Manufacturing Rev. 9, 21 (2022)

https://doi.org/10.1051/mfreview/2022020

Manufacturing Review
Available online at:
https://mfr.edp-open.org

Research Article
Open Access

Using fault detection and classification techniques for machine breakdown reduction of the HGA process caused by the slider loss defect

Thanasak Wanglomklang[1], Phathan Chommaungpuck[2], Kontorn Chamniprasart[1], and Jiraphon Srisertpol[1,*]

[1] School of Mechanical Engineering, Suranaree University of Technology, Nakhon Ratchasima Province, Thailand
[2] Western Digital (Thailand) Co.Ltd, Bang Pa-in Industrial Estate, Ayutthaya Province, Thailand

Received: 30 March 2022 / Accepted: 18 July 2022

Abstract. Fault Detection and Classification (FDC) based on Machine Learning (ML) approach was used to detect and classify mount head fault in the slider attachment process which causes the machine alarm 71 to occur which leads to 2% of machine downtime. This paper has focused on the use of classified pixel surface of mount head with fault difference conditions including Healthy, Fault I, Fault II, and Fault III to detect and diagnose mount head before a vacuum leak. The Artificial Neural Network (ANN) algorithm was a proposed classification model and has to be evaluated before using in the real processes. Three features of mount head surface pixel, i.e., inner, outer, and overall areas were investigated and used as model training data set. The experiment result indicates that the classification using the ANN model with three features performed with an accuracy of 94.3%. According to the result, it was found that the reliability of the production processes of FDC technique has increased as a result of the reduction of machine downtime by 1.886%.

Keywords: Fault detection and classification / data analytics / machine learning / artificial neural network / machine automation

1 Introduction

The vacuum system has been applied in industries to automation, high-speed machine, which is an essential part of modern industry to high production volume and product quality. The Hard Disk Drive (HDD) manufacturing process must be reliable and precise due to micron level size. The Head Gimbal Assembly (HGA) as shown in Figure 1 is a vital component in the HDD, responsible for reading and writing data. It has two main parts including suspension and slider. The HGA assembly process demonstrated in Figure 2 is used in Auto Core Adhesion Mounting Machine (ACAM) used for gluing adhesive onto the suspension and attaching the slider on a suspension by mount head. The HGA is considerably small. Therefore, the steps of the slider attaching process have high accuracy and precision at the micron scale. Regarding the slider attachment process, the first step begins with the moving of head pick slider from slider tray to the vacuum table. Then, it was again moved to the position for attaching slider on suspension for HGA product. These attachment processes used vacuum pressure. The investigation of Fault Detection and Diagnosis (FDD) for a vacuum leak is the most important problem because the machine normally shows an alarm 71 which leads to all machine downtime at 2%. The Slider Loss Defect (SLD) occurred due to the fault on the vacuum system from the mount head damage. The mount head is especially important to the process because it performs the slider attachment. Figure 3 presents the conditions of the mount head in actual operation and it was found that the fault start occurred when they were used for a period of time.

The Convolution Neural Network (CNN) was applied to detect the fault on the mount head surface in the slider attachment process. The result demonstrated that CNN could be used to classify the fault condition by using image data [1]. High-Speed automation machines are widely used in HGA production process, therefore Fault Tolerant Control (FTC) utilizing PI servo with observer was used to increase the reliability of the machine control system [2]. Vibration signal analysis is a comprehensive method for machine condition monitoring. It was implemented to classify linear bearing faults by applying the spectrum analysis with the statistical approach to evaluate the vibration signal of each condition [3]. The effects of the laser jet bonding parameter in Head Gimbal Assembly process were investigated by using response surface methodology to analyze the influence of laser energy which affects shears strength of the solder

* e-mail: jiraphon@sut.ac.th

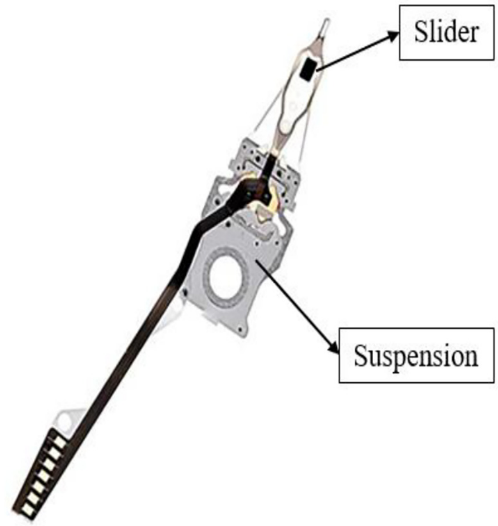

Fig. 1. Head Gimbal Assembly (HGA).

