Noise-Robust Pipe Wall-thinning Detection System Using Deep Learning

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***Abstract*—Pipe wall-thinning is a phenomenon in which materials, water chemistry, and thermal fluids work together to make the thickness of pipes thinner, which damages various industrial facilities. If a pipe with pipe wall-thinning is left unattended, it can lead to pipe rupture. Pipe rupture can cause serious safety issues, as it can result in fluid leakage under high temperature and pressure, potentially leading to loss of life. To prevent such issues, a pipe wall-thinning detection system is essential. However, various types of noise can occur during pipe wall-thinning detection, which can interfere with accurate detection. In this paper, we propose a noise-robust pipe wall-thinning detection system by training on the sequence of pipe wall-thinning.**

I. Introduction

This paper proposes a method for advanced pipe wall-thinning detection in piping systems, even in the presence of noise. The pipe wall-thinning of pipes is a very important matter in the safety facilities. [1] According to the current pipe wall-thinning management program, it consists of pipe DB building, sensitive system analysis, predictive wear rate analysis and pipe thickness inspection and evaluation. Wall thickness measurement-based pipe wall-thinning evaluation has the limitation that accurate evaluation is difficult due to the influence of measurement errors. Furthermore, errors may occur due to differences in people because the person measuring the pipe thickness is not constant.

The conventional pipe wall-thinning detection method uses the rate of change in pipe thickness. For this method, pipe wall-thinning is determined based on the largest difference between the result of n th wall thickness measurement and $n+1$ th wall thickness measurement. [2] In this method, when noise occurs in a part, if the difference value of that part is large, it can be mistakenly determined that pipe wall-thinning has occurred.

The proposed method involves using past data in addition to current data for time-series prediction in pipe wall-thinning detection. Time-series prediction is an analysis technique that predicts future data based on past data collected over time. In this paper, we experimented with a method for determining whether the current pipe wall-thinning state of a piping system is actually due to pipe wall-thinning or an error caused by noise, based on past wall thickness data of the piping system.

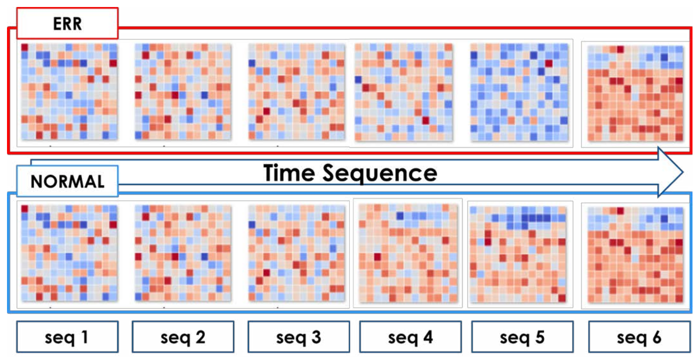

Fig. 1: Example of the occurrence of a pipe wall-thinning due to noise

II. SYSTEM MODEL

The CNN-LSTM model is used for time-series prediction in this paper. Figure 1 illustrates the difference between a CNN and CNN-LSTM model. In the example of judging the 6th sequence of two boxes, CNN receives image data as input and learns patterns in the image. Therefore, if the two boxes look visually identical, CNN can judge both as pipe wall-thinning, while the CNN-LSTM model correctly identifies only the red box as an pipe wall-thinning. This is because the CNN model only considers spatial information of images, so it may mistakenly identify pipe wall-thinning pipes when pipe wall-thinning characteristics suddenly appear in the images. However, the CNN-LSTM model takes into account not only spatial information but also time series analysis, enabling the detection of pipe wall-thinning prediction errors

