperature, and melt temperature as independent variables. Kim et al. [2] investigated the pressure-volume-temperature (PVT) relationship realized in the injection molding process utilizing the ultrasonic technique and tried to predict products' weights using the PVT relationship. As a matter of the quality prediction method, they considered a feed-forward back-propagation neural network. Bataineh and Barney [3] focused on predicting three forces: 1) local part-mold force, 2) local ejection force, and 3) total ejection force in the injection molding process with numerical simulation. Utilizing the experimentally derived coefficients of friction, they developed a simulation system that could forecast forces and insisted that the quality of the injected products could be estimated by the results. Chen et al. [4] developed a self-organizing map-based back-propagation neural-network model for predicting injection molding product's quality considering parameters such as injection stroke, injection velocity, injection pressure, and switch over time as input variables of the algorithm. They utilized weights of products as indicators of quality. Tsai et al. [5] examined how the eight process parameters of temperature and pressure affect the quality of the optical lenses' surface. They especially considered waviness, transmission rate, and roughness as quality factors. They developed three regression models that predicted each quality factor and compared the accuracy of the model with numerical experiments. Lee et al. [6] took the approach of a rule-based quality prediction framework. They proposed system architecture consists of three layers: 1) the application layer, 2) the engine layer, and 3) the database layer, but did not provide any experimental results. Yin et al. [7] tried to predict the warpage of plastic products produced by the injection molding process and developed a back-propagation neural network. They mainly considered five process parameters: mold and melt temperature, packing pressure, packing time, and cooling time of the injection molding process. Moayyedian et al. [8] evaluated the effects of diverse processing parameters (e.g., filling time, part cooling time, pressure holding time, and melt temperature) on short shot defect. They insisted that melt temperature mostly affects the possibility of short shot defects, with a contribution of 74.25%. Ramana et al. [9] also considered short shot defects and developed a statistical automated neural networks algorithm, a general chi-square automatic interaction detector algorithm, and an association rule algorithm to predict the quality of the injection molding products. Ramana et al. [10] proposed three algorithms based on a decision tree, k-nearest neighbor, and polynomial by binomial classification

methodologies to predict short shot of injection molding product considering processing parameters such as injection speed, nozzle temperature, and injection time, etc. Kwon et al. [11] especially focused on injection speed among the processing parameters. They analyzed how injection speed in the injection molding process affects physical variations of the products, such as shrinkage and deformation, utilizing a simulation-based mold-flow analysis program. Ogorodnyk et al. [12] proposed a multi-layer perceptron-based algorithm to predict the quality of thermoplastic products. Besides, many other studies, such as [13–21], have developed machine learning-based quality prediction algorithms for injection molding products.

These previous studies have common limitations. First, they only considered the process parameters provided by injection molding machines regarding injection pressure, temperature of nozzles and barrels, switch-over point, and approximate mold temperature. Although they commonly insisted that mold data are important factors that affect the quality of the injection molding process, they did not consider in detail how temperature and pressure change inside the molds. Moreover, data that could be collected by attaching additional sensors, such as vibration of the injection molding machines did not be considered. Second, they did not consider practical types of defects that could be utilized in the real field. Most previous research has dealt with defects regarding the weights of products or the approximate transform of the shapes. However, in the real field, more specific types of defects regarding injection molding products' shapes should be considered. There are some studies considering defects of the injection molding products detected by vision images (e.g., [22–24]); however, they only concentrated on detecting flaws on the surface of the injection molding products, and the detected defects were not analyzed with the processing parameters. Third, previous studies have conducted experiments in the laboratory, not in the real field. This research examines the quality prediction problem of injection molding products, considering the limitations of previous research.

1.3 Overview of the research

The purpose of this research is to develop a neural-network-based quality prediction algorithm for injection molding products targeting a real injection molding factory in Korea. We consider a Fanuc injection molding machine (Roboshot S-2000I100B), and the considered machine of the real field is shown in Fig. 1. Target product of this research analyzed is a printed-circuit-board (PCB) connector, which is a part of automobile.

As independent variables of the algorithm, we used the online temperature and pressure data of the mold collected by cavity sensors that we installed inside the mold of the machines. By utilizing the data collected from additionally installed sensors inside the mold, we can consider more directly related data when the process of a product is injected. We also utilized vibration data collected by sensors installed on the cylinder and motor of the injection molding machine as independent variables. Dependent variables, which are classifications of injection molding products' quality, are derived from vision-image data of the products collected by the vision camera that we installed. We classified the quality of the products into three grades with two indicators regarding the shape of the products: 1) flection of the housing and 2) alignment of pinholes. The overview of this research is presented in Fig. 2.

The rest of this paper is organized as follows. Section 2 explains how we constructed an infrastructure for collecting data for the injection molding machine. Section 3 presents in detail how the collected raw data are processed into the independent and dependent variables and then proposes a neural-network algorithm for quality prediction. Section 4 shows the performance of the developed quality prediction algorithm and discuss the results. Finally, Section 5 concludes the paper and discusses future studies.

2. Infrastructure For Collecting Data

2.1 Cavity sensors

To detect and collect online changes in temperature and pressure inside the mold, we installed temperature and pressure sensors inside the cavities (i.e., cavity sensors). The temperature sensor and pressure sensor installed can measure temperature (T) in the range of $[-40, 1000]$°C with the maximum error of $\pm 0.004 \times T$ and can measure pressure in the range of $[0, 29008]$psi with sensitivity of 5pC/bar. Note that the machine we analyzed in this research has four cavities, so we installed a temperature sensor and a pressure sensor in each cavity of the mold. As shown in Fig. 3, pressure sensors are installed near the inlets where the melt material is injected, and temperature sensors are attached at the middle of each cavity. Figure 4 presents the temperature and pressure sensors installed in the real field.

2.2 Accelerometer

In this research, we assume that vibration data generated from the cylinder, where the screw rotates to inject the melt material into the cavity, and the motor of the machine, would affect the quality of injection molding products. Therefore, we installed three accelerometers, which have 100mV/g sensitivity and measurement range of ± 50g pk, to detect and collect the vibration data of the machine. As presented in Fig. 5 (a), two vibration sensors are attached to the cylinder of the machine. One was installed at the endpoint of the cylinder near the inlet, and the other was installed at the middle of the cylinder. A vibration sensor is attached near the motor of the machine to collect the vibration data of the motor, as shown in Fig. 5 (b).

2.3 Vision camera

To collect vision images of the products that are used to derive quality classifications of the injection molding products, we installed a vision camera that can take pictures of four products produced in each cavity respectively with 2448 × 2050 black and white pixels. Whenever injection molding products are injected from the machine, the robot handler automatically handles the products, and the vision camera gathers a vision image of them. Figure 6 presents the vision camera installed in a real field.

3. Development Of A Quality Prediction Algorithm

3.1 Independent variables

3.1.1 Temperature and pressure data of the mold

The temperature and pressure data inside the mold were collected for eight seconds when a product was produced in the mold. Shapes of temperature and pressure data collected for a cycle of injection molding are presented in Fig. 7. We can divide a cycle into four periods as four stages of injection molding: 1) Gate close, 2) Injection, 3) Hold pressure, and 4) Cooling. To transform changes of temperature and pressure data of the mold during a cycle of injection molding into quantified values that could be used as input of the quality prediction algorithm, we calculated statistical values of each data. We considered the maximum, average, minimum, standard deviation, and integral value of each period.

3.1.2 Vibration data

Examples of three raw vibration data, acceleration 1–3 corresponding to the sensors attached on the end of the cylinder, middle of the cylinder, and motor, respectively, for a product are presented in Fig. 8. Similar with temperature and pressure data of the mold, we can divide a cycle of data with four periods. Since it is not possible to utilize the raw data as input variables of the quality prediction algorithm, we first conducted preprocessing procedures for the raw vibration data utilizing root mean square (RMS) and fast Fourier transform (FFT) techniques. The preprocessing procedures were conducted for each period, which was divided according to the stages of the injection molding process. The shape of the data presented in Fig. 8 preprocessed into forms of RMS and FFT are shown in Fig. 9 and Fig. 10. We then calculated statistical values that can be quantified and utilized as independent variables of the quality prediction algorithm. For RMS data, we considered the maximum, average, minimum, standard deviation, and integral values of each period. In the case of the FFT data, we can check out that meaningful data were observed over the peak amplitude value of 0.05 for all four periods from Fig. 10. Thus, we consider the statistical value of the number of frequencies that exceeds 0.05 and the average, maximum, and standard deviation of the peak amplitude exceeding 0.05 as independent variables of the quality prediction algorithm.

3.2 Dependent variables

3.2.1 Indicators of classifying quality grade

Utilizing the vision images collected by the vision camera, classifications of the quality grade utilized as dependent variables are derived. An example of a vision image of a product is shown in Fig. 11. Interviewing workers and administrators of the factory, two shapes regarding indicators—1) flection of the products' housing and 2) alignment of pinholes—that mostly affect the quality of the target injection molding products were determined. The first indicator, the flection of the products' housing, indicates how much the exterior shape of the product is bent. As shown in Fig. 12 (a), some of the target product's upper part of housing might be bent, and the heavily bent products have to be regarded as low-quality products. Figure 12 (b) describes the second indicator, the alignment of pinholes. The target product has 40 pinholes in the middle. Since metal pins are assembled later into those pinholes, the alignment of pinholes is an important indicator of the product's quality. If the pinholes are not located in a straight line,

it can cause assembly defects. Therefore, we can consider a product in which the alignment of pinholes is not as straight as a low-quality product.