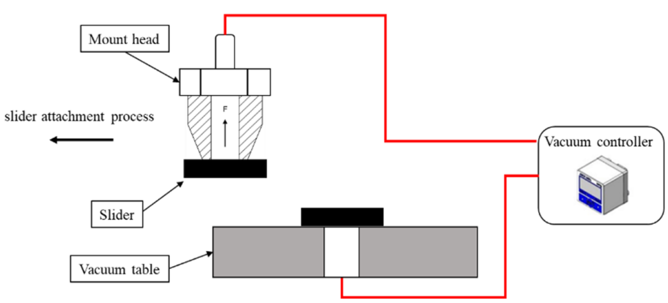

Fig. 2. Diagram of a slider attachment process.

joints [4]. The Fault Detection and Diagnosis (FDD) technique is the development of modern mechanical equipment and industrial production of automation. The production efficiency was higher according to the requirements provided by Xu et al. [5]. Proposed classification was designed based on fault detection and isolation. The classification method programmed by a k-fold cross-validation error can detect irregular data pattern [6]. The Fault Detection and Isolation (FDI) creates warning signal that can work online and in real-time. This advanced technology helps increase the reliability of process automation. FDD has enormous potential for pattern recognition and classification. Consequently, it increases equipment reliability and avoids the failure of systems [7]. This study proposes Artificial Intelligence (AI) with a vacuum decay to efficiently diagnose a leak for slider attaching process. It aims to detect operating conditions when leakages occur under different conditions. The leak detection using pressure sensor was used to identify vacuum degradation. The detection of the smallest leakage size requires an algorithm. This approach has been successfully evaluated by Krysander [8]. The intelligence FDD using supervised learning classifiers achieved high accuracy for classification. The model of Artificial Neural Network (ANN) has been used to predict and identify the root of the problem. These feature extractions are used to interpret for making a decision and

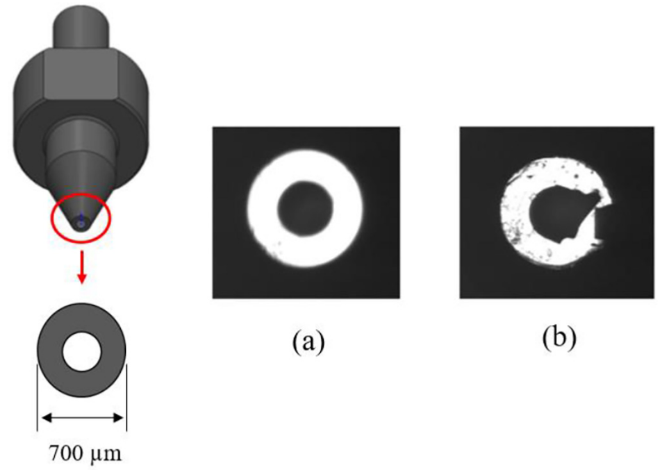

Fig. 3. Conditions of the mount head (a) healthy and (b) faulty.

classification. The ANN inspects microscopy cell images (600,000 pixel-level spectra) and classifies four-class of human biological nervous system). As a result, rule-based classification model was on accuracy average of 85% [9]. The ANN technique has been employed for the fault detection and identification. The results show an ability to detect and identify the fault in a wide range with rapid response [10]. Similar to ANN, the Convolutional Neural Networks (CNN) ability of a strong network is excellent at the representation of deep structure which helps increase the performance of artificial neural networks. Proposed by [11], image classification by CNN was used to investigate the vacuum leak for slider attachment process in Head Gimbal Assembly (HGA). The pixel quality/resolution of an image is vital to its accurate classification. The CNN models are built from the feature map to evaluate its performance on image recognition and detection datasets. It is an important factor in computer vision processing [12]. The technique was applied to analyze fault conditions. The classification of the features using supervised learning was developed by Dey et al. [13]. A diagnosis method for investigating vacuum leakage is used for monitoring discharge vacuum in order to prevent faults and ensure reliability suggested by Yokomichi et al. [14].

This research studies the Fault Detection and Diagnosis method based on Artificial Neural networks (ANN) to detect and classify faults that occur on the mount head surface. The ANN has a very wide application and great function in pattern classification. Therefore, it was used to predict the condition of the mount head by pixel of the image. This approach is well suited to the detection and diagnosis of abrupt faults in order to reduce Alarm 71, the risks of production malfunction for the Slider attachment process, Slider Loss Defect (SLD), and Machine downtime.

1.1 Artificial neural network (ANN)

An Artificial Neural Network (ANN) is the most popular supervised algorithm of machine learning technique. Nowadays the computational use of computers has become efficient for solving the numerical and mathematical problems that impose its spread in the engineering field. The ANN has the

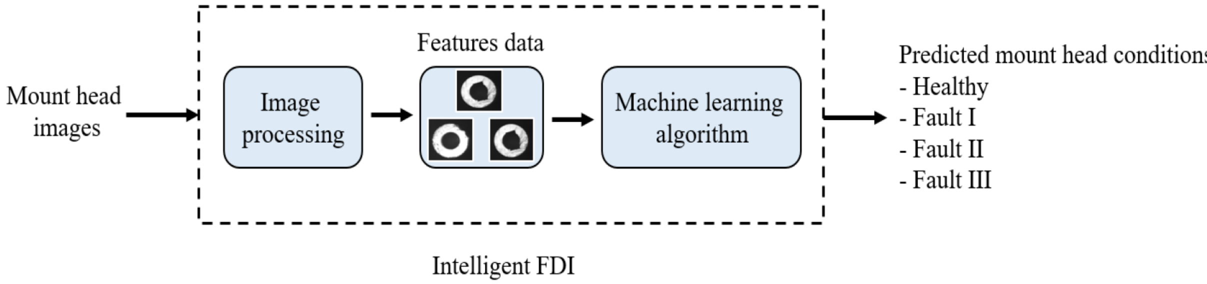

Fig. 4. Purpose of FDI architectures for the slider attachment process.

