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# IMAGE ANALYSIS-BASED DEFECT DETECTION MODEL FOR SMALL-DIAMETER PIPES

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**Abstract**

In Korea, houses are heated using the ondol method. This is a method of burying pipes that allow hot water to pass through the concrete of the indoor floor and send hot water through a boiler to warm the floor. The pipes used in this system are buried in the concrete that forms the floor, and once the concrete is constructed, the entire system must be reconstructed, even if there is a problem with part of it. Therefore, there are methods to inspect pipes to check for leaks before use; however, current methods have limitations. Most of these methods are indirect, which makes the detection of small construction defects challenging. To this end, a small device was developed in a previous study for inspecting pipes buried in concrete. The device identifies defects based on images captured by the device; however, there is a need to automate it because of the disadvantage of relying on manpower. Therefore, in this study, we developed a prototype model for automatically identifying defects in images captured by this device. To develop the model, an artificial intelligence method was selected to process the images and videos. The proposed model is divided into four classes: 'normal,' 'bent,' 'foreign object,' and 'punching,' and utilizes SqueezeNet, which shows similar performance with fewer parameters compared with AlexNet. The loss function of the model was CrossEntropyLoss, the optimizer was AdamW, and label_smoothing was set to 0.1 to prevent overfitting by smoothing the circle-hot-vector shape of the prediction distribution. A total of 1,873 image datasets were divided into training and validation datasets in a ratio of 8:2. The training results indicated an accuracy of 99.7%. The proposed model can automate the existing human inspection process, making it faster and easier to identify defects inside pipes.



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**Keywords:** defect, image analysis, inspection, ondol heating method.

## 1. Introduction

Ondol heating is the preferred method for heating homes in South Korea. This is a method of raising the temperature of a room by burying pipes that allow hot water to pass through the concrete of the floor and then sending hot water heated by a boiler to warm the floor. As the pipes used in this method are buried in the concrete that forms the floor, it is difficult to check the condition of the pipes from the outside. Buried pipes can leak after a period if there is an accidental punching problem during pipe construction. In this case, the leak can only be detected if it persists and the water leaks out of the concrete. By the time the leak is visible from the outside, it has caused significant property damage to the home, including furniture and floor coverings.

The problem with concrete is that once it is installed, the entire system must be reconstructed, even if there is a problem with part of it. Pipes are inspected after they are buried in concrete, which has a weakness in that they are not easy to see inside using conventional inspection methods. Existing inspection methods include listening to the sound of leaking water on the floor to find the leakage point and checking the leakage point with a thermal imaging camera after running hot water. However, all of these are indirect methods that cannot accurately identify the actual leakage point. To overcome this problem,  a small instrument to inspect pipes buried in concrete for internal defects was developed in a previous study [1].

To analyze defects in pipes buried in concrete by directly photographing them, a model that automatically analyzes and identifies images is required. This is because it is too time-consuming and costly for humans to check all images captured by humans. Therefore, a method is required to upload the images and automatically identify the images to check for defects. Therefore, we intend to utilize artificial intelligence-based image processing methods that have been widely used recently.

Previous studies identified pipe defects. Sinha [2] utilized unified image processing and artificial intelligence methods to analyze the conditions of underground pipes. Sharma [3] used an SVM classifier to identify gas leakages in gas pipes. Wang et al. [4] analyzed the deterioration of sewer pipes and proposed a non-destructive testing method. There are various other studies, but most of them are on large-diameter pipes in infrastructure, and there are no studies on small-diameter pipes (20 mm or less), which is the focus of this study.

Therefore, we developed a prototype model for determining defects based on images obtained using small devices.

## 2. Image collection device

In Korea, heating pipes are installed on concrete floors, as shown in Fig. 1. (a) to heat the room. This is known as the ondol pipe heating method. Thin and long polyvinyl chloride (PVC) pipes are installed on the floor, as shown in the figure, and concrete is poured over the pipes to complete the floor. The pipes used are 16 mm outside diameter and 1.5 mm thick.  As shown in Fig.1. (c), hot water from the boiler is supplied to each room via a distributor.

