Pipe Corrosion Inspection System based on Human-in-the-Loop Machine Learning

Toshihiro Shimbo[1], Yousuke Okada[2], and Hitoshi Matsubara[3]

[1]*Mitsubishi Gas Chemical Company, Inc., Chiyoda-ku, Tokyo, Japan*
toshihiro-shinbo@mgc.co.jp

[2]*ABEJA, Inc, Minato-ku, Tokyo, Japan*
yousuke@abejainc.com

[3]*The University of Tokyo, Bunkyo-ku, Tokyo, Japan*
matsubar@ai.u-tokyo.ac.jp

ABSTRACT

The aim of this study was to improve the efficiency of external corrosion inspection of pipes in chemical plants. Currently, the preferred method involves manual examination of images of corroded pipes; however, this places significant workload on human experts owing to the very high number of such images. To address this issue, we developed an artificial intelligence (AI)-based corrosion diagnosis system and implemented it in a factory.

Initially, interviews were conducted to understand the decision-making processes of human experts. Subsequently, we converted their tacit knowledge into explicit knowledge, which was used to define the training data for the machine learning (ML) model. The predictions of the ML model were compared with the manually obtained results, exhibiting an accuracy of 70 %.

The proposed architecture was based on human-in-the-loop ML. It included a process to retrain the ML model using manual results gathered during operation. It was operated using a collaborative approach, in which human experts supported the ML model under development.

The proposed model enhanced the efficiency of the inspection process successfully.

1. INTRODUCTION

The central aim of Prognostics and Health Management (PHM) take necessary decisions and actions to safeguard system health. This requires the detection and location of failures, diagnosis of their causes, and prediction of the remaining life expectancy of systems and their components, such as social infrastructure and products. In recent years, the amount of available data has increased significantly owing to advances in measurement and communication technologies, such as the Internet of Things (IoT). To deal with this burgeoning volume of data, several artificial Intelligence (AI)-based tools have been developed and machine learning (ML) approaches are on the rise.

Japanese chemical companies, initially buoyed by economic growth in Asia, are currently at an important crossroads, facing challenges such as the relocation of manufacturing bases overseas, the retirement of skilled workers due to an aging population, and productivity reviews due to work style reforms. Thus, they need to improve productivity and reinforce their international competitiveness amid competition from overseas companies. Improving the operational reliability of equipment is essential for this purpose. However, the risk of accidents is a concern for Japanese chemical plants owing to aging equipment and a decline in skilled maintenance personnel. Therefore, appropriate measures are required to maintain stable operation in plants.

IoT and AI technologies can now be used as substitutes for skilled workers. The introduction of AI in smart maintenance aims to construct ML models and improve their accuracy using proof-of-concept (PoC) activities. However, few such cases of AI implementation have been reported. One reason for this is the difficulty of developing highly accuracy ML models using PoC.

In this context, this study utilized a human-in-the-loop (HITL) process during the implementation of the ML model. Thus, the challenge of constructing highly accurate ML models during the development phase is circumvented by developing an incomplete ML model and operating it with human support.

The proposed model was implemented as an AI-based corrosion diagnosis system in a chemical company as a case study. To this end, the design concepts for implementing

HITL and the verification results of actual operations were also analyzed.

2. Methods

2.1 Utilizing Human-in-the-Loop Machine Learning

In this study, we defined HITL as a loop involving human experts in the decision making of the ML model and operated the ML model while simultaneously improving it. Several existing studies have reported the successful application of ML-based approaches in cases with well-defined problems and abundant data. However, in production environments, these requirements are often not fulfilled. Therefore, further research is required to develop effective HITL methods for ML loops. However, we still adopted HITL, based on collaboration between human experts and AI, to compensate for the difficulty of developing highly accurate ML models during the PoC phase. Thus, if the ML model exhibited an accuracy of 60 % during development, human experts supported the remaining 40 % of cases during operation. Accuracy was measured in terms of the harmonic mean of Recall and Precision. Recall represents proportion of cases identified as positive by human experts that are also identified as positive samples by the ML model. Precision represents the proportion of the ML model's positive predictions that agree with those of human experts.