Table 1. Camera features used for this study.

Feature details	Value
High-rate scanning	180 fps
Resolution	648 (H) × 494 (V) pixels
Shutter speed	1/15000 s
S/N ratio	High S/N ratio: 58 dB
Sensor type	1/3 type progressive scan IT CCD

architecture of the human biological nervous system. The working process first accepts and weighs multiple inputs, then linear summation, and sends to the mathematical activation function to make decisions. The accuracy of the model depended on the number of hidden layers and the feature selection of the training data set. The sigmoid was applied as a weighting function to enable the model to classify the output that relates to the linear summation state. So as to classify the condition, the nozzle tip image of the mount head in each condition was used to develop the ANN model.

1.2 The purpose of fault detection and Identification (FDI)

The machine conditions monitoring system is important for HGA automation processes which have been produced on a micro-scale operated by using a high-speed machine, which can result in fault occurrence during the process. Therefore, the fault detection and identification (FDI) technique was applied. In general, the FDI can be classified into two methods which include the model-based and non-model based approaches. Intelligent FDI as shown in Figure 4 was used to analyze mount head fault symptoms by investigating mount head trip images. They are captured from progressive scan type high-resolution cameras which display the detailed features in Table 1. The major purpose is to use the image processing technique to gain more significant information on the image pixel of each mount head conditions.

2 Experiment

2.1 Analysis of mount head condition and vacuum behavior

The surface condition of the mount head is a causal key that directly affects vacuum leaks for the slider attachment process. In actual production, the ACAM machine was operated at a high-speed and continuous time. It caused the fault condition on the mount head surface which can make the slider loss and machine downtime. To demonstrate a real production of 10 HGA which installs on the pallet shown in Figure 5. The influence of mount head surface area includes Healthy, Fault I, Fault II, and Fault III on vacuum behavior were discussed in this section.

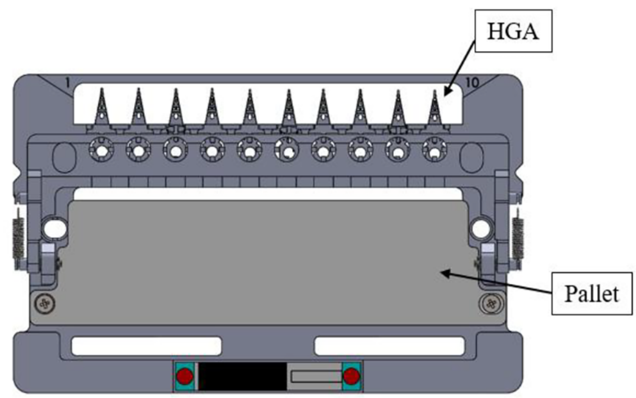

Fig. 5. Position of HGA on pallet.

Fig. 6. The healthy condition of the mount head.

2.1.1 Healthy

The mount head surface image as shown in Figure 6 is presented in good condition which is used in the process. The visual inspection is clearly performed and it does not have a defection or contamination on the surface area. The vacuum response informs the voltage from the pressure controller as illustrated in Figure 7 which was collected during the production of 10 HGA. It was found that the signal is normal while the mount head surface and slider are attached.

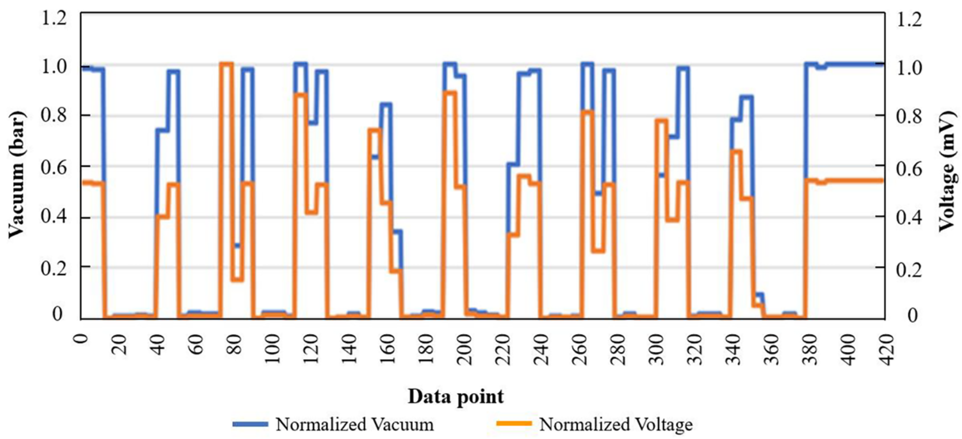

Fig. 7. Vacuum pressure of healthy condition.

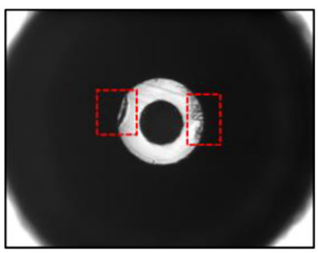

Fig. 8. The Fault I condition of the mount head.

