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Boiling regime prediction by deep learning and acoustic spectrogram-based model

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1. Introduction

In most systems using boiling and two-phase heat transfer methods, including nuclear power plants, figuring out the state of internal flow and boiling phenomena is important for accident prevention and effective operation, which is related to predict heat transfer coefficient and critical heat flux. The measurement of temperature, pressure, and flow rate used for system monitoring have difficulties in identifying real physical phenomena inside the system, only calculation of DNBR correlation is possible. Such that, when there is a high probability that boiling or two-phase phenomena will occur, there is no monitoring tools such as instantaneous thermal power increase of a nuclear reactor, ECCS injection during LOCA, and ex-vessel cooling using boiling heat transfer. This paper is a basic study on real-time diagnosis of internal flow and boiling phenomena with critical heat flux in systems utilizing boiling or two-phase heat transfer where it is difficult to directly identify internal phenomena. To this end, a convergence study of acoustic emission signal measurement technology, which is excellent for detecting minute changes, and deep learning technology, which has excellent predictive diagnostic performance, was conducted.

The acoustic emission signal is an elastic wave generated by propagating deformation energy according to the physical change of materials or a change in system pressure along the medium. The change in the displacement of the interface according to the generated acoustic wave is converted into an electrical signal and the signal is measured. Not only plastic deformation or solid crack, but also phenomena in which pressure changes such as chemical reactions, phase transformations, and phase changes occur are the source of acoustic emission (AE) signals. The AE signal related to boiling and two-phase is a sound generated when the nucleate boiling is grown, or the liquid-gas interface is broken on the free surface due to the rise of bubbles in the liquid. Another example is the high-frequency sound, which is initially loud when the electric kettle is turned on, is caused by the formation of unsaturated nucleate boiling bubbles and rapid condensation. As such, this study starts from the simple idea that a change in boiling state generates an acoustic emission signal. We postulated that the characteristics of the acoustic emission signal will be different for each boiling heat transfer regimes that have different mechanisms.

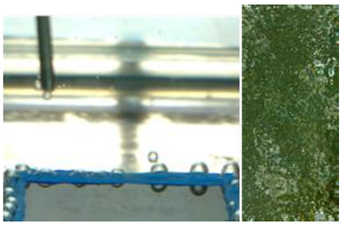
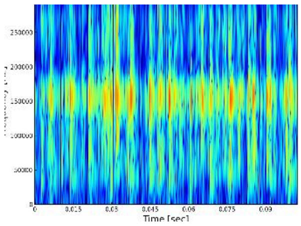
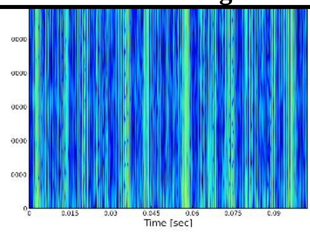
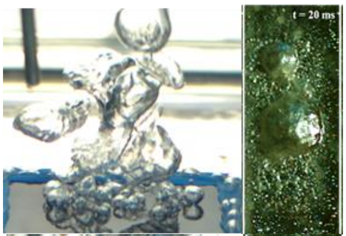
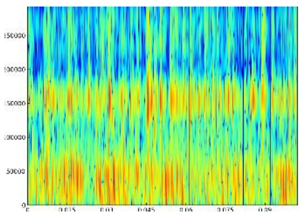
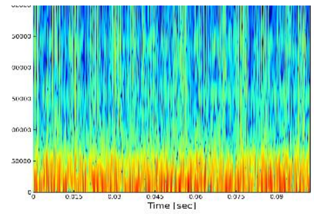
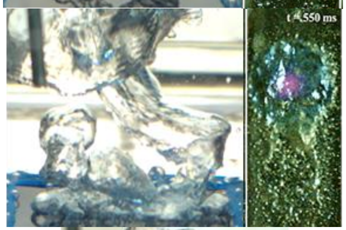
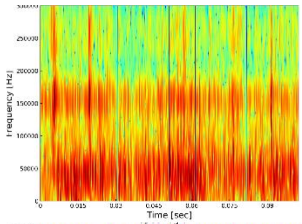
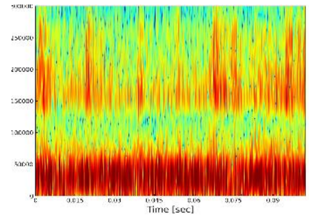
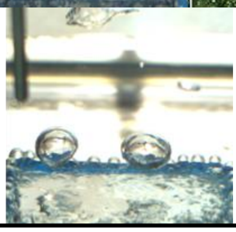
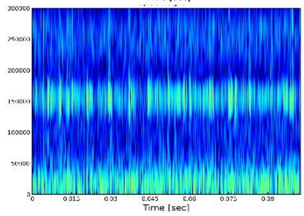
Deep learning is composed of various linear algebraic functions and a differential-based optimal function and has the advantage of easily figuring out non-linear relationships that are difficult to grasp with human cognitive ability.