2.2 Defining the Concept of an AI Corrosion Diagnosis System Utilizing Human-in-the-Loop Machine Learning

The conventional external corrosion inspection method for chemical plant piping at the Niigata Factory of Mitsubishi Gas Chemical Company, Inc., comprises the following steps. First, operators take photographs of the corroded pipes and paste them into an Excel file (Primary Inspection). Next, maintenance personnel (skilled workers) review the images and determine appropriate measures (Secondary Inspection). Preventing oversight during inspections is crucial for safety of the operators. Further, the number of captured images is usually very high, placing significant burden on maintenance personnel in the subsequent step. Thus, reducing the workloads of both operators and maintenance personnel is a major challenge. Moreover, inspection results are subjective, which have significant room for improvement. Figure 1 illustrates the workflow of the conventional inspection method for corroded pipes.

Two challenges were considered in this study, as depicted in Figure 1. Challenge 1 involved utilizing AI to reduce workload on humans and improve inspection quality and Challenge 2 involved designing a system to manage inspection information centrally. Instead of pasting the images into an Excel file, they were uploaded to a dedicated website for evaluation. Further, the need for a system that includes a search functionality and AI retraining data creation was identified.

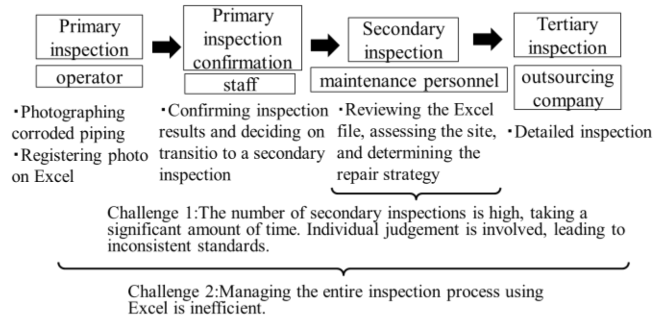

Figure 1: Existing workflow and challenges

The desired state is depicted in Figure 2.

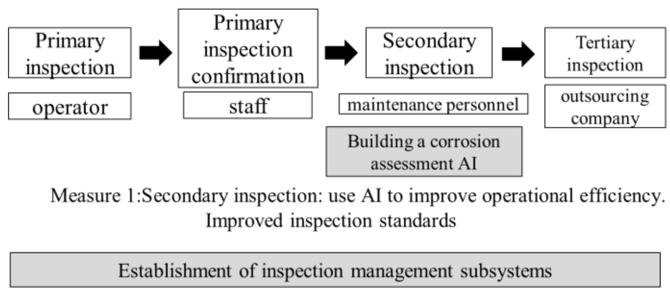

Figure 2: The desired state

The system image to be created, including the AI implementation and workflow efficiency, is depicted in Figure 3.

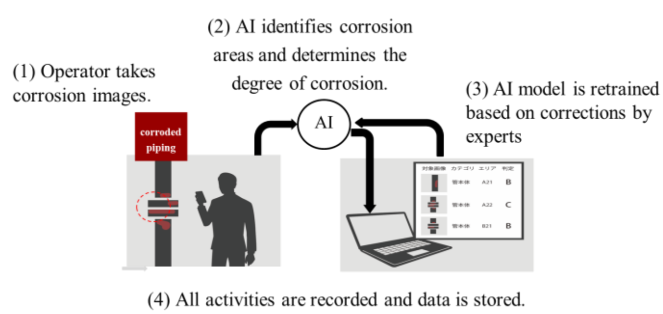

Figure 3: Image of desired system

A use-case diagram of the system of interest based on Figure 3 is depicted in Figure 4. Figure 4 illustrates the functionalities of the proposed AI Corrosion Diagnosis System, including automatic detection of corrosion based on images, linking images to related information, and allowing the ML model to relearn based on the corrected results.

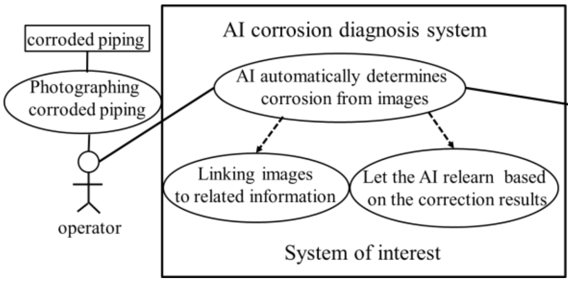

Figure 4: Use-case diagram of the system of interest

To achieve the aforementioned functionalities, the AI Corrosion Diagnosis System comprised two subsystems by design—the AI subsystem and the Master subsystem (depicted in Figure 5).