2.1.2 Fault I

The fault appears on mount head surface when the machine was operated for one cycle of the production process. In this condition, it was found the abrasion begins on the outer surface as shown in Figure 8. The relation of vacuum pressure signal and the number of attractions as displayed in Figure 9 have a condition close to healthy condition because there is perfect contraction between the slider and inner surface area. This state will not affect the SLD problem and machine downtime.

2.1.3 Fault II

The mount head surface condition as reflected in Figure 10 indicates that the HGA was produced for several pallets. It can be established the scratch to the inner and outer diameter of the circular surface. In this circumstance, the vacuum pressure begins to leak when the suction starts at the first HGA depicted in Figure 11. However, the machine has a pressure controller which could maintain a vacuum during the attachment process.

2.1.4 Fault III

According to Figure 12, this is a critical condition of the mount head caused by multiple collisions of the contact surface. Referring to Figure 13, it is clearly seen the pressure controller could not control the vacuum at the sixth one of HGA. Then, it starts to leak. The SLD occurred at this state because the system has a heavily damaged condition. Thus, the slider attachment process is unable to achieve as alarm 71 affects the machine downtime.

According to the behavior of vacuum and voltage during attaching operation, the condition of mount head is directly affected to slider suction process. However, a comparison of voltage signal on Figures 7–11 are difficult to distinguish because it contained the same detail due to the controllable suction process. The mean of voltage and mount head condition are presented in Figure 14. It indicated that the Fault III is clearly separated from other faults. However, Healthy, Fault I and Fault II conditions could not be obviously classified by using voltage signal. Hence, the analysis of fault condition based on image was utilized to establish an ANN model to diagnose the fault symptom before the machine downtime.

2.2 Data acquisition

The slider attachment process in the ACAM machine and the high-resolution camera were installed to examine the mount head trip conditions. Five hundred image data were collected from the machine and divided into four cases that are Healthy, Fault I, Fault II, and Fault III as shown in Figure 15. Raw data are used as input for the FDI model. However, there must be some image computational process to prepare useful information before supervising the model.

2.3 Image processing

2.3.1 Crop image

The initial image from the vision inspection camera has a dimension of 640×480 pixels. The cropping process was applied to improve the quality of the data set by changing the image size to 250×250 pixels as illustrated in Figure 16. This approach was satisfied the influence of fault at the mount head trip to the vacuum behavior of the slider attachment process.

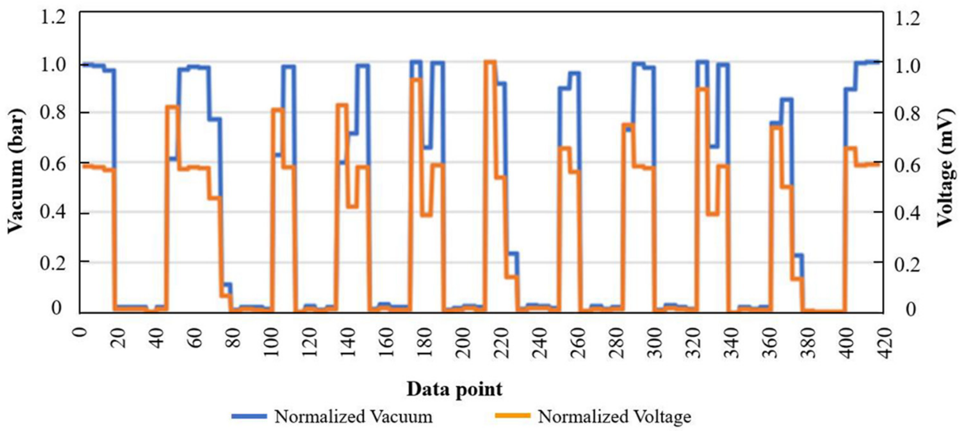

Fig. 9. Vacuum pressure of Fault I condition

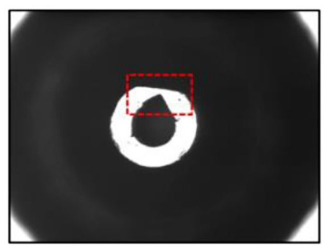

Fig. 10. The Fault II condition of the mount head.

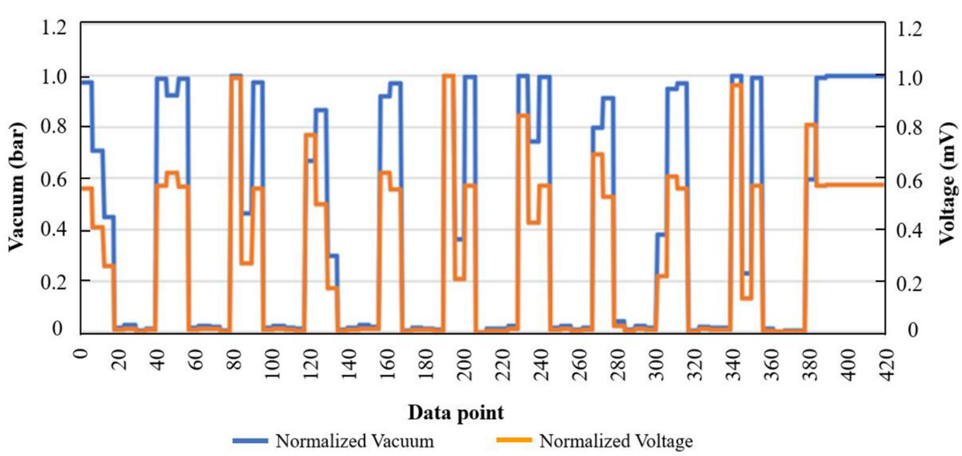

Fig. 11. Vacuum pressure of Fault II condition.