This paper is for predicting and diagnosing the boiling regimes inside the system using acoustic signals that measured outside the boiling heat transfer system and deep learning technology. Section 2 of this paper describes the acoustic signal data measured for each boiling heat transfer regimes, Section 3 describes the deep learning-based real-time boiling heat transfer regimes prediction diagnostic model, and Section 4 describes the model performance evaluation.

2. AE data from pool and flow boiling experiment

Acoustic signal data measured for each boiling heat transfer regime were obtained from pool boiling experiment [1] and flow boiling experiment [2]. Table I summarizes the spectrogram analysis results of acoustic emission signals and spectrogram images for convection, nucleate boiling regime, CHF and transition regime, and film boiling regime. In Table I, the characteristics of the acoustic emission signal for each boiling regime from the two experiments did not show any common characteristics in the convection regime. When nucleate boiling occurred on the heated surface, a signal with a frequency in the range of 10 to 50 kHz was generated, which was due to rapid bubble growth and departure. When the critical heat flux occurred, the frequency signal in the range of 10-50 kHz as well as the signal near 150 kHz and 280 kHz increased rapidly, and this was due to the violent vapor film collapse or the collapse of the vapor column in which the heat transfer region was transitioned. The heating surface covered with bubbles and formed with a vapor film generated a very low-intensity signal and a stable frequency signal in the range of 40-50 kHz at film boiling regime. Therefore, based on the results of this study, it was expected that results similar to those in Table I will be obtained in most systems in which boiling heat transfer occurs regardless of the heat transfer test method. This was used as a training data set for the deep learning-based real-time boiling heat transfer regime prediction diagnostic model.

Table I. spectrogram images corresponding to each boiling regime of pool and flow boiling

Boiling regime	**Visualized images**	**AE spectrogram images**	
		Pool boiling	**Flow boiling**
Convection			
Nucleate boiling			
CHF and Transition boiling			
Film boiling			-

3. Deep learning for boiling regime classification

For the development of boiling regime classification technology, we built and trained the model by using the acoustic emission signal data obtained from pool and flow boiling experiment. An optimal deep learning algorithm with the best performance for predicting the boiling heat transfer regime was derived, and a real-time monitoring technology was developed using the model as shown in Fig. 1. This technology firstly converted an analog acoustic emission signal (voltage) of an acoustic sensor into digital data in real time. A series of pre-processing steps were performed from the converted binary data to the extraction of the acoustic emission signal waveform and the spectrogram conversion. The pre-processed data was used as an input value to train the deep learning algorithm model, and the real-time boiling heat transfer regime was finally diagnosed. The entire process in Fig. 1 was built on the MATLAB platform, and the data processing speed of the entire process was 0.1~0.4 seconds, showing fast processing performance.

Since the performance of the deep learning algorithm for predicting and diagnosing boiling regimes was the most important, and various algorithms were tested to select the optimal algorithm model. As an test matrix, Convolutional Neural Network (CNN), which shows excellent performance in image classification, was used, and experiments were performed to derive an optimal algorithm using four representative CNN algorithms as shown in Fig. 2: LeNet[3], AlexNet[4], VGGNet[5], and ResNet[6].