3.2.2 Flection of the product's housing

Figure 13 presents the stages of deriving the flection of the product's upper housing with a quantified value. In the first stage, the region of interest (ROI), which is the upper part of the image in this case, is set for the vision image. Then, noises of the ROI are removed by conducting a Gaussian filter in the second stage. In the third stage, adaptive histogram equalization is conducted, and the vision image of the ROI transforms into a black and white inversed image to elevate the effectiveness of the edge detection. In the fourth stage, the Cany-edge algorithm is conducted, and the edge (i.e., shape of upper housing of the product) is detected. Then, interpolation process is conducted to link the disconnected parts of the detected edge. Finally, average distance between the detected edge and the standard-coordinate line is calculated. The higher the distance, the lower the quality level of the product.

3.2.3 Alignment of pinholes

Figure 14 presents a procedure for deriving a value of indicator that stands for how well the pinhole is aligned. When a vision image of a product is collected by the vision camera, we set to generate a black box that reverses the brightness of the image in the middle of the product to detect pinholes more clearly. For the first of the procedures, the ROI was set as the middle of the product. Then, the Cany-edge algorithm was conducted and angular points of each pinhole were detected. In the next stage, the center point of each pinhole, which is the diagonal intersection of the angular points is derived. Finally, distances between the center points of each pinhole and the standard-coordinate line are calculated. Utilizing the distances, we derive the upper line and lower line pinholes' standard deviations of distances, respectively. When the average value of the two standard deviation values becomes larger, the quality level becomes lower.

3.2.4 Determination of quality grade

Utilizing the two indicators we derived in Section 3.2.2 and 3.2.3, we finally classify the products into three quality grades: A, B, and C, which can be utilized as dependent variables of a quality prediction algorithm. First, in terms of each indicator, flection of the product's housing, and alignment of pinholes, products are classified into three grades by the values of sigma.

Figure 15 shows the criteria for the products to be classified into specific grades in terms of each indicator. In aspect of the flection of the product's housing, products that satisfy $(\mathrm{x} < \mu - 1.5\sigma)$, ($\mu - 1.5\sigma \leq \mathrm{x} \leq \mu + 1.5\sigma$), and $(\mathrm{x} > \mu + 1.5\sigma)$ are classified as grade A, B, and C, respectively, where x is value of the indicator regarding flection of the product's housing, μ and σ is average and standard deviation of x respectively. In the case of the alignment of pinholes, products that satisfy $(\mu - \sigma \leq \mathrm{y} \leq \mu + \sigma)$, $(\mu - 2\sigma \leq \mathrm{y} < \mu - \sigma \mathrm{and} \mu + \sigma < \mathrm{y} \leq \mu + 2\sigma)$, and $(\mathrm{y} < \mu - 2\sigma \mathrm{and} \mathrm{y} > \mu + 2\sigma)$ where y is the average standard deviation, are classified as grade A, B, and C, respectively, where y is value of the indicator regarding alignment of pinholes.

After the product grades in terms of each indicator are classified, the total grade of each product is determined. Products in which their classified grades are (AA and AB), (BC, BB, and CB), and CC are determined to be the final grade of A, B, and C. The final product grades were utilized as dependent variables.

3.3. Development of a quality prediction algorithm

Utilizing the statistical values of temperature and pressure data of the mold and vibration data that we calculated in Section 3.1 as independent variables and the quality grade of each product derived in Section 3.2 as dependent variables, we developed a neural-network-based quality prediction algorithm. We considered 153,425 samples of data to develop the quality prediction algorithm and adopted the K-fold cross validation strategy (k = 10) to train, validate, and test the developed algorithm. Since the number of products for each quality grade is unbalanced with a proportion of 1.2 : 8.1 : 0.7 (quality grade A : B : C), we first conducted the synthetic minority oversampling technique (SMOTE) to solve the data imbalance problem. We make the proportion of each quality grade be 3 : 4 : 3 by applying the SMOTE.

A neural network that we designed for predicting the quality of the injection molding product has 39 hidden layers and 40 interlayer weight matrices U^l where l is an index of layers. For each layer of weight matrices, we set 20 nodes to be existed. There are 88 input nodes since we consider 40 and 48 independent variables (total 88) regarding the temperature and pressure data of the mold and the vibration data of the machine. Since we consider three quality grades of the product, there are three output nodes in the neural network. We use the categorical cross-entropy loss function defined as $-\sum_i t_i \log\left(f\left(s_i\right)\right)$ where t_i and s_i denote real quality grade and predicted quality grade of sample i respectively. We also utilize softmax activation function $f\left(s_i\right) = e^{s_i} / \sum_j e^{s_j}$. The structure of the neural network we constructed is presented in Fig. 16. Note that four quality prediction algorithms are developed for each cavity of the product.

4. Results And Discussion

Table 1 shows the performances evaluated with mean absolute percentage error (MAPE) of the developed quality prediction algorithms for each cavity of three cases: 1) considering only the temperature and pressure data of the mold as independent variables, 2) considering only the vibration data of the machine as independent variables, and 3) considering both the temperature and pressure data of the mold and vibration data of the machine as independent variables. When only the temperature and pressure data of the mold were utilized as input variables, the average MAPE was observed to be 24.9%. In the case of considering only the vibration data of the machine as independent variables, the performance of the model is realized to be poor, with an average MAPE of 60.8%, so that it is impossible to use the model in the real field. However, when the temperature and pressure data of the mold and vibration data of the machine are utilized simultaneously, MAPE is significantly improved by 6.8%. This results indicate that although vibration data of the machine cannot be solely utilized as independent

variables of the quality prediction algorithm, it can help the performance of the algorithm be improved when we utilize it with other data.

Table 1
Performance of the quality prediction algorithms (Comparison of the cases that considering cavity sensor data, vibration data, and both data as independent variables)

	Cavity sensor	Vibration	Both
Cavity 1	26.5%	47.6%	7.4%
Cavity 2	23.9%	67.1%	6.3%
Cavity 3	28.8%	58.2%	8.6%
Cavity 4	20.4%	70.3%	5.1%
Average	24.9%	60.8%	6.8%

Table 2
Performance of the quality prediction algorithms (Comparison of the cases that considering processing parameters, cavity sensor and vibration data, and all the data as independent variables)

	Processing parameters	Cavity sensor & Vibration	All
Cavity 1	31.2%	7.4%	9.2%
Cavity 2	33.7%	6.3%	10.8%
Cavity 3	30.5%	8.6%	8.9%
Cavity 4	28.4%	5.1%	8.2%
Average	30.9%	6.8%	9.3%

To verify that developed quality prediction algorithms considering temperature and pressure data of the mold for each cavity and vibration data of the machine outperform that of considering processing parameters utilized in the previous work, we compare performances the two quality prediction algorithms. As independent variables of the quality prediction algorithm for comparison, we considered eight processing parameters that is mostly utilized by previous studies and can be obtained by the injection molding machine itself: injection pressure, switch over pressure, switch over point, injection velocity, nozzle temperature, barrel temperature, hopper temperature, and cooling time. Table 2 shows performances of the three quality prediction algorithms that consider processing parameters utilized in the previous works, pressure and temperature data of the mold and vibration data of the machine, and all the data, respectively. As shown in Table 2, the algorithm considering cavity sensor data and vibration data out performs that of considering eight processing parameters. One noticeable thing is that, even when eight processing parameters are considered with the cavity sensor and vibration data

simultaneously, the MAPE of the algorithm is higher than that of the algorithm considering cavity sensor and vibration data. This is because overfitting happens when all the data are considered independent variables. All the experimental results verify that the quality prediction algorithm that considers cavity sensor data and vibration data outperforms the others.

5. Conclusion

This research developed a neural-network algorithm for predicting the quality of the injection molding products. Targeting the injection molding factory in Korea, we constructed an infrastructure for collecting vision images of the products, temperature, and pressure data of the cavity, and vibration data of the machine. We preprocessed the data collected from the vision camera, cavity sensors, and accelerometers that we installed into the input and output variables that could be utilized for the quality prediction algorithm. We considered temperature and pressure data of the cavity and vibration data of the machine as independent variables, and three grades of the products derived from the vision-image data as dependent variables. With the experimental results, we verified that the proposed neural-network algorithm for quality prediction, considering cavity sensor and vibration data, outperforms the others.

The adaptation of the developed quality prediction algorithm to the real field of the injection molding industry can solve the following problems. First, service level of customers can increase by managing the low quality of the products separately. Second, total cost of the factory can decrease by preventing penalties or urgent production caused by delivering low-quality products. Third, breakdown of the assembly machines, which are located in the flowing process line of the injection molding process, can decrease by preventing flows of low-quality products. Finally, plastic waste can decrease by reducing the over-production carried out to make spare stocks preparing for the supplement production of low-quality products.

In future work, we will develop an automated data analysis system for the target factory, including the developed quality prediction algorithm in which a sequence of data collection, data preprocessing, data analysis, visualization of the analysis results, and system control utilizing the results is automatically conducted, referring to Kim et al. [25] and Kim and Lee [26]. We will also reveal how the processing environment should be managed to elevate the quality grade of injection molding products.

Declarations

Conflict of interest

The authors declare that they have no conflict of interest.

Data availability

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request. However, data belonging to the company cannot be provided even if requested.

