Development of a Model for Predicting Defects in Radiation Shielding Aprons Using Machine Learning

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ABSTRACT
This study attempted to conveniently and accurately determine the radiation images of the normal lead shielding fabric and the cracked lead shielding fabric using a convolutional neural network to confirm cracks or cracks in the radiation protective apron. Normal and cracked radiation images were determined through a synthetic neural network constructed using a MATLAB by dividing them into lead shielding fabrics of 0.125mm and 0.25mm lead equivalents. The results were analyzed using loss function, accuracy, confusion matrix, and Spearman's rho, and since the method of detecting defects in the lead apron for radiation protection in the current clinical practice is not simple and accurately organized, the applicability in clinical practice was confirmed by making a high-level judgment using deep learning.

Keywords: lead shielding fabric, microcracks, convolutional neural network, deep learning

Ⅰ. INTRODUCTION

Radiation is widely used for diagnosis and treatment in the medical field, but the risks it can cause cannot be ignored. In particular, the use of radiation equipment and radiologic interventional procedures due to the increase in tests such as medical examinations due to the improvement of medical welfare and the increase in people's interest in their health have increased, and the importance of radiation protection equipment to protect[1] radiation-related workers and patients is increasing. Ways to reduce the dose to these individuals include wearing radiation protection aprons, lead goggles, and thyroid protectors.[2] Of these protective devices, the radiation protection apron, which has been in common use from the past to the present, is an important secondary device that workers should wear at all times.[3] It serves to protect the body from radiation. The apron is made of lead or other radiation-blocking material with a suitable thickness to minimize unnecessary radiation exposure to the human body, and is essential in radiological medical environments. Since the apron protects and minimizes direct and indirect radiation exposure, the ability to shield radiation must be confirmed when wearing it,[4] and if the protection performance is not good, the exposure of the apron wearer is bound to be relatively high, so thorough management measures and good performance apron are essential to reduce the exposure dose.[5] However, in general, the performance of aprons deteriorates due to damage such as crumpling or dents in the lead as the period of use increases and improper storage during and after use,[6] and the occurrence of microcracks is a particular problem. Microcracks can degrade the radiation shielding performance of aprons, which in turn poses a serious risk to the safety of radiation personnel and patients. Therefore, it is important to regularly check the condition of aprons and detect microcracks early. According to domestic and foreign medical institutions, the performance evaluation of aprons in the radiation protection concept requires visual inspection and fluoroscopic inspection once a year.[7][8] However, evaluating the shielding efficiency through fluoroscopic inspection, which only covers the presence of visible cracks through simple visual inspection, has been cited as a management limitation.[9] These methods are time-consuming and subject to the inspector's subjective judgment, which can be inaccurate. In addition, microcracks of small size are often difficult to detect with the naked eye, making early detection and prevention difficult. To overcome these limitations, this study proposes a method to automatically determine the presence of microcracks in aprons by utilizing a convolutional neural network (CNN), a deep learning-based image recognition technique. Deep learning, one of the machine learning techniques, is a statistical method that allows computer systems to perform tasks on their own without explicit instructions and build mathematical models to make predictions or decisions.[10] cnns are powerful tools that can automatically extract features from image data, offering the possibility to more precisely assess the condition of radiation protection aprons. This study aims to build a CNN model in MATLAB environment to effectively identify microcracks in radiation protection aprons. This is expected to contribute to improving the safety of radiation protection equipment and enhancing the protection of radiation workers and patients.

Ⅱ. MATERIAL AND METHODS

1. MATERIALS

1.1 Laboratory Equipment: Digital diagnostic x-ray machine GXR-40SD by DRGEM

1.2 Program: MATLAB (R2022a, MathWorks, USA, MA)

1.3 Measurement Materials

SKMD Light Lead Sheet (0.125mm, 0.25mm lead equivalent): In this study, two thicknesses (0.25mm, 0.125mm) of lead shielding fabric with half-layer of lead equivalent were provided and used to prepare a total of four samples. For each thickness, a total of four samples were created, including a normal sample and a sample with randomly generated microcracks.