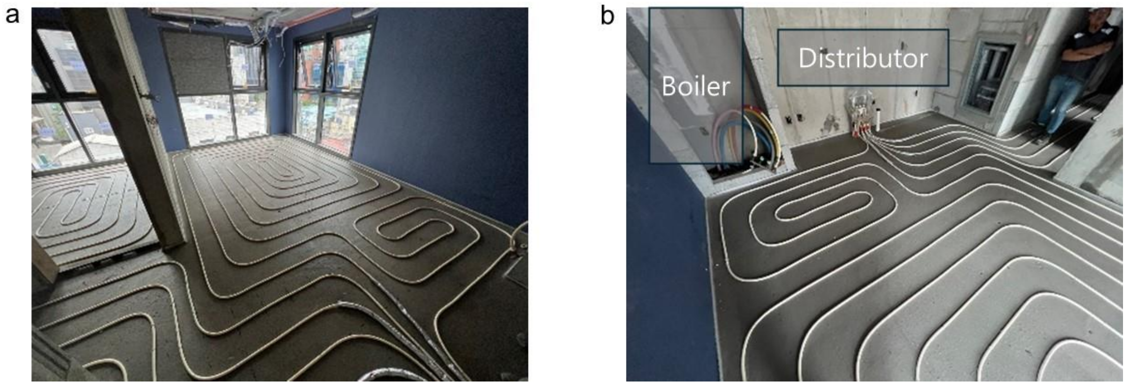



Fig. 1. (a) Example of pipe installation; (b) Boiler location and distributor

Once the concrete is covered, it is difficult to see the inside of the pipes. The equipment for this was developed in a previous study [1]. The pill-shaped inspection device  shown in Fig. 2(a) & (b) can be inserted into a pipe and moved to obtain images of the pipe. The camera module takes a 300,000-pixel video of the interior and transmits the information to a computer via a communication module. The video is captured at more than 24 frames per second and the video information is decomposed into 24 pictures per second.

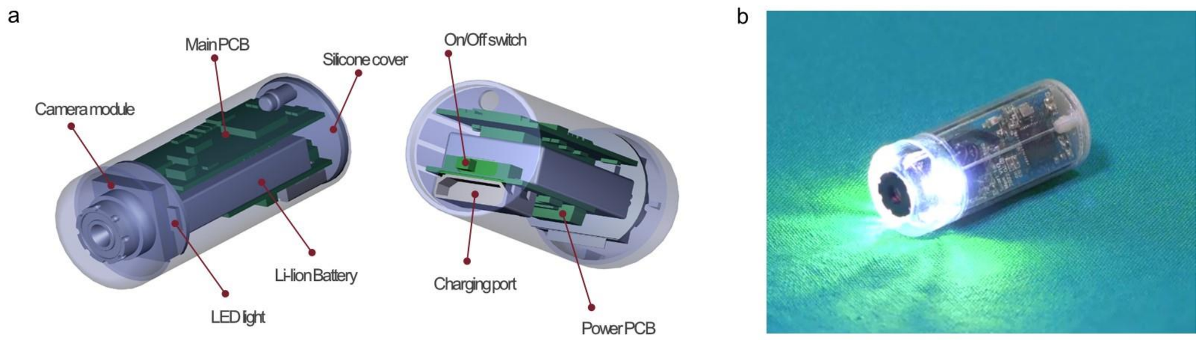



Fig. 2. (a) Configuration diagram of the device; (b) developed device

## 3. IMAGE ANALYSIS-BASED DEFECT DETECTION MODEL

### 3.1 Defect catergization

The photographic data collected using the equipment described above were classified into four types based on expert judgement: 'Normal,' 'Bending,' ‘Debris,’ and 'Punching,’ and each image is labelled as shown in Fig. 3.

(a) Normal (b) Bending (c) Debris (d) Punching

Fig. 3. Image for pipe defect categories

When the pixel values of the images to be trained were checked, it was found that they were biased in the range of 80–100 and 110–140 due to the interiors of the pipes. In this case, gradient vanishing or gradient explosion occurs, and the model cannot be smoothly trained. To facilitate training, the mean and standard deviation of all the pixel values in the pipe defect image were calculated for each RGB channel and normalized to a normal distribution with zero mean and one standard deviation for each channel [5].

### 3.2 Deep learning-based defect image classification model

SqueezeNet [6] was selected as the model for determining the pipe defects (Fig. 4). Compared with AlexNet, SqueezeNet is a lightweight model with 50 times fewer parameters and similar performance, making it an advantageous model for embedding on mobile devices. SqueezeNet adopts a fire module to reduce the number of parameters (Fig. 5). The fire module is divided into two main stages: a squeeze convolution layer, which utilizes a 1 × 1 convolution, and an expanded convolution layer, which uses a combination of 1x1 / 3x3 convolution. To improve the accuracy of the model, it was downsampled later such that the convolution layer had a large activation map, thereby reducing losses due to information compression.

SqueezeNet has 1,000 classes, but the piping defect identification problem targeted in this study has a total of four classes; therefore, we changed the head of SqueezeNet such that the output of the linear layer was four classes.