Code availability

Not applicable

Ethics approval

Not applicable

Consent to participate

Not applicable

Consent for publication

Not applicable

Author Information

Affiliations

Korea Institute of Industrial Technology, 143 Hangaul-ro, Ansan, 34141, Republic of Korea

Jun Kim

Department of Mechanical System Design Engineering, Seoul National University of Science and Technology 232 Gongneung-ro, Seoul, 01811, Republic of Korea

Ju Yeon Lee

Contributions

Jun Kim collected and analyzed quality relevent data of injection molding processes, designed the structure of this paper, and wrote the manuscript. Ju Yeon Lee supervised the entire process of data analysis, examined the structure of the paper, and made suggestions on the details of the paper.

References

1. Sadeghi BHM (2000) "A BP-Neural Network Predictor Model for Plastic Injection Molding Process,". J Mater Process Technol 103(3):411–416
2. Kim JG, Kim H, Kim HS, Lee JW (2004) "Investigation of Pressure-Volume-Temperature Relationship by Ultrasonic Technique and Its Application for the Quality Prediction of Injection Molded Parts,". Korea-Australia Rheology Journal 16(4):163–168
3. Bataineh OM, Barney E (2005) Klamecki., "Prediction of Local Part-Mold and Ejection Force in Injection Molding,". J Manuf Sci Eng 127(3):598–604

4. Chen WC, Tai PH, Wang MW, Deng WJ, Chen CT (2008) A Neural Network-Based Approach for Dynamic Quality Prediction in a Plastic Injection Molding Process. Expert Syst Appl 35(3):843–849
5. Tsai KM, Hsieh CY, Lo WC (2009) "A Study of the Effects Process Parameters for Injection Molding on Surface Quality of Optical Lenses,". J Mater Process Technol 209(7):3469–3477
6. Lee KH, Lee YH, Kang. YS (2011) "Rule-based Quality Prediction Framework in Injection Molding Process," Proceedings of the Korean Society of Precision Engineering Conference. Korean Soc. Precis. Eng., pp. 707–708,
7. Yin F, Mao H, Hua L, Guo W, Shu M (2008) "Back Propagation Neural Network Modeling for Warpage Prediction and Optimization of Plastic Products during Injection Molding,". Mater Design 32(4):1844–1850
8. Moayyedian M, Abhary K, Marian R (2008) "The Analysis of Defects Prediction in Injection Molding,". Int J Mechanical and Mechatronics Eng 10(12):1883–1886
9. Ramana DE, Sapthagiri S, Srinivas P (2016) Int J Mechanical Engineering and Technology 7(6):31–40"Data Mining Approach for Quality Prediction and Improvement of Injection Molding Process through SANN, GCHAID and Association Rules,"
10. Ramana EV, Sapthagiri S, Srinivas P (2017) "Data Mining Approach for Quality Prediction and Fault Diagnosis of Injection Molding Process,"Indian J. Science and Technology, Vol. 10, No. 17,
11. Kwon SY, Cho JH, Roh HJ, Cho SH, Lee YJ, Lyu MY (2017) Analysis of the Physical Quantity Variation in the Cavity and the Quality of the Molded Product According to the Injection Speed in Injection Molding. Elastomers & composites 52(4):317–325
12. Ogorodnyk O, Lyngstad OV, Larsen M, Wang K, Martinsen K (2018) “Application of machine learning methods for prediction of parts quality in thermoplastics injection molding,”Int. workshop of advanced manufacturing and automation, pp.237–244,
13. Zou M, Zhao L, Wang S, Chang Y, Wang F (2018) Quality Analysis and Prediction for Start-up Process of Injection Molding Processes. IFAC-Papers OnLine 51(18):233–238
14. Yuan Q, Zhao L, Wang S, Chang Y, Wang F (2018) “Quality Analysis and Prediction for Multi-Phase Multi-Mode Injection Molding Processes,” 2018 Chinese Control And Decision Conference (CCDC), pp. 3591–3596,
15. Nasiri S, Khosravani MR (2018) Faults and failures prediction in injection molding process. Int J Advanced Manufacturing Technology 103(5):2469–2484
16. Zhuang JY, Huang MS (2019) Monitoring, Prediction and Control of Injection Molding Quality Based on Tie-Bar Elongation. J Manuf Processes 46:159–169
17. Abdul R, Guo G, Chen JC, Yoo JJW (2019) Shrinkage Prediction of Injection Molded High Density Polyethylene Parts with Taguchi/Artificial Neural Network Hybrid Experimental Design. Int J on Interactive Design and Manufacturing (IJIDeM) 1(13):345–357
18. Chen JC, Guo G, Wang WN (2020) Artificial Neural Network-Based Online Defect Detection System with in-Mold Temperature and Pressure Sensors for High Precision Injection Molding. Int J Advanced Manufacturing Technology 110(7):2023–2033

19. Ahmed T, Sharma P, Karmaker CL, Nasir S (2020) “Warpage Prediction of Injection-Molded PVC Part Using Ensemble Machine Learning Algorithm,” Materials Today: Proceedings,
20. Jung H, Jeon J, Choi D, Park JY (2021) Application of Machine Learning Techniques in Injection Molding Quality Prediction: Implications on Sustainable Manufacturing Industry. Sustainability 13(8):4120
21. Ogorodnyk O, Lyngstad OV, Larsen M, Martinsen K (2021) “Prediction of Width and Thickness of Injection Molded Parts Using Machine Learning Methods,” In EcoDesign and Sustainability I, pp. 455–469,
22. Lee JY, Bong W, Lee S, Han CH, Ko KW (2016) “Development of the Vision System and Inspection Algorithms for Surface Defect on the Injection Molding Case,” In Advances in Computer Science and Ubiquitous Computing, pp. 963–970,
23. Otieno A, Mirman C (2006) Machine Vision Applications in Plastics Injection Molding: A case Study of Automated Inspection. J Eng Technology 23(1):26
24. Muresan MP, Cireap DG, Giosan I (2020) “Automatic Vision Inspection Solution for the Manufacturing Process of Automotive Components Through Plastic Injection Molding,” In 2020 IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP), Vol. 23, No. 1, pp. 423–430,
25. Kim J, Kang HS, Lee JY (2020) ” J Korean Soc Precis Eng 37(4):247–254“Development of Intelligence Data Analytics System for Quality Enhancement of Die-Casting Process
26. Kim J, Lee JY (2021) ” Rob Computer-Integrated Manuf 67:102040“Server-Edge Dualized Closed-Loop Data Analytics System for Cyber-Physical System Application