2. METHOD

In this study, the irradiation condition (kVp, mAs) was fixed at 2.5 mAs at a tube voltage of 70 kVp. This condition was derived from previous experiments, where the presence or absence of microcracks was not visually distinguishable when the images were obtained. The source-to-detector distance (SDD) was 100 cm and the field of view was fixed at 13 × 13 inches, with the Pb placed on the test table. All images were extracted in jpg format.

3. SET UP A DEEP LEARNING MODEL

3.1 Preparation and Processing of Data

The data preparation process for this study consists of three sequential steps for application to a deep learning model. The first step was to collect 50 images of lead shielding fabrics with 0.125 mm lead equivalent with microcracks, 50 images of lead shielding fabrics with 0.125 mm lead equivalent without microcracks, 50 images of lead shielding fabrics with 0.25 mm lead equivalent with microcracks, and 50 images of lead shielding fabrics with 0.25 mm lead equivalent without microcracks to define two classes by thickness and classify them into folders according to the presence or absence of microcracks for labeling. The second step was data equalization to batch train the CNN using MATLAB (R2022a, MathWorks, USA, MA). The data images were resized to 256×256. As a final step, we used four data augmentation scenarios for data augmentation: left-right flip, contrast variation, XY shift, and rotation. Each image was augmented 300 times, 15,000 images each, for a total of 60,000 training image sets. The proportions of training, validation, and testing were set to 70%, 15%, and 15%.

3.2 Designing and Training Deep Learning

The deep learning model in this study has a CNN architecture to determine the presence of microcracks in lead shielding fabrics from input images. Basically, the model has a convolutional layer, a layer containing batch normalization and rectified linear units (ReLUs), and a fully connected layer before a softmax layer and a classification layer, for a total of seven layers. The convolutional kernel and pooling kernel are set to 3×3 and 2×2 (stride:2), respectively. The convolutional layer has zero padding to prevent the image size from being lost. The input image of size 256×256×1 was passed through all convolutional layers to extract a feature map of 4×4×512. Adam Optimizer was used as the optimizer for this model and the initial learning rate was set to 0.001. The maximum epoch and mini-batch size were set to 10 and 64, respectively. The specific architecture of the deep learning model used in this study is shown in Figure 1. The convolutional neural network was trained and validated on a dataset consisting of 60,000 images by data augmentation for 200 images. The hardware specification of the training model is a 3.70GHz Intel(R) Core(TM) i5-9600KF CPU processor with 16GB of RAM and an NVIDIA GeForce GTX 1660 GPU with 4GB of GPU memory used for training.

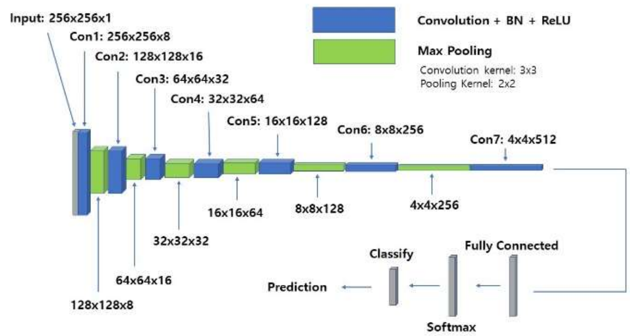


Figure 1. Detailed structure of the proposed convolutional neural network model for determining the presence of microcracks.

Ⅲ. RESULT

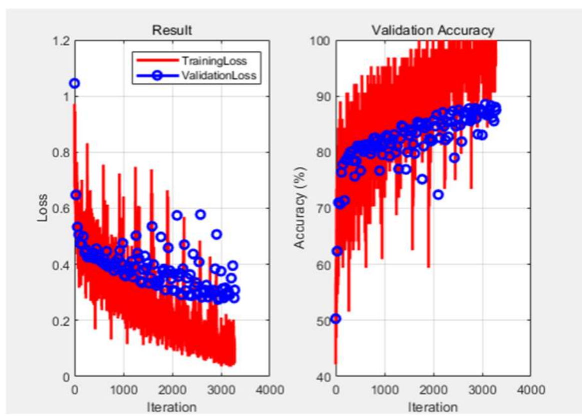


Figure 2. Loss and accuracy variation by training a convolutional neural network on a 0.25 mm lead equivalent.