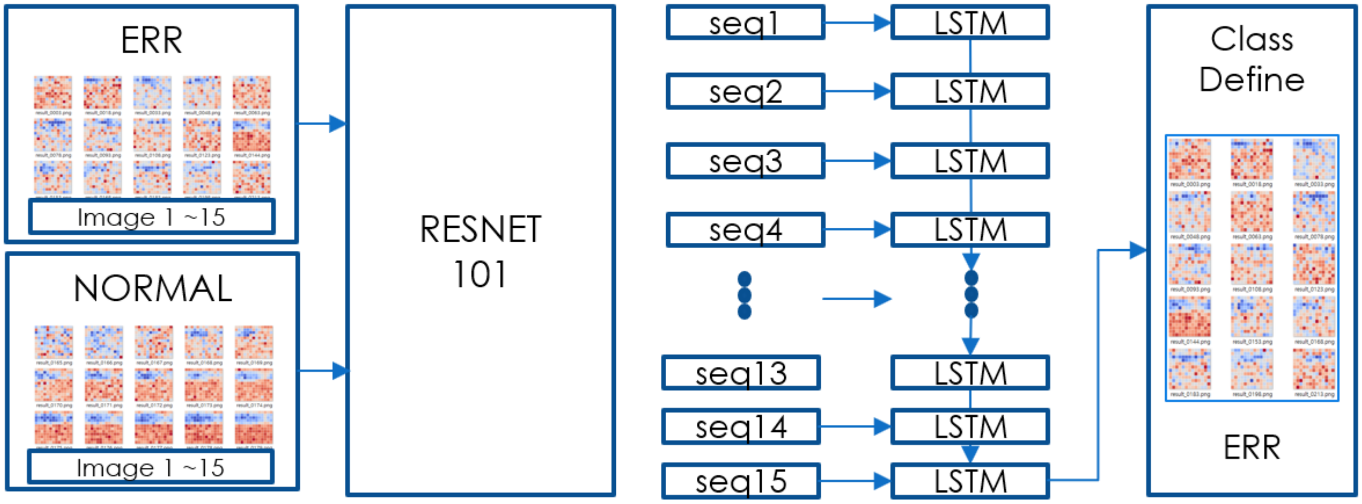

Fig. 2: CNN-LSTM pipe wall-thinning Discrimination System Model

caused by noise. Therefore, using the CNN-LSTM model is more accurate in predicting the future behavior of time series data. The CNN-LSTM model is a combination of the Convolutional Neural Network (CNN), which is commonly used for image analysis, and the Long Short-Term Memory (LSTM) model, which is used for time-series prediction. The operating principle of the model is illustrated in Fig. 2. First, the CNN part extracts features from each image. The features of the image refer to the patch shapes where pipe wall-thinning occurred, as shown in Fig. 3. The extracted features are stored as a sequence, as shown in Fig. 2, and used as the input to the LSTM part. The LSTM model analyzes the time-series characteristics of the input to detect pipe wall-thinning in the current input sequence.

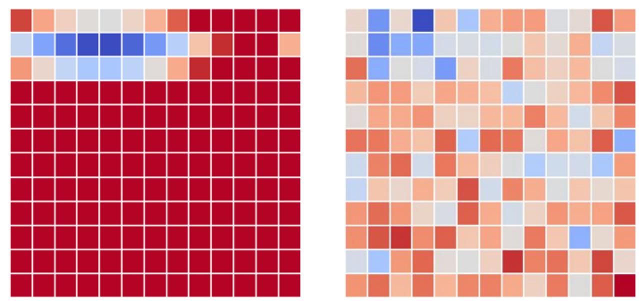

Fig. 3: Example image with the characteristic of a pipe wall-thinning

A. Dataset

The dataset used in this paper is shown in Figure 4. For the ERR dataset, the information of a pipe without pipe wall-thinning is inputted, but a rapid pipe wall-thinning occurs during the input. For the NORMAL dataset, it can be seen that the pipe wall-thinnings area expands sequentially. The dataset is classified into NORMAL sequences and ERR sequences, and 900 sequences are used for training. One sequence consists of 15 time-series images. The data used in this study is a virtual pipe system layout generated using seven variables:

- N_a: Number of grids in the axial direction
- N_c: Number of grids in the circumferential direction
- depth_r: Depth ratio (depth of pipe wall-thinning / NOMINAL thickness)
- area_r: Area ratio (area of pipe wall-thinning /total area of the rectangle when unfolded)
- aspect_r: Aspect ratio of the pipe wall-thinning area (length in axial direction/width in circumferential direction)
- cen_a: Axial center position of the pipe wall-thinning area ($0 \sim 1$)
- cen_c: Circumferential center position of the pipe wall-thinning area ($0 \sim 1$)

For convenience, a 13x12 grid was used in the experiment, and the data was composed of pipe wall-thinningd depth ratio and area data that gradually increased. The pipe wall-thinning locations were generated sequentially from the top left to the bottom right. In addition, this paper attempted to obtain a similar effect to real data by adding Gaussian noise. In Figure 3, there is data without noise on the left, and data with noise on the right. It can be seen that the data with noise is more similar to real data. By training the model with added noise, the model can be made to work well in more realistic situations.