Figures

Figure 1

Injection molding machines analyzed

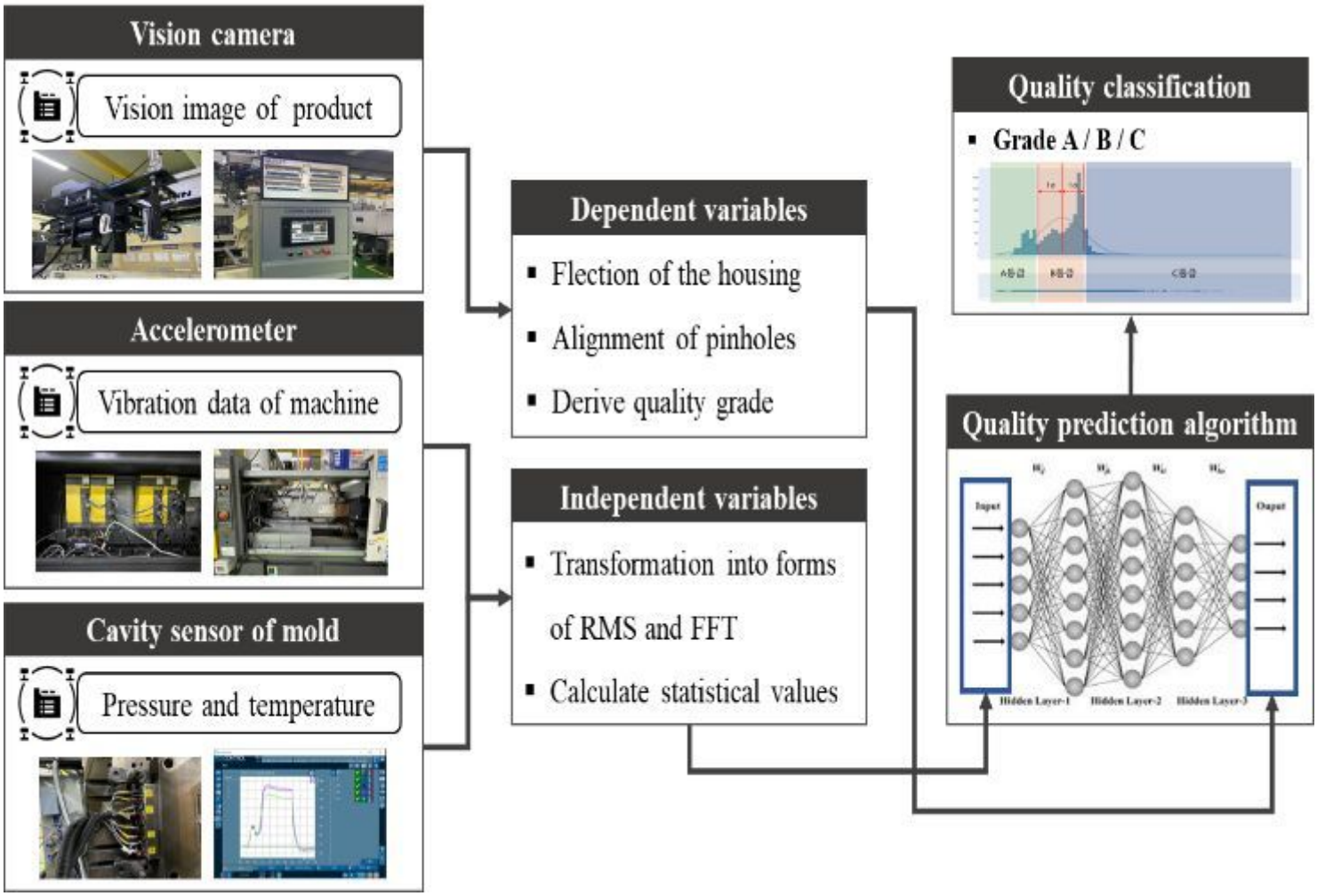


Figure 2

Overview of the research

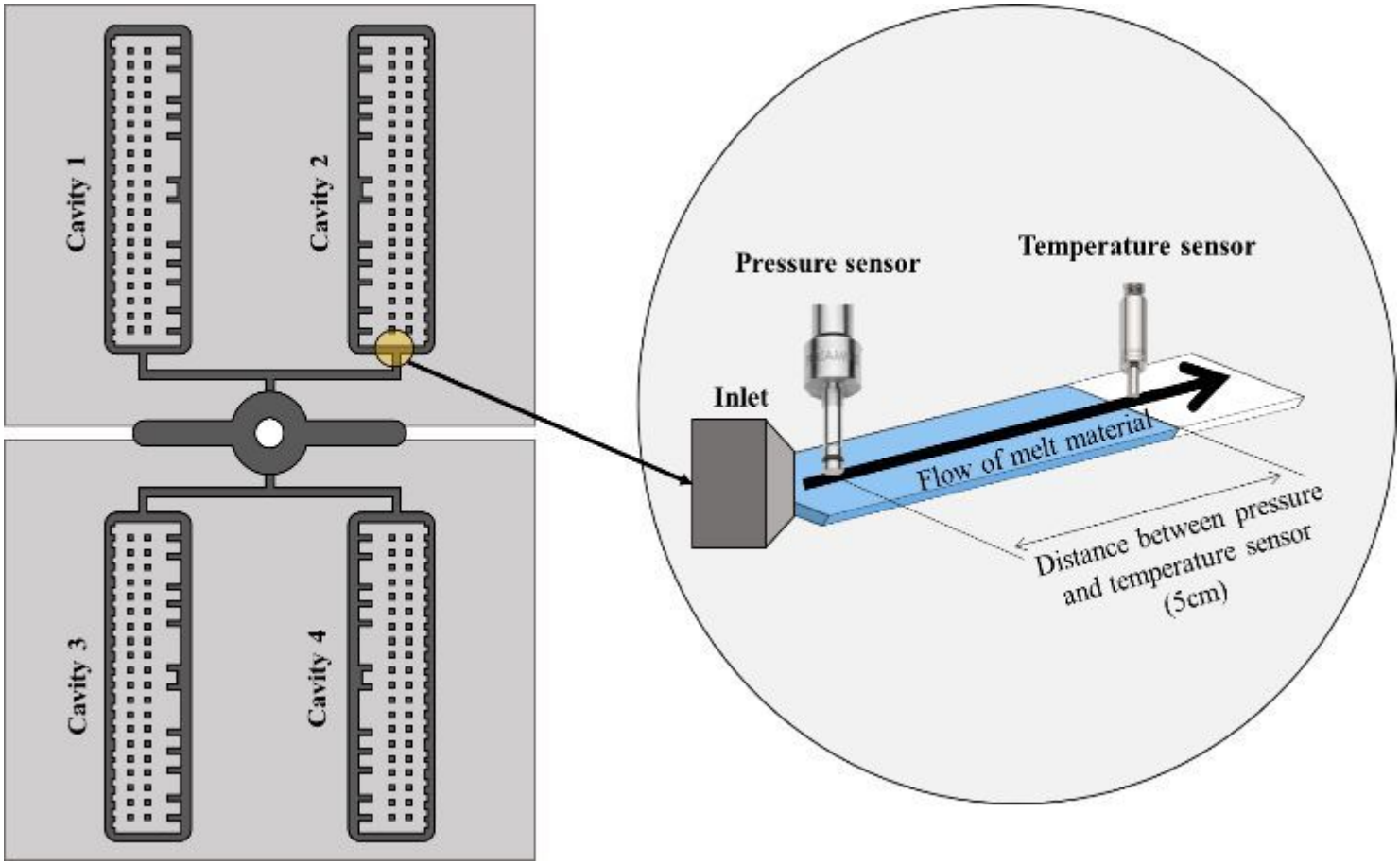