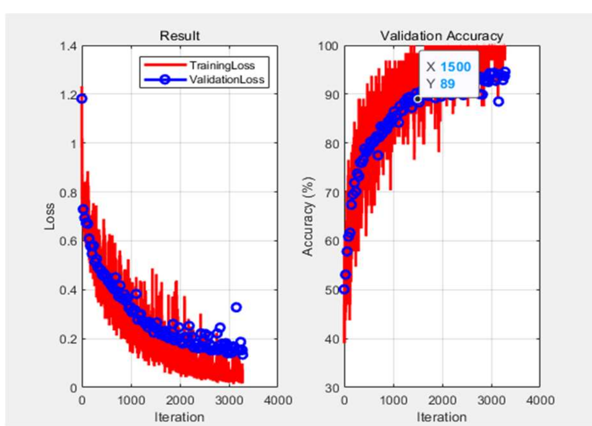


Figure 3. Loss and accuracy variation by training a convolutional neural network on a 0.125 mm lead equivalent.

1. Deep Learning Training Results

There are two kinds of evaluation metrics for training: loss change and accuracy change, which are the evaluation metrics for CNN training. The results of the training are shown in Figure 2 for lead shielding fabric with 0.25 mm lead equivalent and Figure 3 for lead shielding fabric with 0.125 mm lead equivalent. The final verification loss and verification accuracy were 0.24, 87.7% and 0.14, 94.49%, respectively.

2. Clinical Validity and Statistical Analysis Results

To evaluate the clinical validity of the proposed deep learning's ability to determine the presence of microcracks, the comparison between human judgment and the actual presence of microcracks and the perfect agreement (Exact Accuracy) between the deep learning's judgment and the actual presence of microcracks were evaluated. The Exact Accuracy of human and deep learning was 56% and 87.7% for lead shielding fabrics with 0.25 mm lead equivalent and 51.5% and 94.49% for lead shielding fabrics with 0.125 mm lead equivalent, respectively.

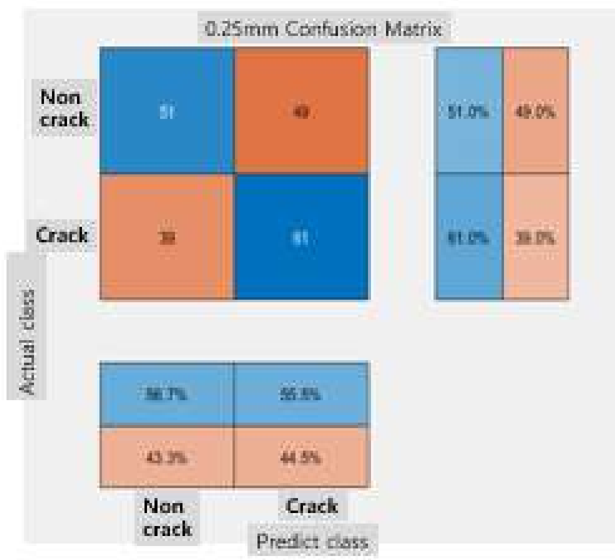
The confusion matrices for the presence of microcracks in lead shielding fabric with 0.25 mm lead equivalent and the presence of microcracks in lead shielding fabric with 0.125 mm lead equivalent are shown in Figure 2, respectively. In general, the x-axis and y-axis represent the classes of microcracks determined by deep learning and actual microcracks, respectively. Figure 4-(a) shows the confusion matrix determined by the researcher at 0.25 mm lead equivalent, and Figure 4-(b) shows the confusion matrix determined by deep learning at 0.25 mm lead equivalent. Figure 5-(a) shows the confusion matrix determined by the authors at a 0.125 mm lead dose, and Figure 5-(b) shows the confusion matrix determined by deep learning at a 0.125 mm lead dose. The blue color index along the diagonal direction means that the researcher's judgment, the deep learning's judgment, and the actual microcrack presence are in perfect agreement, and the red color index means that the researcher's judgment, the deep learning's judgment, and the actual microcrack presence are not in perfect agreement, i.e., the researcher's judgment and the proposed deep learning's judgment are correct or incorrect, and the number of them is shown. To the right and bottom of each confusion matrix, additional tables show the overall agreement and disagreement rates along the horizontal (right) and vertical (bottom) directions. The Exact Accuracy of the proposed deep learning is 87.7% for 0.25 mm lead equivalent lead shielding and 94.49% for 0.125 mm lead equivalent lead shielding, and when checking the confusion matrix, it can be seen that 554 out of 4,500 X-ray images of 0.25 mm lead equivalent lead shielding are inconsistent with the actual presence of microcracks, and 248 out of 4,500 X-ray images of 0.125 mm lead equivalent lead shielding are inconsistent with the actual presence of microcracks. Finally, the normality test results and Spearman's rho values are shown in Tables 1 and 2. In the case of microcrack detection, the rho values for the researcher's detection and the proposed deep learning are reported to be 0.09 and 0.50 for 0.25 mm lead shielding and 0.25 and 0.82 for 0.125 mm lead shielding.