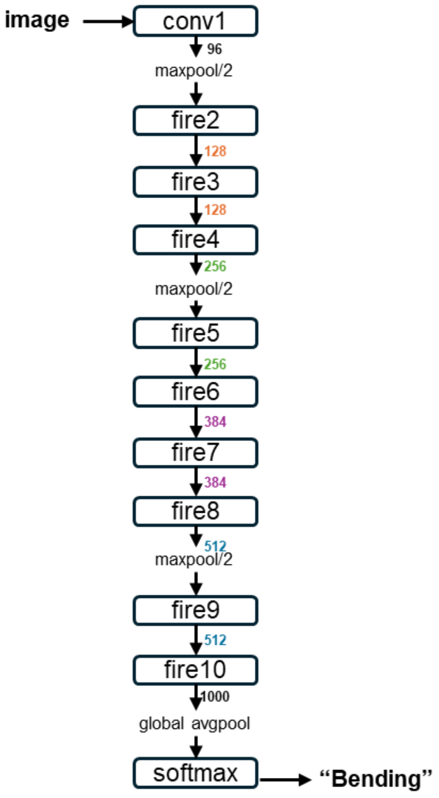



Fig. 4. Macroarchitectural view: SqueezeNet architecture (revised from Iandola et al. 2016)

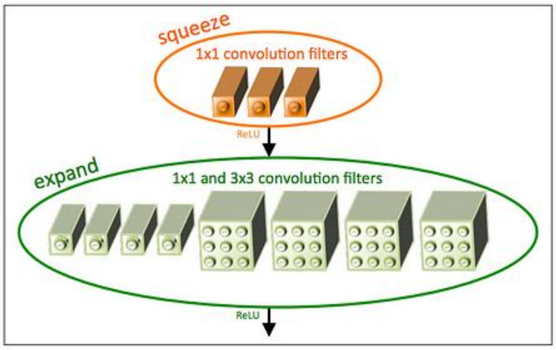



Fig. 5. Microarchitectural view: Organization of convolution filters in the Fire module[6]

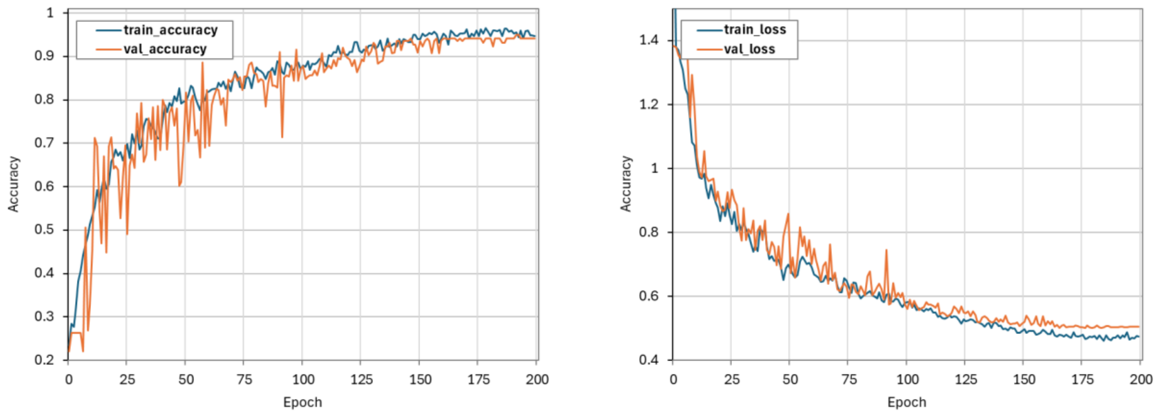
### 3.3 Training

The full dataset was 'Normal': 1505, 'Bending': 145, 'Debris': 35, and 'Punching': 188. To balance the unbalanced amount of data in each category, image augmentation techniques, such as vertical flip, horizontal flip, rotation, and perspective were randomly applied to prepare 300 images for each category. The prepared data were divided into training, validation, and testing data in a ratio of 7:1.5:1.5.

The loss function was cross-entropy loss, which is used for multi-classification tasks, and label smoothing was applied to 0.1 to smooth out the circle-hot-vector shape of the prediction distribution to prevent overfitting [7].

We used accuracy as the evaluation metric, 200 epochs, AdamW as the optimizer, and Weight_decay of 0.05 to vary the weights used in each training to increase the robustness of the model [8].

The learning curve of the proposed model is illustrated in Fig. 6. The accuracy increased rapidly up to approximately 50 epochs, and at 192 epochs, we constructed a model with the highest accuracy of 95.0% and a loss of 0.5055.




(a) Accuracy (b) Loss

Fig. 6. Learning curves for the proposed model

### 3.4 Test

The trained model was tested using 180 images from the test dataset. Consequently, the model correctly predicted 173 out of 180 images, with an accuracy rate of 96.1%; the results for each image are shown in Fig. 7.