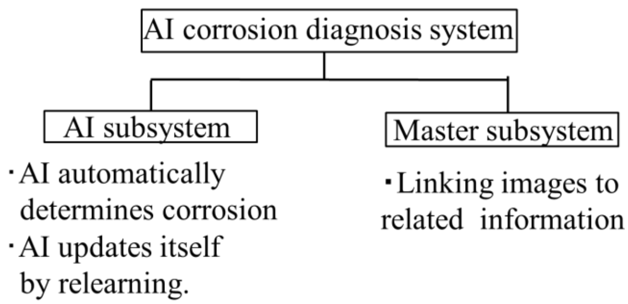

Figure 5: Constituents of the AI Corrosion Diagnosis System

Based on Figures 4 and 5, we constructed a business flowchart to guide the interaction between humans and the system of interest, as depicted in Figure 6. This incorporates the HITL architecture during operation of the ML model.

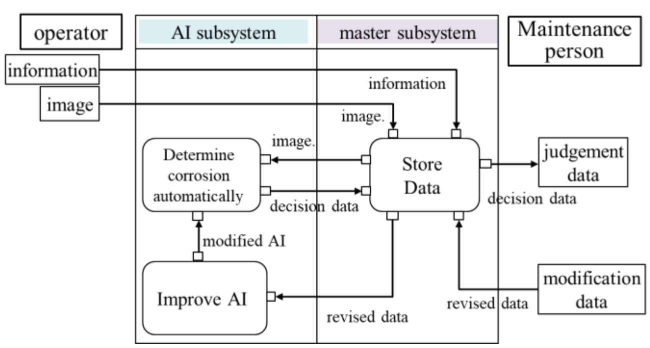

Figure 6: Overview of the proposed system

First, the operator transmitted the images and information to the Master subsystem, where the data were stored. The images were then transmitted to the AI subsystem for automatic corrosion detection. The prediction results were verified by maintenance personnel via the Master subsystem and corrected if required. The corrected data were transmitted to the AI subsystem via the Master subsystem. The AI subsystem re-trained the prediction model based on these corrections. Thus, inspection quality was improved by incorporating the evaluations of maintenance personnel into the ML model via the Master subsystem. Based on the architecture depicted in Figure 6, we designed, developed, and implemented an AI-based corrosion diagnosis system.

2.3. Points of Ingenuity in System Development

2.3.1. Standardization during the Creation of Learning Data

Standardization of evaluation by multiple skilled workers was necessary to create learning data for the ML model. Eleven skilled workers were involved in the following activities over three months:

1. They were interviewed to verbalize their judgment methods.
2. Differences between the judgment criteria of different skilled workers were identified.
3. The verbalized information was recorded in a manual.

These activities clarified the criteria and processes for manual decision making, enabling corrosion location and corrosion severity of the piping to be presented as learning data for the ML model. Corrosion severity was categorized into five stages in ascending order of severity—paint peeling, rusty appearance, mild corrosion, corrosion, and severe corrosion. However, the perceptions of the skilled workers were not completely identical. An operation based on human-AI collaboration was necessary to account for this variation in training data.

2.3.2. Utilization of Human-in-the-Loop Machine Learning

We developed a system based on the concept of human-AI collaboration, comprising an incomplete ML model in the developmental phase supported by human experts in the operational phase. To implement the workflow depicted in Figure 6, the Master subsystem, which manages image information, was required to be linked to the AI subsystem, which performs image diagnostics. Moreover, relearning data had to be created using the Master subsystem to retrain the ML model. This ensured that the prediction accuracy of the ML model would improve over time with the progressive accumulation of retraining data. The aim of the proposed AI-based corrosion diagnostic system was to contribute to the improvement of safety management in plants.

3. Results and Discussion

3.1. Verification of Results obtained during Operation

An AI-based corrosion diagnostic system was developed for carbon steel and stainless-steel piping without insulation. Figure 7 depicts the AI-identified corrosion location and progression in corrosion severity based on images of pipes.

Table 1 summarizes the development of carbon steel and stainless steel piping. 3,800 annotation data were required for carbon steel piping development.