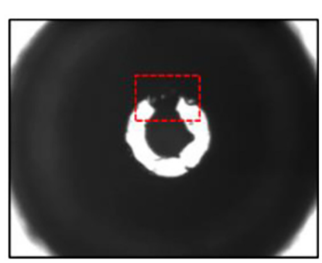

Fig. 12. The Fault III condition of the mount head.

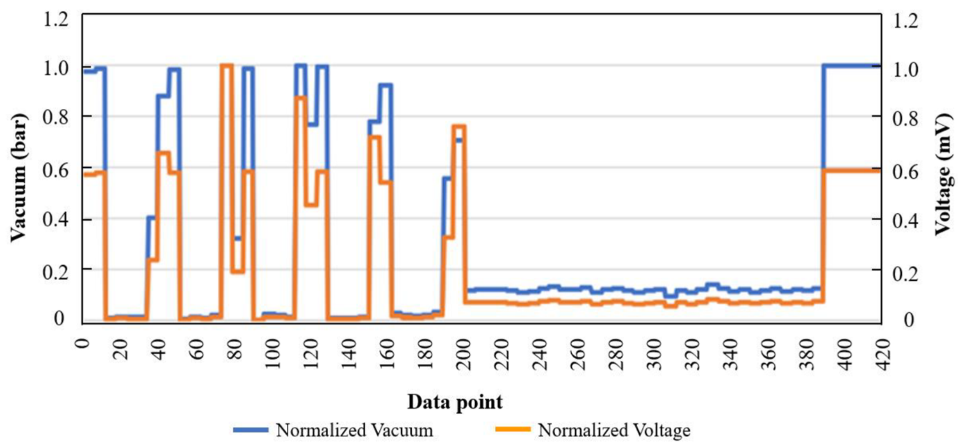

Fig. 13. Vacuum pressure of Fault III condition.

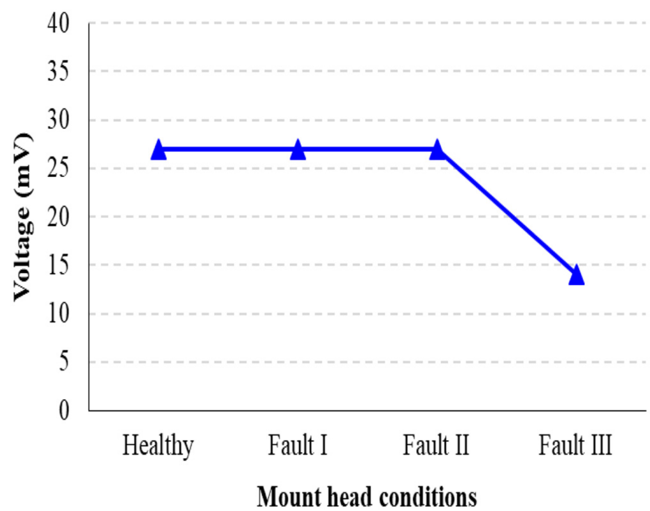

Fig. 14. The relation between sensor voltage and mount head condition.

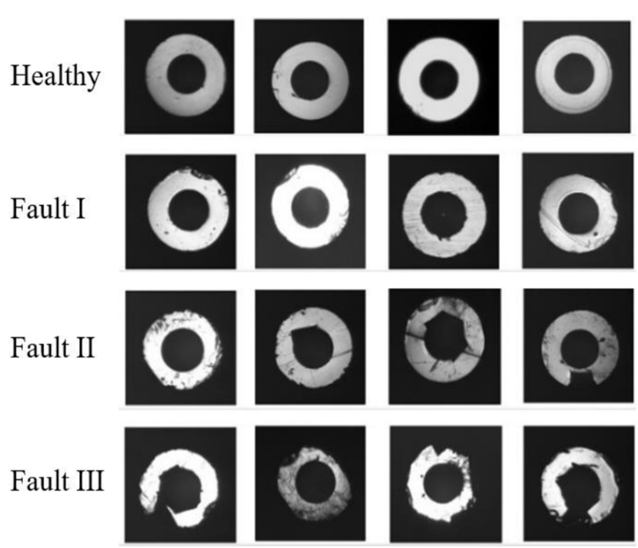

Fig. 15. Sample data of mount head image for each condition.

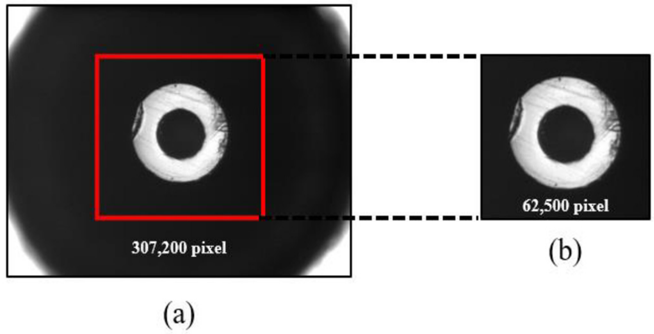

Fig. 16. (a) Original image, (b) Resize an image.