Figure 3

Location of the pressure and temperature sensors

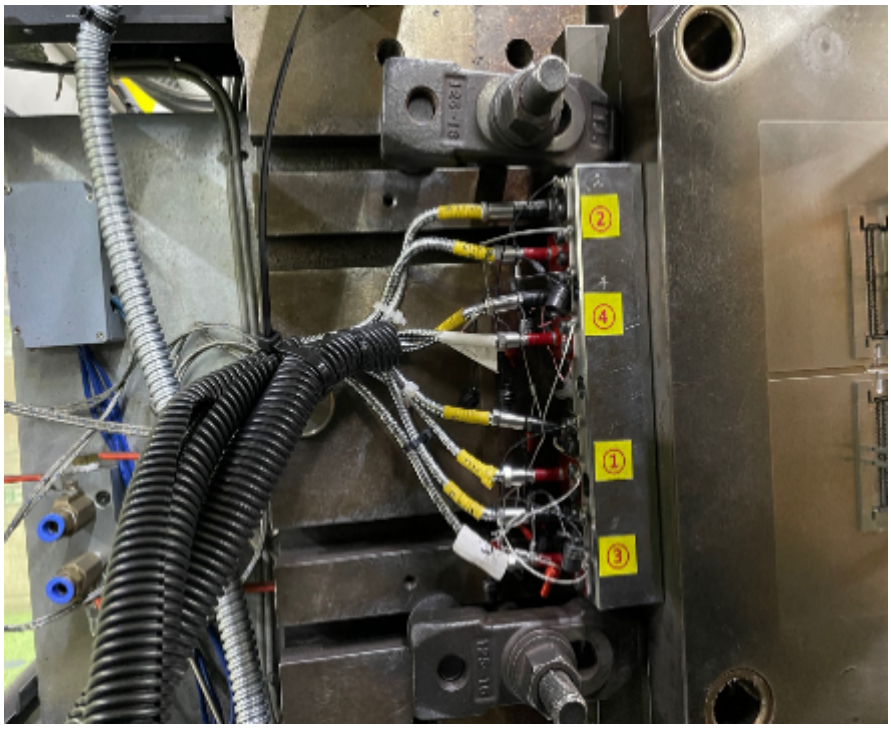
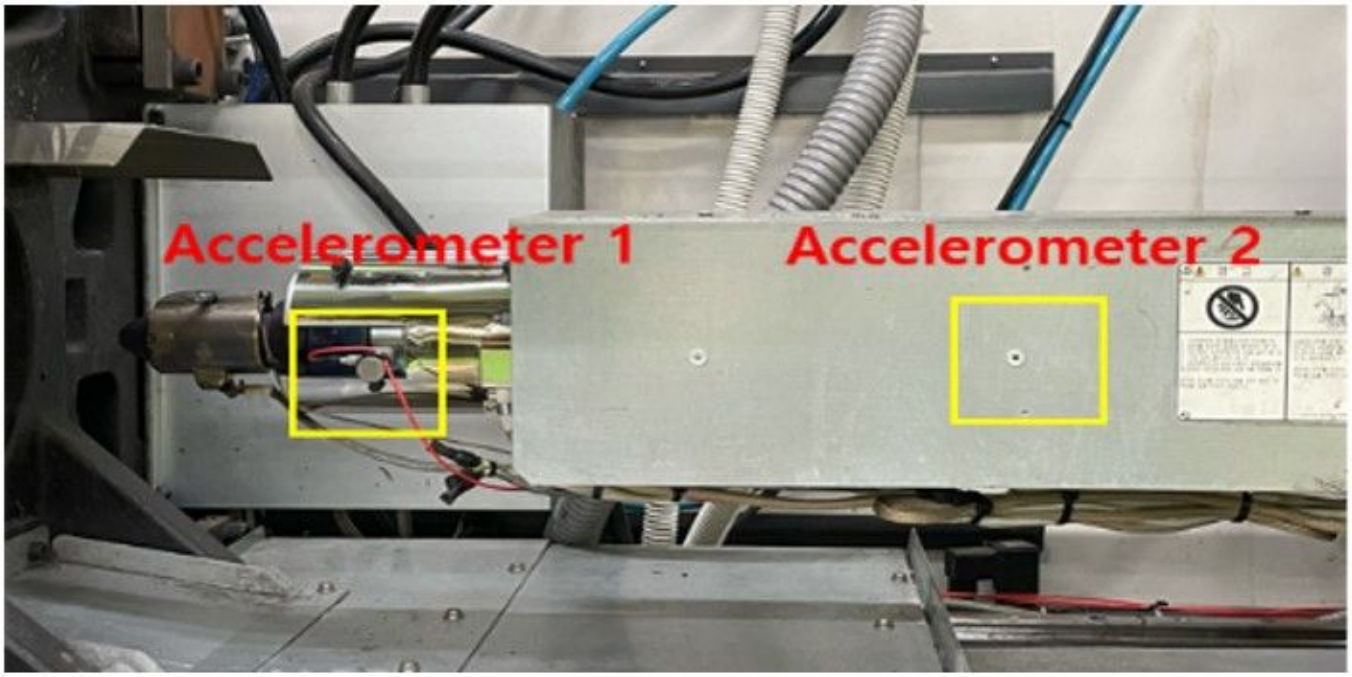
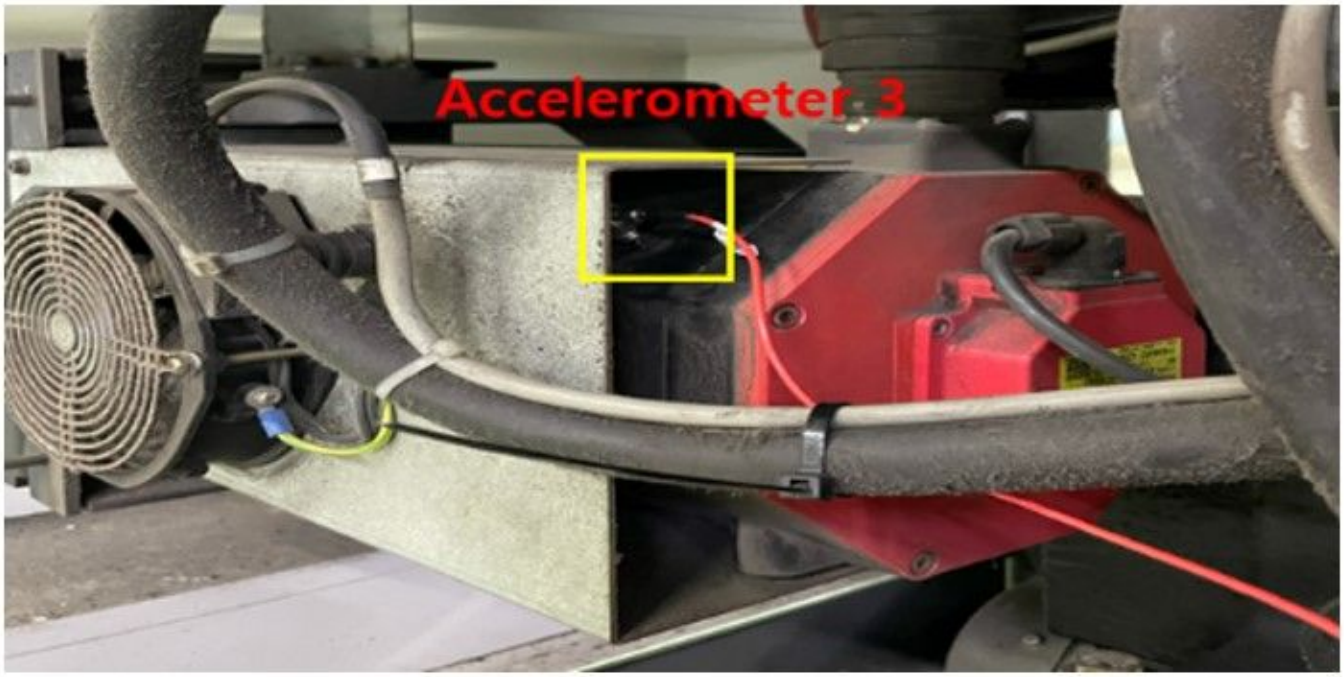