For stainless steel piping, the proposed ML model exhibited a prediction accuracy of 74 % based on 500 training data points, leveraging the development experience of carbon steel piping. The Master subsystem focused on improvements during operation, such as quick manual access to information, efficient image storage, and efficient creation of relearning data.

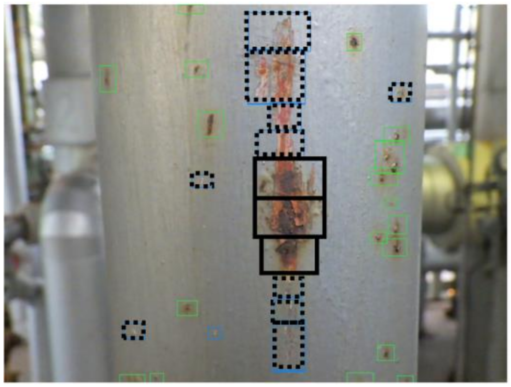

Figure 7: AI-identified corrosion sites and progression in corrosion severity based on images of pipes.

Table 1: Development Summary for Carbon steel piping and stainless steel piping

	development period	Number of annotated images	Degree of corrosion determination	AI accuracy	Remarks
Carbon steel corrosion piping	2019.11-2021.3 (16 months)	3800 sheets	5 steps	69%	It was the first time an AI was developed and two stages of PoC were conducted.
Stainless steel corrosion piping	2021.9-2022.1 (4 months)	500 sheets	4 steps	74%	Carbon steel experience enabled the development of an operational level system in a short time.

Table 2 lists the effects of the proposed AI-based corrosion diagnostic system.

Table 2: Effects of the AI-based Corrosion Diagnostic System (Initial Implementation)

	Before implementing the system	After operating the system	Effects after introduction of the system
Operator	• Taking corrosion images and pasting them into Excel	• Captures corrosion images and uploads them to the system	• 67% reduction in workload
Maintenance person	• Corrosion images are captured and attached to Excel • Perform image diagnosis • Input diagnosis results into Excel	• AI automatically performs corrosion assessment • Check AI results and relearn if different	• Improved human inspection variability • AI accuracy 69%, workload reduction 30%

• Overall, the workload is reduced by approximately 50%

The introduction of the proposed AI-based corrosion diagnostic system reduced the workloads of the operators and maintenance personnel by 67 % and 30 %, respectively, resulting in an overall workload reduction of approximately 50 %. The following conclusions were drawn based on interviews with actual operators and maintenance personnel:

- Even with an AI accuracy of only 69 %, skilled workers could fully utilize the system without any concerns.
- Image input time for operators was reduced from 3 minutes to 1 minute (67 % reduction).
- Comparison between AI-based judgment and human expectations of corrosion severity was a learning experience.
- Learning from AI-based corrosion diagnostic systems may improve the accuracy of manual image detection by maintenance personnel.
- Owing to the high interest in AI judgment among both maintenance personnel and operators, human-AI collaboration is expected to advance significantly in the future, thereby further improving safety measures.
- In future works, we intend to improve the accuracy of the proposed system by retraining the ML model based on re-annotation results using actual data, such as pipe thickness measurements.
- The accumulated data can eventually be used for corrosion trend analysis and prediction in plants.
- Future data accumulation is expected to be beneficial in several ways.

These opinions were shared by the interviewed operators and maintenance personnel.

3.2. Insights obtained from Human-AI Collaboration

3.2.1. Insights on Relearning

The proposed system was developed based on 3,800 pieces of training data that were carefully reviewed by skilled workers (maintenance personnel). Relearning during operation involved relearning 110 pieces of incorrectly predicted data by the AI. However, the prediction accuracy of the ML model remained almost constant even after relearning. This may be attributed to the small volume of relearning data compared to the original training data. To investigate this issue, we evaluated the relationship between the number of training images and accuracy of the ML model. An accuracy of 60 % was observed when 1,000 training images were used. This accuracy increased as the number of training data points increased up to 1,500, after which the accuracy improvement stagnated. Thus, in this case, as the M model was trained using 3,800 images, relearning was not expected to be effective unless a large amount of relearning data was collected. Because of the involvement of human experts in the creation of retraining data, the AI accuracy is not expected to reach 100 %.