Fig. 17. Brightness adjustment of mount head image.

Table 2. The pixel range data of the mount head image.

Conditions	Pixel range (Outer area)	Pixel range (Inner area)	Pixel range (Total area)
Healthy	18,500–23,000	5500–6500	23,000–28,000
Fault I	16,000–18,500	5500–9500	22,000–27,000
Fault II	14,000–16,000	5500–12000	21,000–27,000
Fault III	<14,000	7000–16,000	14,000–26,000

2.3.2 Brightness adjustment

The brightness adjustment method is an essential step to produce the quality of training data sets that are related to light intensity variation in the actual production process. The original picture data were conducted by increasing and decreasing of 20% brightness as shown in Figure 17.

2.3.3 Feature extraction

The characteristics of the mount head picture in each condition were transformed in pixel data using the image processing technique. The inner, outer, and total areas were examined for this step in order to get more detail of the feature. Table 2 presents the range of pixels, which was calculated to the mean value as described in Figure 18. It revealed that the tendency of the outer and inner areas is contrasted by the fault level. Considering in the overall area, the result indicated when the mount head has a fault, the number of pixels decreases. Hence, the traits of the pixel feature could be used as training data to fabricate the intelligence model.

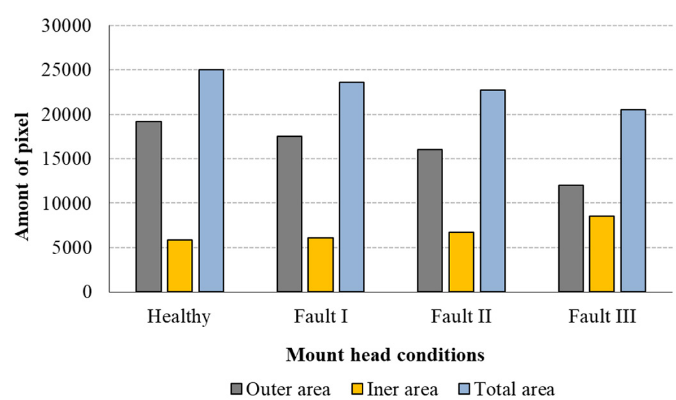

Fig. 18. Mean area pixel of the mount head.

3 Result and discussion

3.1 ANN model

To train the ANN model, the input data set was separated into training 80% and validation 10% for model learning