Figure 4

Cavity sensors installed to machine



(a) Location of accelerometers for cylinder



(b) Location of accelerometer for motor

Figure 5

Accelerometers installed on the machine

Figure 6

Vision camera installed in the real field

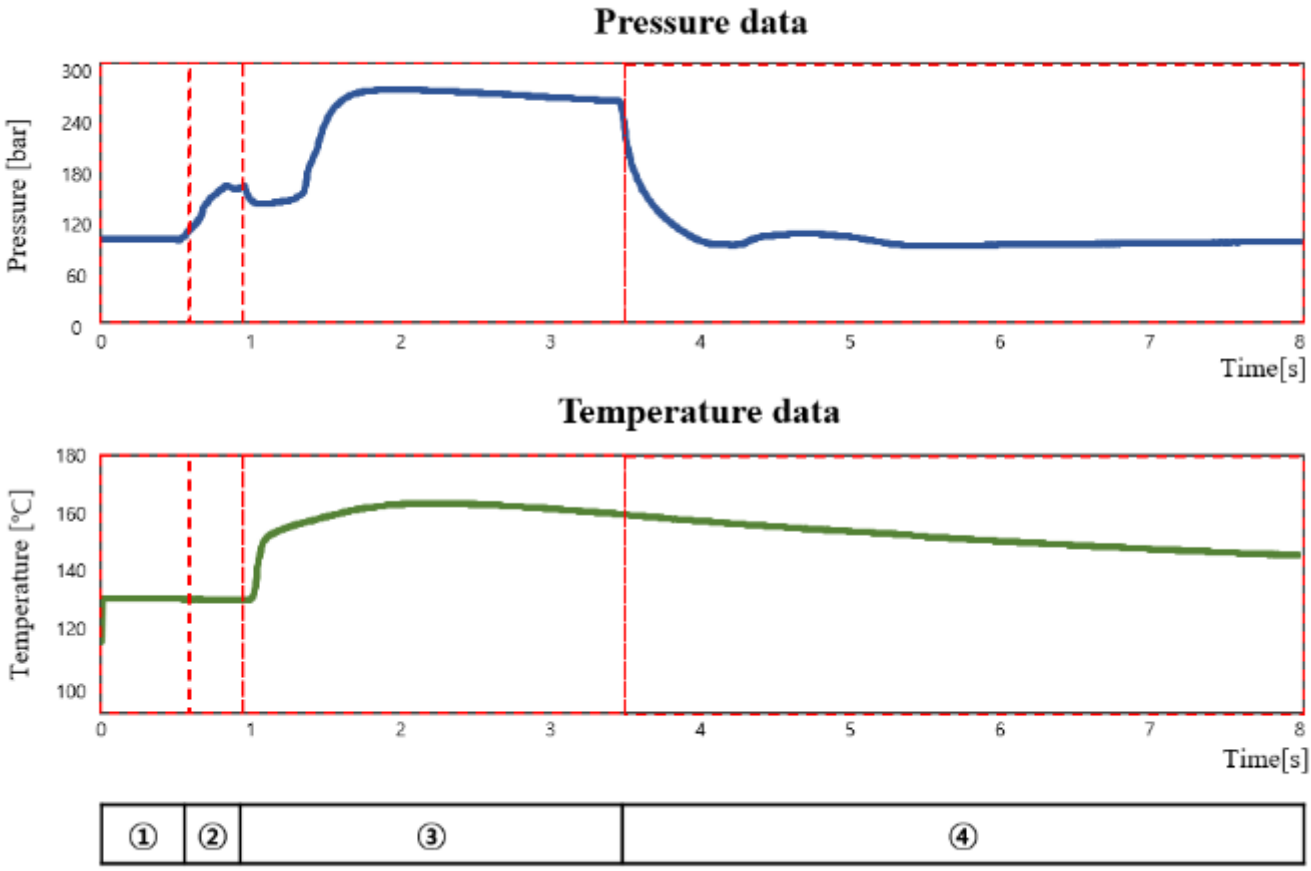


Figure 7

An example of collected cavity sensor data of the mold

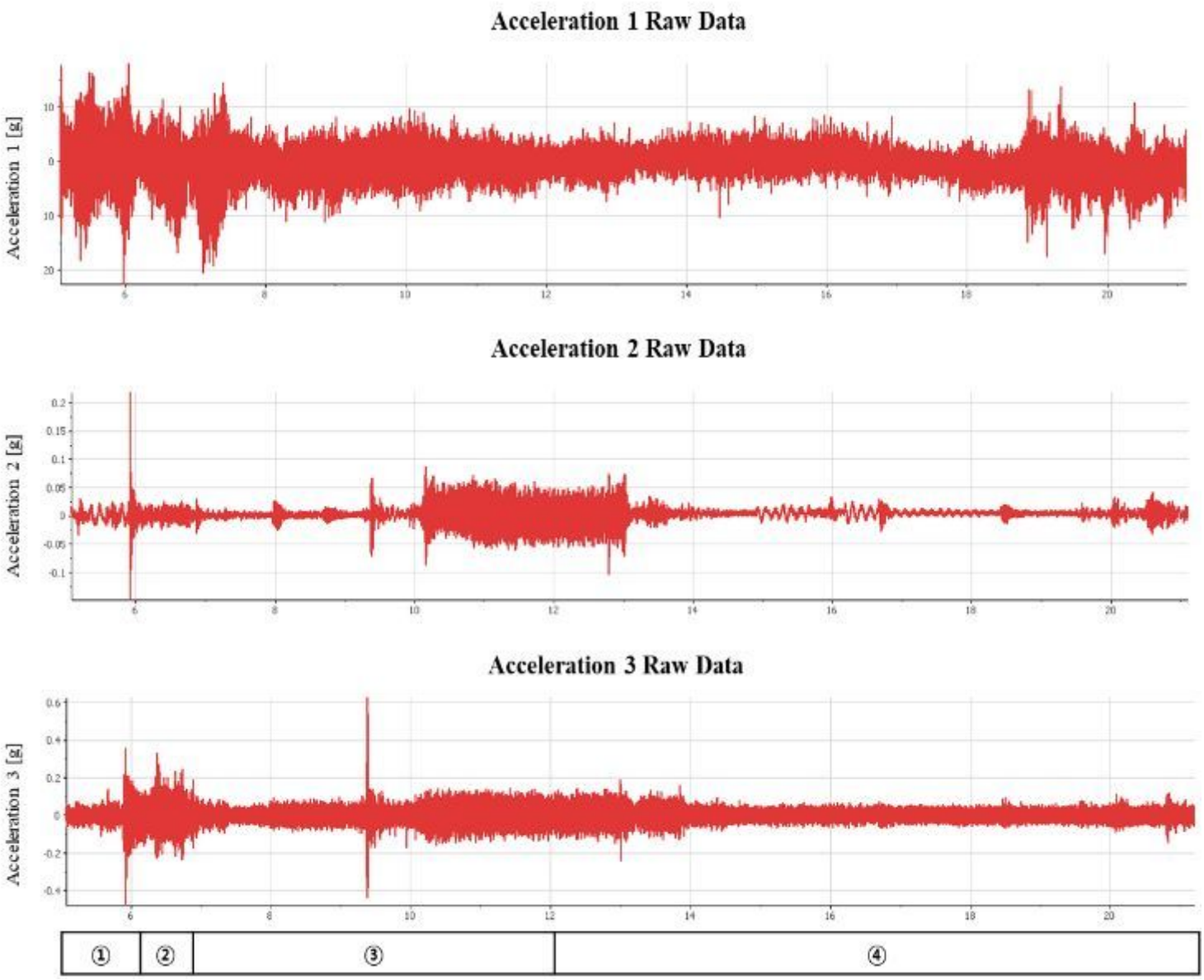


Figure 8

Raw vibration data of the machine