3.2.2 Limitations of the proposed system

New challenges emerged when the ML model put into operation. For instance, its accuracy did not improve during relearning owing to the difference in image quality between the developmental and operational phases—ideal corrosion images obtained from skilled maintenance personnel during development and real corrosion images obtained from operators during operation were of different qualities. During surgery, images with blurred and hard-to-identify target piping were included. These differences in image quality were attributed to noise. In future works, photography methods will need to be improved. Moreover, during the operation of the ML model on stainless steel pipes, corrosion severities different from the 4 levels defined during development were observed. We are currently considering adding a new model to the existing AI-based method to address these shortcomings.

3.2.3 Insights on the Roles of AI and Humans

It was suggested that the discrepancy between manual evaluation and AI-based diagnostic results was induced by differences in the diagnosis of delamination—paint delamination or thickness-reduction delamination. Human experts are capable of distinguishing between the two based on images. However, the proposed AI-based method failed to do so. In the implementation described in this study, AI-detected delamination cases were checked by human experts to determine their types. In future works, development of AI models capable of distinguishing between different delamination types is expected to contribute to further improvements in accuracy.

4. CONCLUSIONS

In this study, we developed an AI-based corrosion diagnostic system that utilizes HITL ML for external inspection of corroded pipes in chemical plants. The model was trained based on the expertise of skilled workers and reduced the workload on human operators by approximately 50 % with a prediction accuracy of 70 %. An operational version of the AI system was constructed and implemented in a real-world factory. The benefits of HITL, which was used to improve the accuracy of the ML model over time, are not yet clear; however, we plan to improve the HITL model and enhance its effects in the future.

The collaboration between humans and AI provided valuable insights into operational safety. Enhancing the proposed AI-based corrosion diagnostic system through collaboration between humans and AI, addressing specific issues, and incorporating human experience into operations is essential. By examining AI diagnostics and safety operations in practice, we demonstrated the importance of collaboration between humans and AI based on actual operations and the new value that it creates. In future works, we intend to consider AI diagnostics using video recording in high-altitude locations. We plan to expand this approach to include insulated piping.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to ABEJA Corporation and the Niigata Plant of Mitsubishi Gas Chemical Company, Inc., for their contributions to the development of the AI-based corrosion diagnosis system.

REFERENCES

DoD Modeling and Simulation (M&S) Glossary, DoD 5000.59-M, DoD, January 1998 "Directives Division" (PDF). Archived from the original (PDF) on 2007-07-10. Retrieved 2009-04-22.

Christos E, Petros P, Luka B, Vassilis K, Apostolos F, Christos K, Cristobal R (2019). *Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems*, Annual Reviews in Control 47, pp. 249–265

Hata M (2019). *Corrosion Diagnosis System for Pipe Outer Surface by Image Data Analysis*, Accenture, 49th Petroleum and Petrochemical Conference (Yamagata Conference) (in Japanese)

Tanaka T, Takeda K (2020). *Development of a Management Target Selection Method by Automatic Recognition of Pipes Using AI*, Shizuoka University, 63rd Joint Automatic Control Conference (in Japanese)

Toshihiro Shimbo graduated from Tokyo University of Science with a Master's degree in Industrial Chemistry in 1990 and joined Mitsubishi Gas Chemical Company, Inc. in the same year. He is currently engaged in the application of AI for DX promotion, specializing in chemical engineering and project management. He is also qualified as a Professional Engineer (Chemistry Division and General Engineering Management Division).

Yousuke Okada was born in 1988 in Nagoya, Aichi Prefecture, and started programming at the age of 10. He received the Ministry of Education, Culture, Sports, Science, and Technology Award at the age of 17. He visited Silicon Valley to research computer science and witnessed revolutionary advances in artificial intelligence (particularly deep learning). After returning to Japan, he founded ABEJA, Inc., the first startup company specializing in deep learning in Japan, and was appointed CEO of the company. In 2017, he was appointed Director of the Japan Deep Learning Association. In 2021, he was appointed a DX Fellow of Nasushiobara.

Hitoshi Matsubara graduated from the Department of Information Science, Faculty of Science, University of Tokyo, in 1981. He received his doctoral degree from the Department of Computer Science and Engineering, University of Tokyo, in 1986. He joined the Electrotechnical

Laboratory of the Ministry of International Trade and Industry (MITI) in 1986 and became a professor at Future University Hakodate in 2000 and a professor at the Center for Next-Generation Intelligence Science at the University of Tokyo in 2020. He is the President of the Japanese Society for Artificial Intelligence.