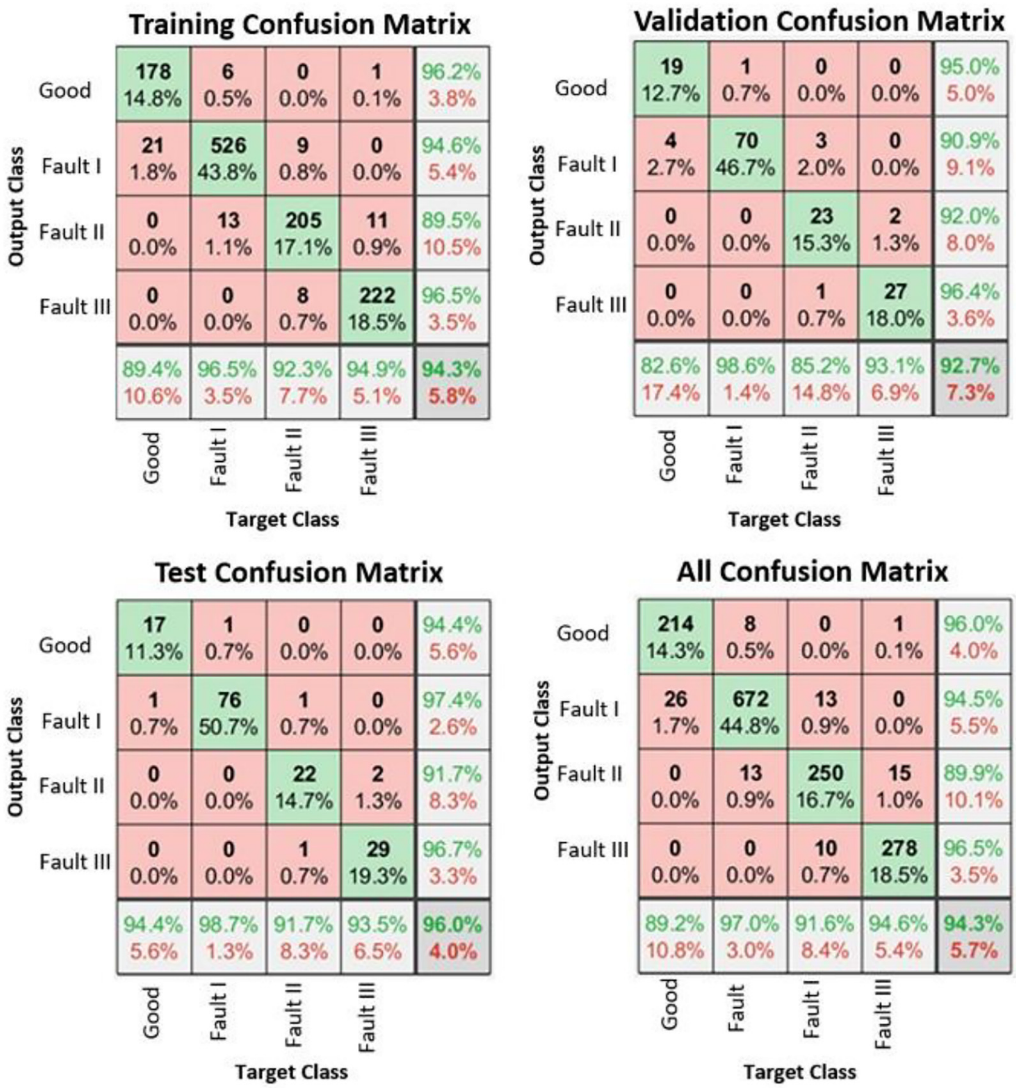

Fig. 19. Confusion matrix of ANN model.

processes which achieve the appropriate adjusting of the model weight parameter. However, the crucial step to evaluate the performance of model prediction is obtained by splitting input data into 10% for testing. The pattern recognition approach is recommended for this model for utilizing the neural network application tool supported in MATLAB software. Three input feature data of inner, outer, and total area pixels have been implemented. The model parameter configuration contains 2 hidden layers of model structure and uses one output layer to predict 4 mount head conditions. The performance of classification using ANN is displayed by the confusion matrix as shown in Figure 19, which displays the prediction detail of the mount head condition for each input dataset. The result implied that the model can learn the training data and give classification accuracy at 94.3%. This is equivalent to testing accuracy at 96% and overall accuracy at 94.3%. The model error is not significant to classify in Healthy and Fault I, however, Fault III was clearly distinguished from the other conditions with 100% accuracy.

The result ensures that the fault classification level is significantly effective by defining the conditions output of images with Fault I [1,0,0,0], Fault II [0,1,0,0], Fault III [0,0,1,0] and Healthy [0,0,0,1]. Figure 20 demonstrates the classification result, the investigation established that the prediction is not correct for some samples of Healthy, Fault I, and Fault II condition because these groups have similar characteristics. Despite the fact that Fault III is different, it has been badly damaged.

4 Conclusion

The slider attachment process is vital for HGA production. The mount head is the main part used for sucking the slider in the process which is supported by a vacuum system. Fault condition that occurred on mount head surface affected Slider Loss Defect (SLD). This causes the alarm 71 and produces 2% of machine downtime problem which reduces overall production rate. This research presented fault detection and identification