B. CNN part

The CNN part has the role of extracting the pipe wall-thinning feature of the input images. For the data used in this paper, the pattern was simple and the shape was constant, so it was spherical using a relatively simple ResNet structure. If you want to improve the speed of your model or want better performance due to increased complexity of your data, you can use more improved models such as EfficientNet and DenseNet.

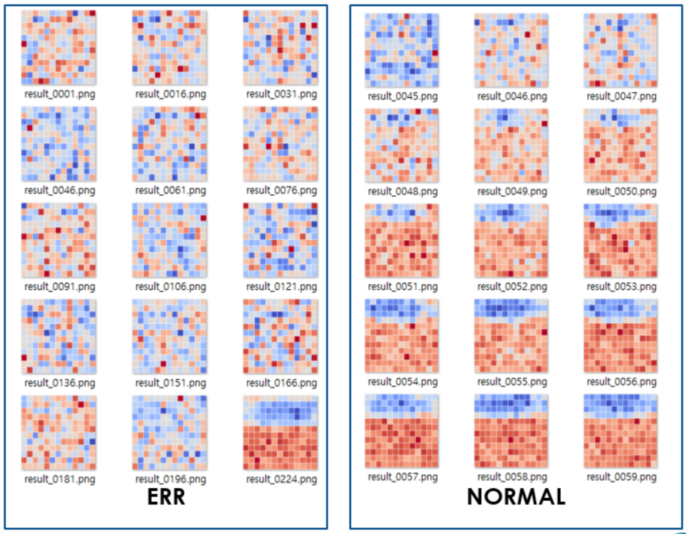

Fig. 4: Example of sequence dataset

[3] [4] the ResNet 101 network provided by PyTorch was used. The input uses 3x224x224 size images. The network has a 300-dimensional output at the last linear layer. [5]

C. LSTM part

The LSTM part receives the output of the CNN as its input. The network uses the features extracted from a total of 15 images, and it takes 300 dimensions as its input. The input sequence of features produces a conclusion of ERR or NORMAL sequence. [6]

III. EXPERIMENT

A total of 900 sequence data were used in the experiment. Each sequence data consists of a total of 15 consecutive time-series images, and they were divided into 450 NORMAL seq and 450 ERR sequences for training. The training result graph is shown in Fig. 5. In the test, 180 data sequences that were not used in the training were used, and the system showed an accuracy of 92

IV. CONCLUSION

In this paper, a pipe wall-thinning detection system using CNN-LSTM is proposed, which is useful in reducing misjudgment caused by noise. The proposed system using 15 sequence of images for detecting pipe wall-thinning allows for more accurate detection compared to using a CNN that only relies on a single image for detection. The ResNet101 model was used for the CNN part in this paper, but using a more suitable model in the future could lead to even better performance. In addition, future studies could apply sequential data to predict the occurrence of pipe wall-thinning in pipes.

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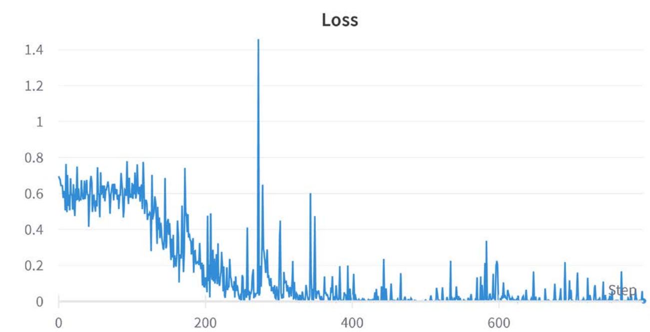

Fig. 5: Train Loss Result

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