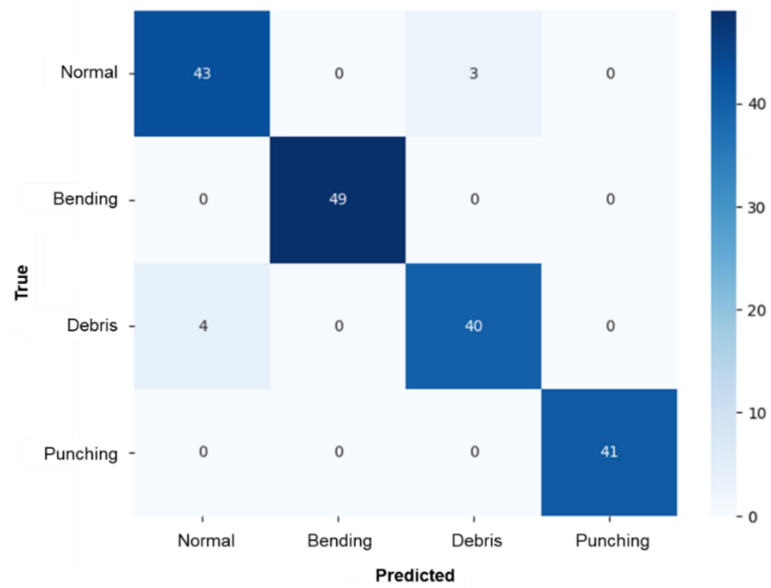
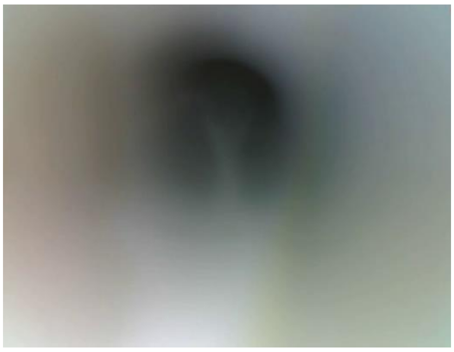



Fig. 7. Confusion matrix

Three normal' images were misclassified as debris, and four debris' images were misclassified as normal. After checking the images, it was found that the misclassification was caused by image blurring (Fig. 8).


(a) True: Normal, Predicted: debris

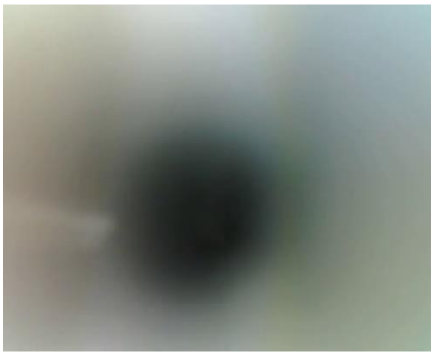

(b) True: debris; predicted: normal

Fig. 8. False result sample

## 4. Conclusion

In this study, we built a prototype model based on image analysis to automatically identify defects in small-diameter pipes. The model was built using SqeezeNet after converting the internal video footage into images. The results indicate an accuracy of 99.7%. The results of this study can be used to build a model for inspecting the defects in small-diameter pipes.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## References


[1] U.K. Lee, “Smart Ball–Building Information Modeling Interlocking Pipeline Maintenance Systems”. Research report. National Research Foundation of Korea. 2023

[2] S. K. Sinha, "Automated Underground Pipe Inspection using a Unified Image Processing and Artificial Intelligence Methodology." Ph.D. dissertation, Civil Engineering and Systems Design Engineering, University of Waterloo, Ontario, Canada, 2000. [Online]. Available: https://uwspace.uwaterloo.ca/bitstream/handle/10012/578/NQ53517.pdf?sequence=1

[3] R. R. Sharma, “Gas leakage detection in pipeline by svm classifier with automatic eddy current based defect recognition method.” Journal of Ubiquitous Computing and Communication Technologies (UCCT), vol. 3, no. 3, pp. 196-212, 2021, doi: 10.36548/jucct.2021.3.004

[4] Y. Wang, P. Li & J. Li, “The monitoring approaches and non-destructive testing technologies for sewer pipelines. Water Science and Technology,” vol. 85, no. 10, pp. 3107-3121. 2022, doi: 10.2166/wst.2022.120

[5] A. Sendjasni, D. Traparic &M. C. Larabi, “Investigating normalization methods for CNN-based image quality assessment”. In 2022 IEEE International Conference on Image Processing (ICIP), pp. 4113-4117, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9897268/

[6] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally & K. Keutzer, “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size”. 2016. doi: 10.48550/arXiv.1602.07360.

[7] R. Müller, S. Kornblith & G. E. Hinton, “When does label smoothing help?.” Advances in neural information processing systems, 32, 2019. [Online]. Availble: https://proceedings.neurips.cc/paper_files/paper/2019/file/f1748d6b0fd9d439f71450117eba2725-Paper.pdf

[8] A. K. Dombrowski, C. J. Anders, K. R. Müller & P. Kessel, “Towards robust explanations for deep neural networks.” Pattern Recognition, 121, 108194, 2022, doi: 10.1016/j.patcog.2021.108194