Table 1: Spearman's rho values for 0.25 mm lead equivalents

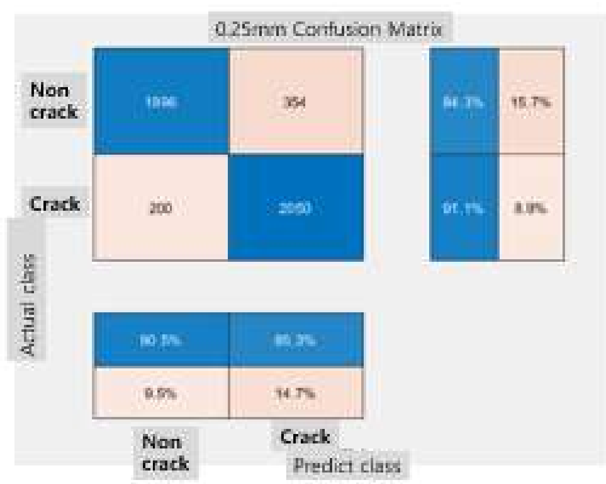
	Differentiation result		
	*True data	Human	*DL
h (Normality)	1	1	1
p-value (h)	<0.001	<0.001	<0.001
rho		0.09	0.50
p-value (rho)		<0.001	<0.001

Table 2: Spearman's rho values for 0.125 mm lead equivalent

	Differentiation result		
	*True data	Human	*DL
h (Normality)	1	1	1
p-value (h)	<0.001	<0.001	<0.001
rho		0.25	0.82
p-value (rho)		<0.001	<0.001