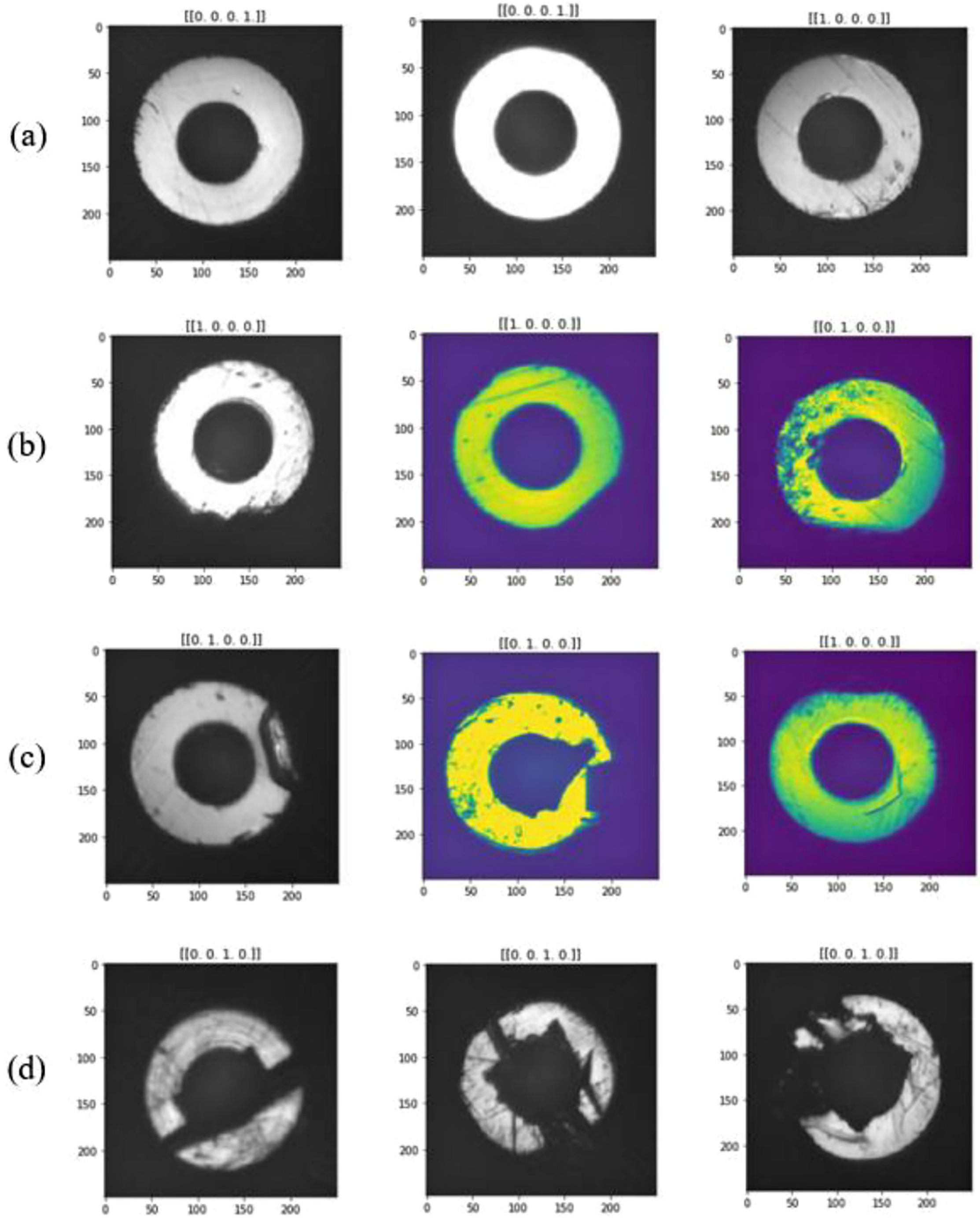

Fig. 20. Prediction result (a) Healthy, (b) Fault I. (c) Fault III and (d) Fault III.

(FDI) based on a machine learning approach. The Artificial Neural Network (ANN) was provided as a learning model and examined the model accuracy for using in the actual process. Image processing techniques were implemented for raw image data manipulation and feature extraction procedure. The image pixel includes the inner, outer, and total area that were provided for the ANN model fabrication. The experiment result explained that the ANN model achieved a fault prediction accuracy of 94.3% which can reduce 1.886% of machine downtime.

Acknowledgements. The authors would like to thank Miss Thanaporn Thamcharoen, Suranaree University of Technology (SUT) and Western Digital (Thailand) Co.,Ltd. for financial support for this research project.

References

1. T. Thamcharoen, P. Chommuangpuck, J. Deeying, J. Srisertpol, Fault detection and classification for slider attachment process using convolution neural network, Int. J. Neural Netw. Adv. Appl. **7** (2020) 60–65

2. P. Chommuangpuck, T. Wanglomklang, S. Tantrairatn, J. Srisertpol, Fault tolerant control based on an observer on PI servo design for a high-speed automation machine, Machines **8** (2020) 22
3. P. Chommuangpuck, T. Wanglomklang, J. Srisertpol, Fault detection and diagnosis of linear bearing in auto core adhesion mounting machines based on condition monitoring, Syst. Sci. Control Eng. **9** (2021) 290–303
4. J. Deeying, K. Asawarungsaengkul, P. Chutima, Multi-objective optimization on laser solder jet bonding process in head gimbal assembly using the response surface methodology, Opt. Laser Technol. **98** (2018) 158–168
5. X. Xu et al., Application of neural network algorithm in fault diagnosis of mechanical intelligence, Mech. Syst. Signal Process. (2020) 106625
6. S.-Y. Lin, S.-C. Horng, A classification-based fault detection and isolation scheme for the ion implanter, IEEE Trans. Semiconduct. Manufactur. **19** (2006) 411–424
7. J.C.M. Oliveira et al., Fault detection and diagnosis in dynamic systems using weightless neural networks, Exp. Syst. Appl. **84** (2017) 200–219
8. M. Krysander, E. Frisk, Leakage detection in a fuel evaporative system, Control Eng. Pract. **17** (2009) 1273–1279
9. P. Manescu et al., Accurate and interpretable classification of microspectroscopy pixels using artificial neural networks, Med. Image Anal. **37** (2017) 37–45
10. A. Jain et al., Intercircuit and cross-country fault detection and classification using artificial neural network, in *2010 Annual IEEE India Conference (INDICON)*. IEEE (2010)
11. V. Veeriah, N. Zhuang, G.-J. Qi, Differential recurrent neural networks for action recognition, in *Proceedings of the IEEE international conference on computer vision* (2015)
12. R. Chauhan, K. Kumar Ghanshala, R.C. Joshi, Convolutional Neural Network (CNN) for image detection and recognition, in *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)*, IEEE (2018)
13. D. Dey et al., A deep learning framework using convolution neural network for classification of impulse fault patterns in transformers with increased accuracy, IEEE Trans. Dielectr. Electr. Insulat. **24** (2017) 3894–3897
14. S. Yokomichi et al., Development of diagnostic methods for vacuum leakage from vacuum interrupter by partial discharge detection, in 2016 27th International Symposium on Discharges and Electrical Insulation in Vacuum (ISDEIV). Vol. 2. IEEE (2016)

Cite this article as: Thanasak Wanglomklang, Phathan Chommaungpuck, Kontorn Chomniprasart, Jiraphon Srisertpol, Using fault detection and classification techniques for machine breakdown reduction of the HGA process caused by the slider loss defect, Manufacturing Rev. **9**, 21 (2022)