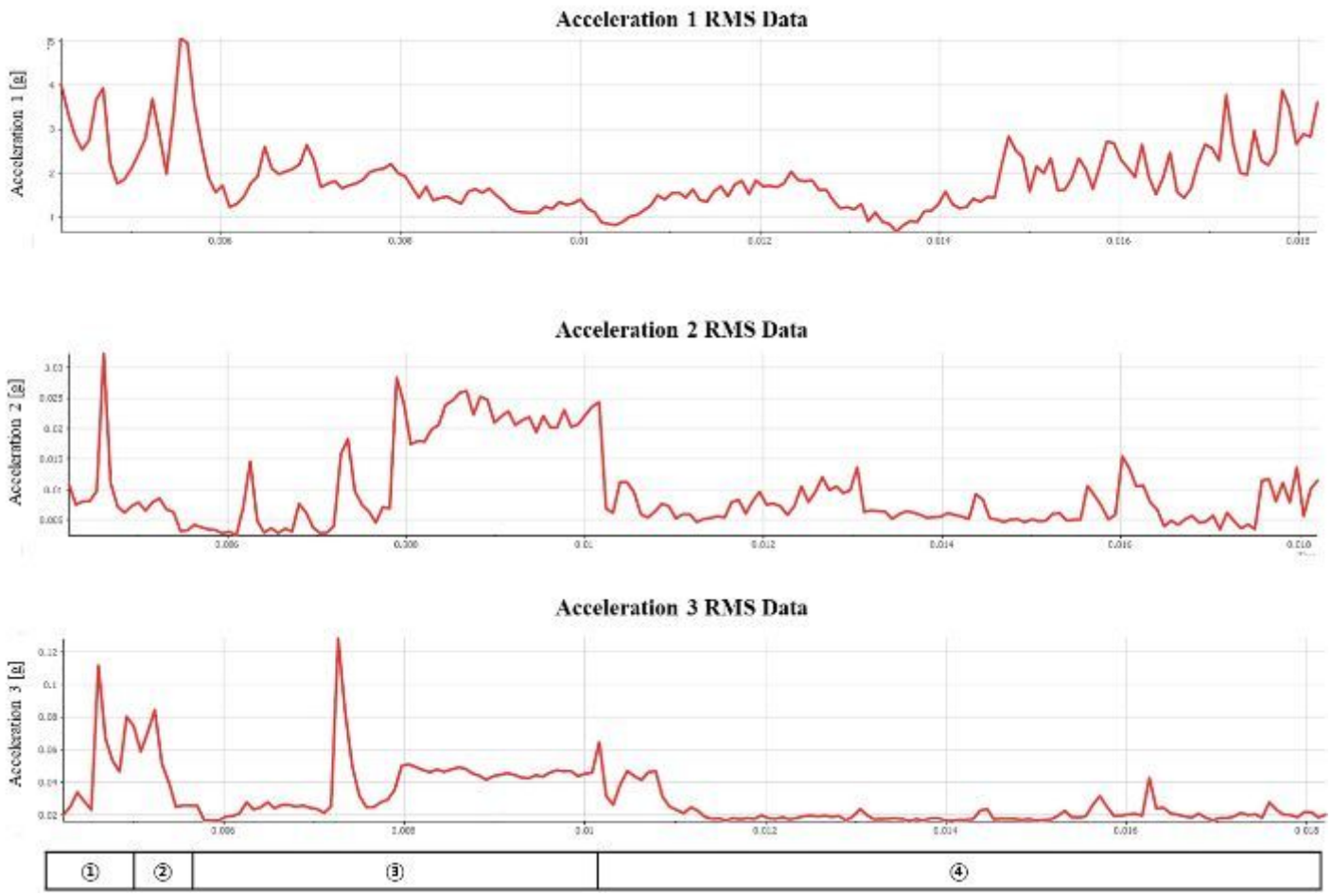


Figure 9

Vibration data (RMS) of the machine

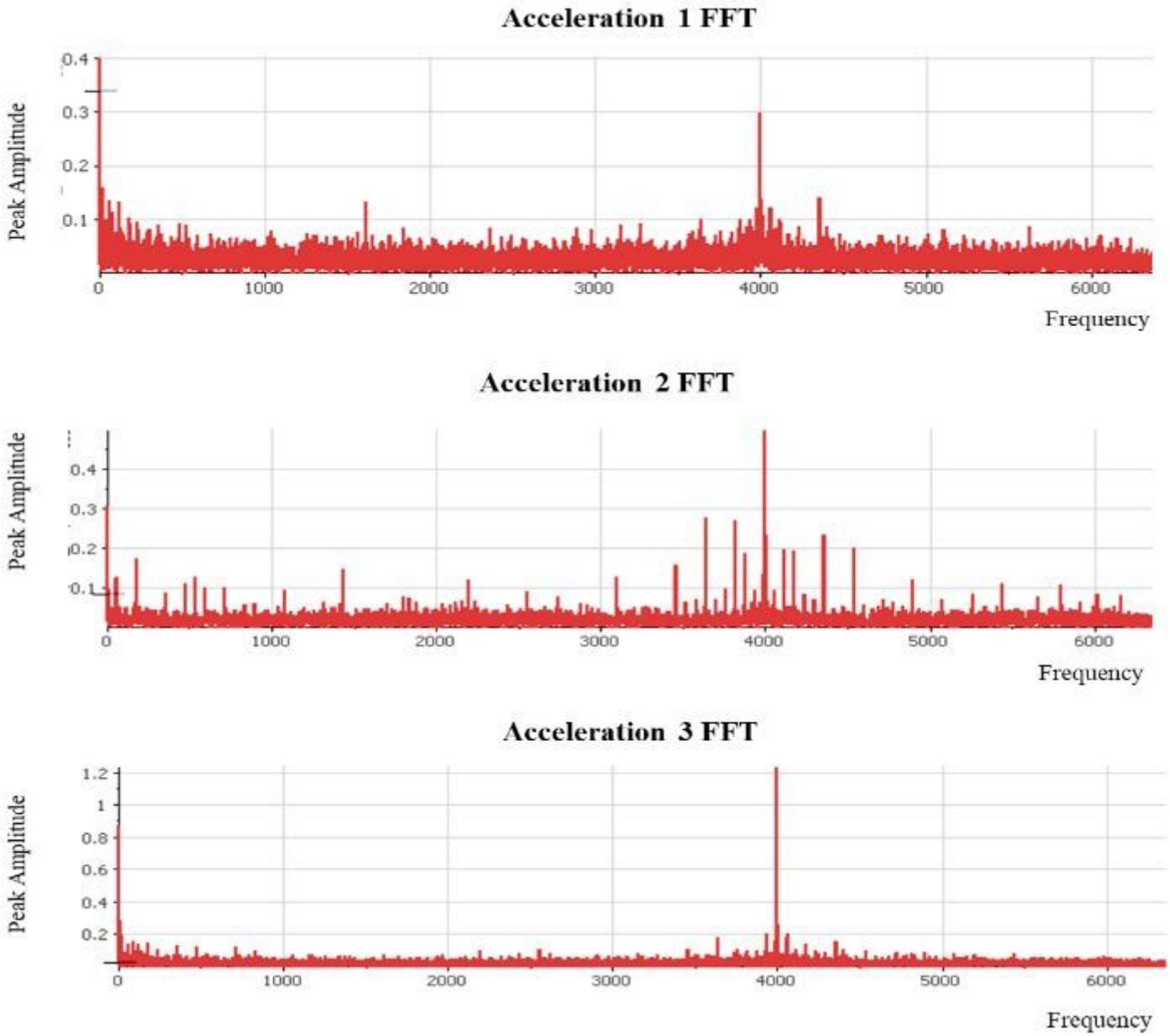


Figure 10

Vibration data (FFT) of the machine

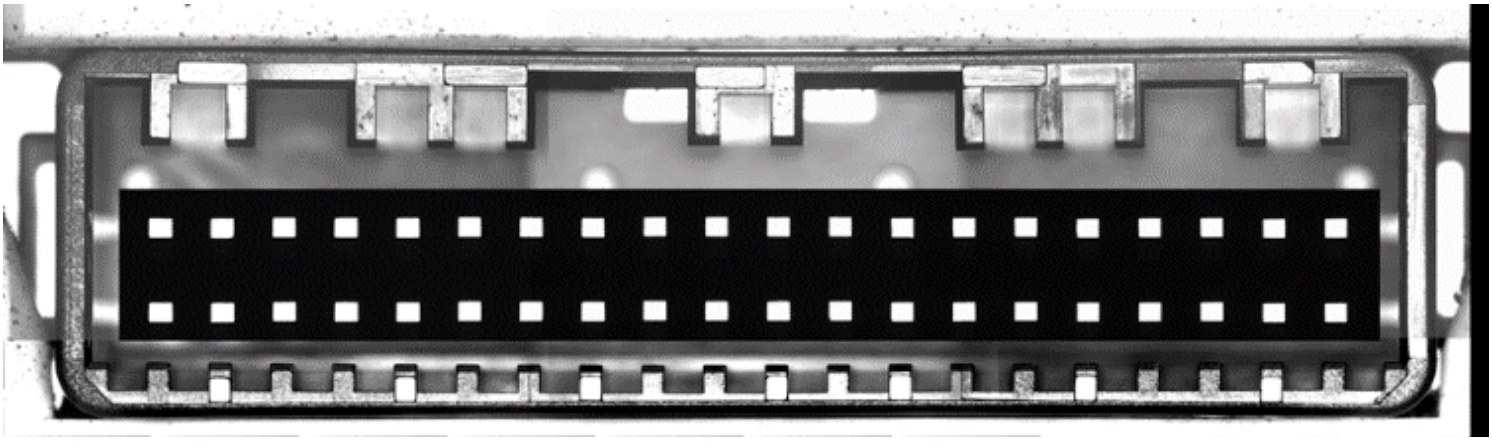


Figure 11

Vision image of the product

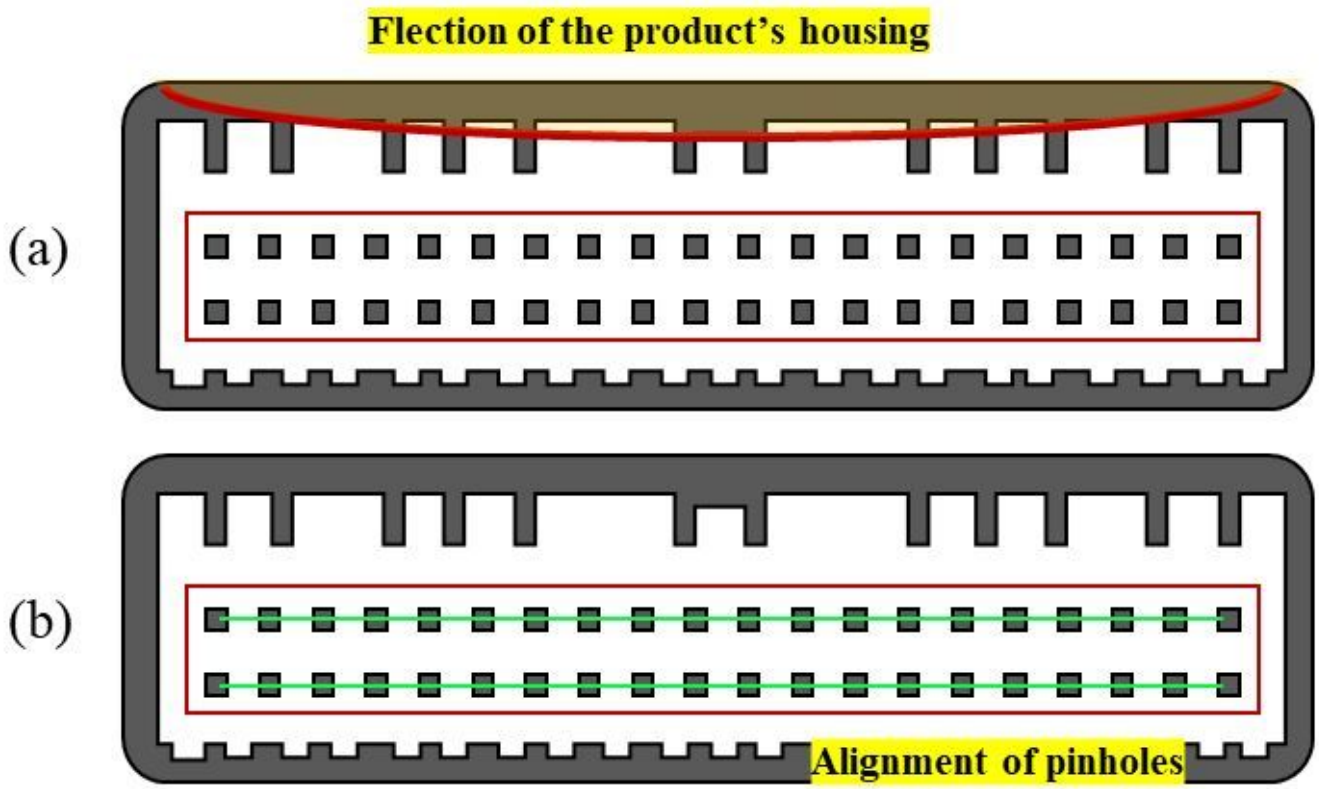


Figure 12

Two indicators of product's quality grade

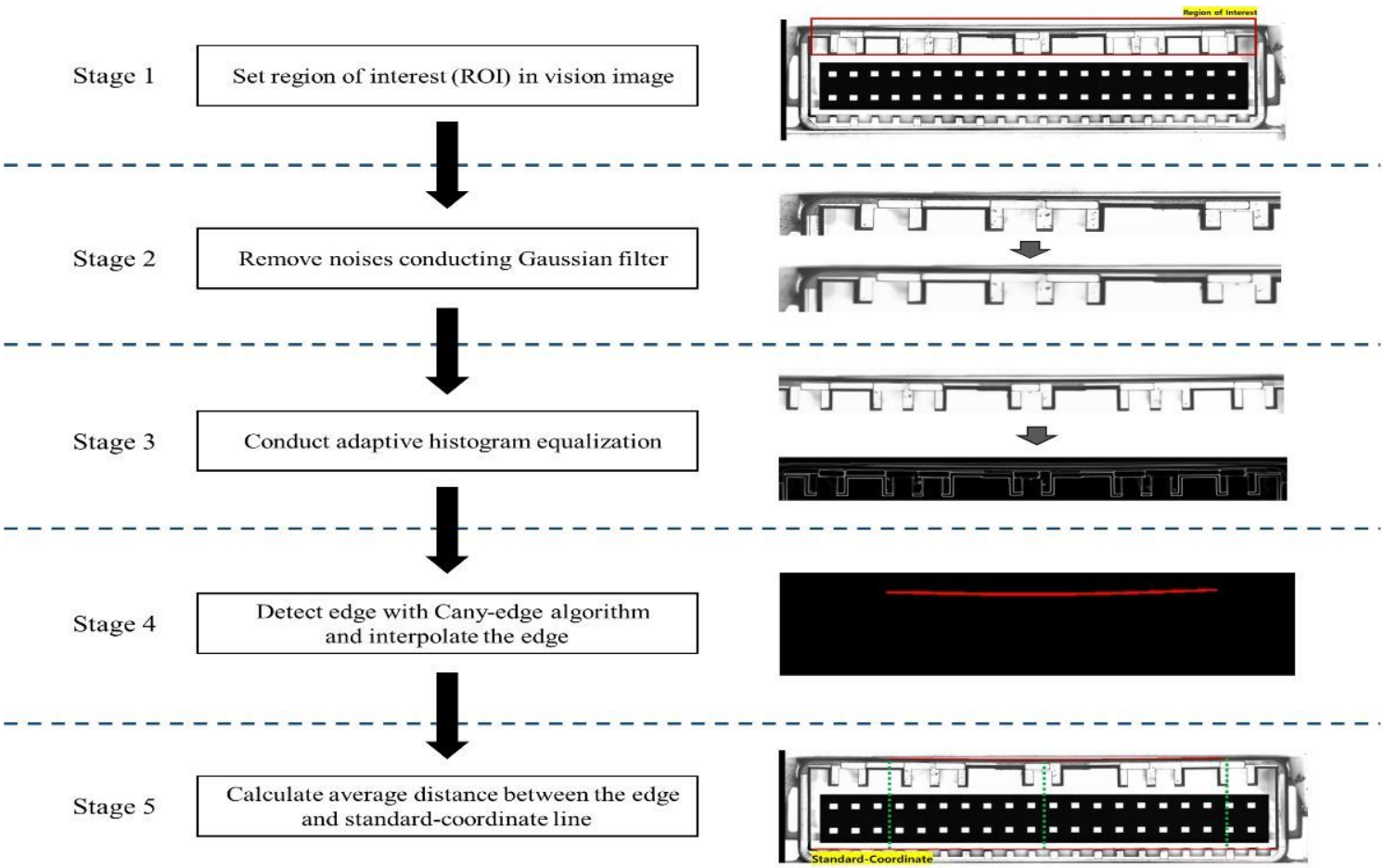


Figure 13

Stages of deriving flection of the product's housing