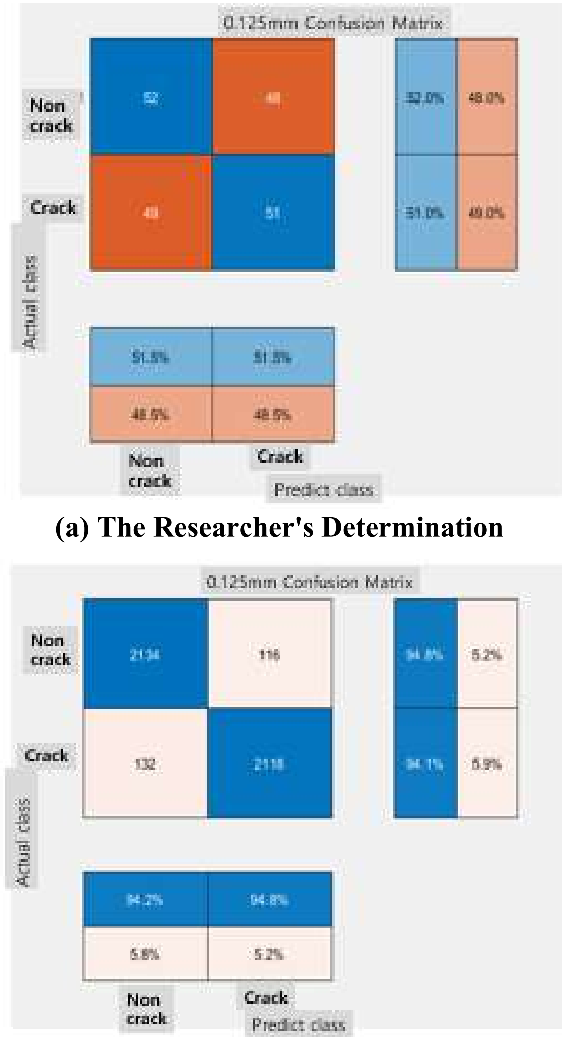


(a) The Researcher's Determination



(b) Determining Deep Learning

Figure 4: Confusion matrix for 0.25 mm lead equivalents



(a) The Researcher's Determination

(b) Determining Deep Learning

Figure 5: Confusion Matrix for 0.125 mm Lead Equivalent

IV. DISCUSSION

The performance evaluation of the proposed deep learning was compared with the human visual inspection method and the actual presence of microcracks. The Exact Accuracy of microcrack detection showed that the agreement between the deep learning's detection and the actual presence of microcracks was higher than 31.7% for lead shielding fabrics with 0.25 mm lead equivalent and 42.99% for lead shielding fabrics with 0.125 mm lead equivalent. To further investigate clinical validity, Spearman's rho coefficients were calculated (Tables 1, 2), and the rho values by deep learning indicated greater similarity between the predicted discrimination results and the actual presence of microcracks, providing a measure of agreement with higher values.

As a result, the application of deep learning can improve the shortcomings of the existing shielding efficiency evaluation methods, and determine the presence or absence of small-sized microcracks that are difficult to detect with the naked eye. The CNN-based microcrack detection system proposed in this study has practical applicability in the regular inspection and maintenance of radiation protection equipment based on its verification accuracy value. The automated inspection system can save time and cost, minimize the subjective judgment of the inspector, and increase reliability. It also has the potential to be applied in large medical institutions, further enhancing the safety of radiation workers and patients.

On the other hand, differences in the values of the evaluation metrics for the deep learning training results occurred depending on the amount of lead, i.e., the thickness of the lead shielding fabric. The reason for the higher verification accuracy and Spearman's rho value of the 0.125mm lead shielding fabric is that the microcracks were randomly generated by the researcher, and the thinness of the fabric allows for greater contrast for the same scratch. Thinner thicknesses are more permeable, making the presence of microcracks more apparent in the image, which favors the recognition of defects in the image. This difference in thickness is partially visible to the naked eye and helps the CNN to recognize defects more precisely during image processing.

However, there are also some limitations. First, the performance of a CNN model is highly dependent on the quality and quantity of training data. Lack of data collection from a variety of environments can reduce the model's ability to generalize. Second, the ability to recognize other types of defects or damage besides microcracks may be limited, which requires further research. Finally, the model needs to be flexible enough to respond to different variables and situations when applied in real-world medical environments.

Future work should be directed towards improving the performance of CNN models by collecting data in different environments and adding multi-defect discrimination capabilities. For example, it is necessary to develop a system that can evaluate physical damage or contamination of the apron in addition to microcracks. It is also important to conduct empirical studies in collaboration with various medical organizations to improve the applicability in real medical environments, and to improve the usability of the system by reflecting user feedback. Such research is expected to lay the foundation for securing the safety of radiation protection equipment and protecting the health of radiation-related workers and patients.

Ⅴ. CONCLUSION

This study utilized deep learning-based CNN technology to automatically identify microcracks in radiation protection aprons. Conventional visual inspection and fluoroscopic inspection are subjective and time-consuming, resulting in low inspection efficiency, and it is difficult to detect microcracks, which are microscopic defects, early. To address these issues, this study demonstrated the feasibility of building a CNN model to accurately assess the condition of radiation protection aprons. The results of the study showed that the CNN model was successful in detecting microcracks in image data, which is expected to improve the safety of radiation protection equipment and contribute to the protection of radiation workers and patients. Future research should focus on collecting data in various environments and improving the performance of the model to increase its applicability in practical medical settings. In addition, the introduction of such an automated evaluation system along with regular inspections of radiation protection equipment can contribute to strengthening the radiation safety management system. In conclusion, this study will serve as an important basis for securing the safety of radiation protection aprons and protecting the health of radiation-related workers and patients, and is expected to contribute to future technological advances in the field of radiation protection.

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