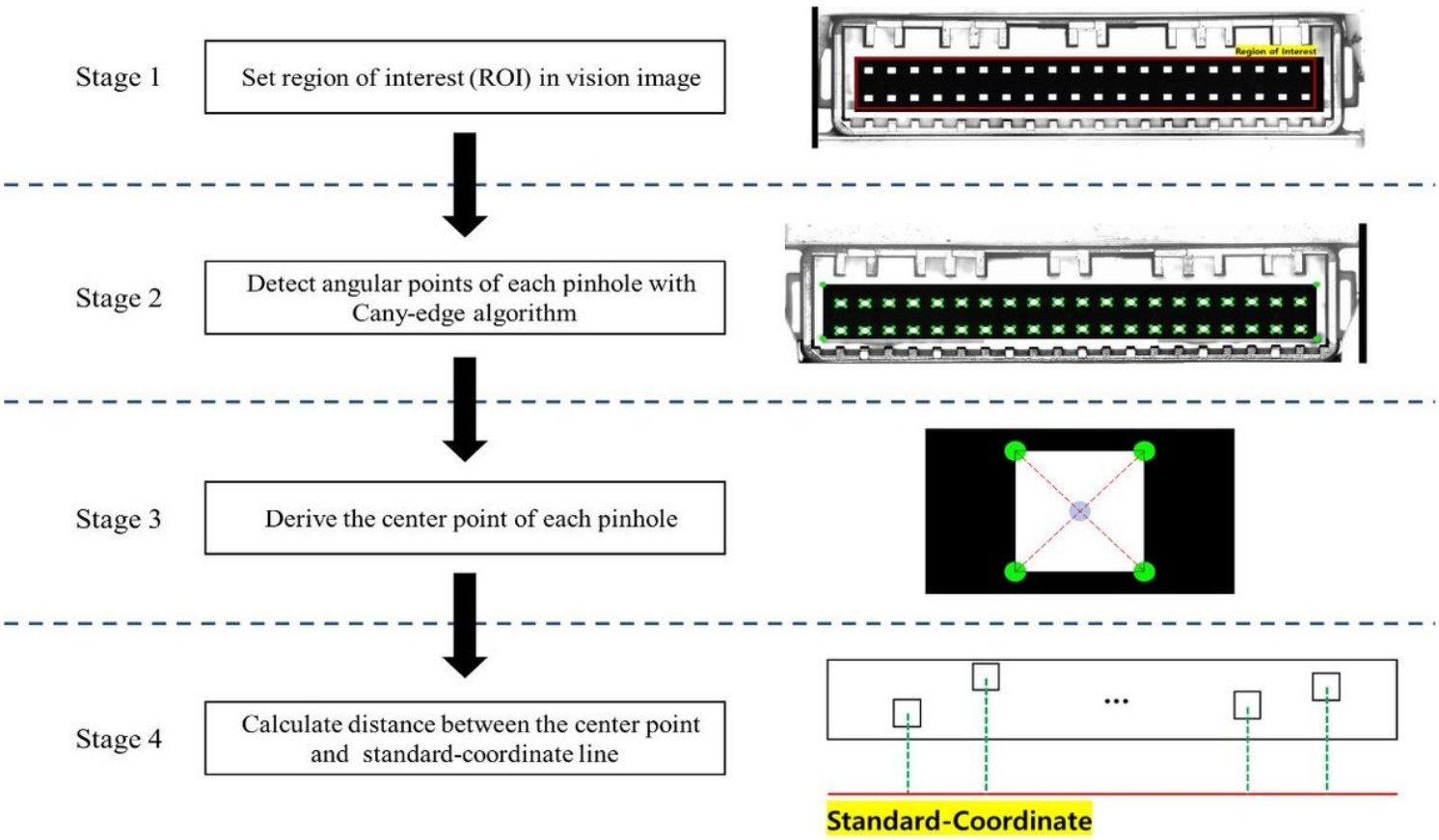


Figure 14

Stages of deriving alignment of pinholes

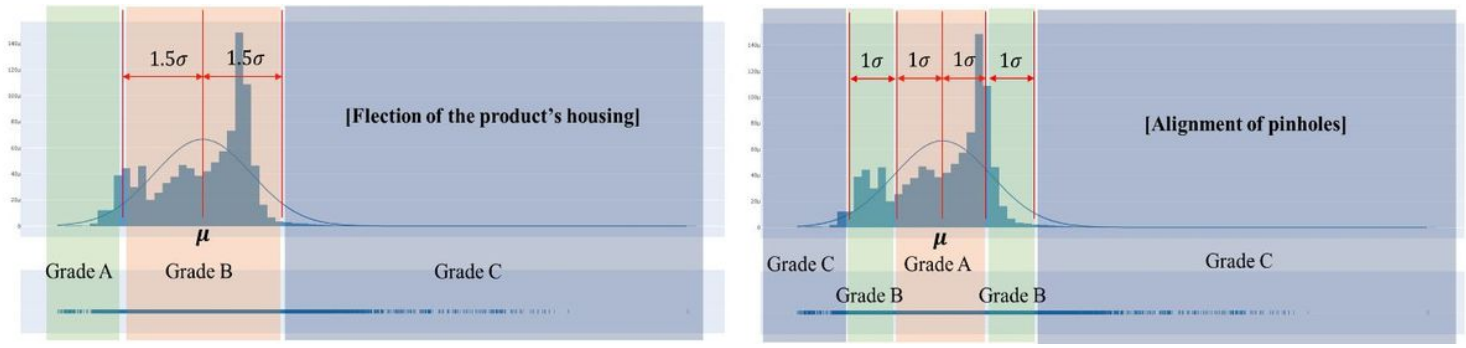
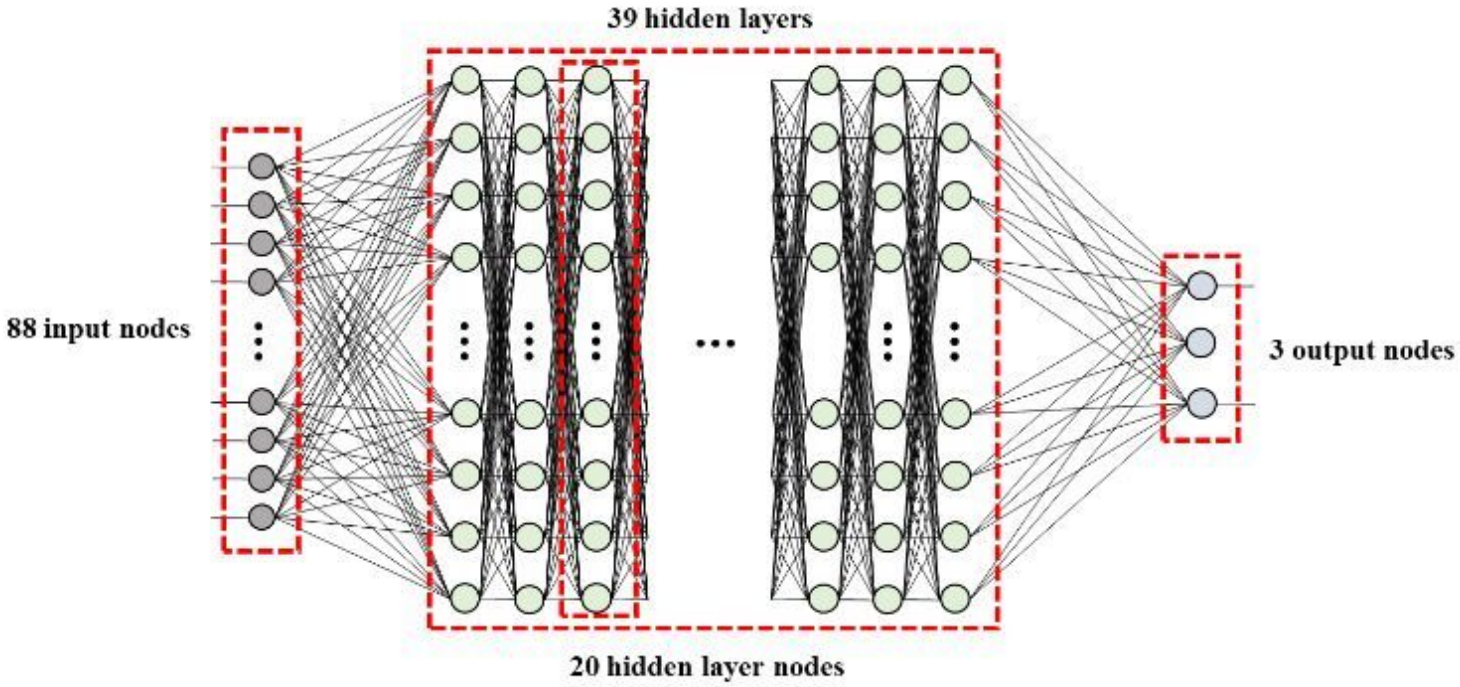


Figure 15

Criteria of grade classification in terms of each indicator



$$\text{Loss function} = -\sum_i t_i \log(f(s_i))$$

$$\text{Activation function} = \text{Softmax} = f(s_i) = \frac{\exp(s_k)}{\sum_i \exp(s_i)}$$

Figure 16

Structure of the developed neural network