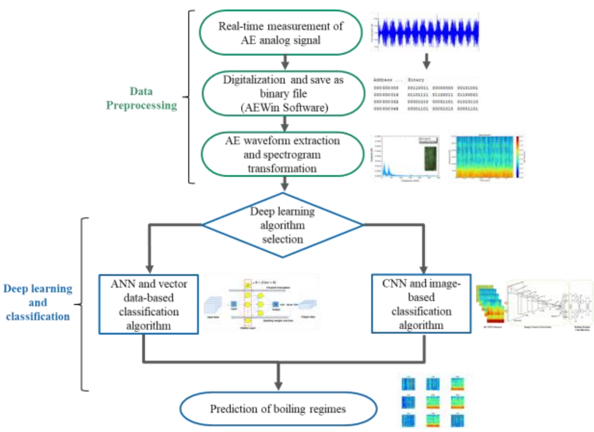


Fig. 1. Flowchart of deep learning-based real-time boiling regime classification technology

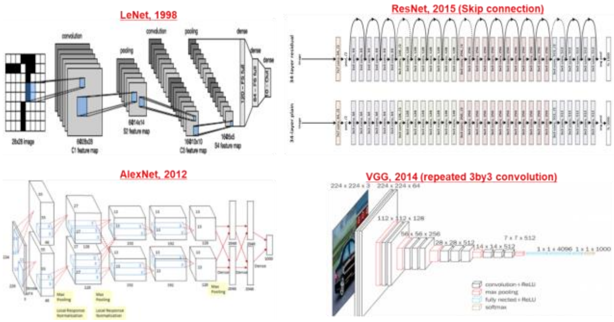


Fig. 2. Representative modern convolutional neural network: LeNet[3], AlexNet[4], VGGNet[5], ResNet[6]

As shown in Table II, pool boiling and flow boiling experimental data sets were used for algorithm training. One thing to keep in mind was that the number of measured CHF data was small because the experiment was abruptly terminated in order to prevent damage caused by a sudden heater temperature increase when CHF and transition occur. The test matrix of algorithm was shown in Table III, and data augmentation to diversify the characteristics of the data was performed. All models were trained using the Adam optimizer and cross-entropy loss function.

Table II: Deep learning dataset for training and test

(a) Pool boiling

Boiling regime	Conv.	Nucleate	CHF, Transition	Film	Total
Train	1,953	7,381	5	307	9,646
Test	217	819	3	34	1,073

(b) Flow boiling

Boiling regime	Conv.	Nucleate	CHF, Transition	Film	Total
Train	450	3,465	60	0	3,975
Test	150	1,155	20	0	1,325

Table III: Test matrix of deep learning model for performance optimization of boiling regime classification

Algori-thm	**Data augmentation**	**Optim.**	**Loss.**	**Epoch**
LeNet	- Random noise - Resize - Cropping	Adam	Cross-Entropy	100~ 2,000
AlexNet				
VGGNet				
ResNet				

4. Results and Discussion

As a result of training each of the four CNN algorithms and checking the boiling regime prediction accuracy, the results were presented as shown in Table IV. For flow boiling, LeNet, AlexNet, and VGGNet showed 49-57% prediction accuracy, whereas ResNet model showed 100% prediction accuracy. For pool boiling, LeNet and VGGNet showed low accuracy of 54.4% and 72.5%, respectively, whereas and AlexNet and ResNet showed high accuracy of 97.9% and 99.7%, respectively. Through both pool and flow boiling data learning and testing, the ResNet algorithm showed the best performance in classifying the boiling regimes. In the case of flow boiling, all data of the entire boiling regime were accurately classified, whereas in the case of pool boiling, only CHF and transition boiling regime data could not be classified. As described above, it was judged that the amount of data was not sufficient to distinguish the boiling regime because the number of data was very small. The model for classifying the optimal boiling heat transfer regime derived through this deep learning experiment was a CNN-ResNet and spectrogram image-based model.

In general, the deep learning algorithm has an error of losing the features originally possessed by the input data during training as the network layer is deeper. For that reason, it was reported that the deeper the network, the more the training was saturated at some level due to the gradient vanishing problem. On the other hand, the reason that Resnet's performance was superior to the other three CNN models was because the skip connection algorithm that train the network with the previous information, and thanks to this, it can be easily optimized in the deep network and showed high accuracy [6]. For this reason, it was analyzed that ResNet showed the best performance in this algorithm test experiments.

Table IV: Comparison of boiling regime classification performance

Case	CNN Algorithm	Test Acc. (%)	
		Pool boiling	Flow boiling
1	LeNet	54.4	49.2
2	AlexNet	97.9	57.1
3	VGGNet	72.5	57.1
4	ResNet	99.7	100.0

5. Conclusions

In this paper, with the aim of diagnosing the two-phase flow and boiling regime, including the critical heat flux of a nuclear power plant, the fundamental study was performed to classify the internal boiling regime in real time through acoustic emission signals and deep learning technology. Through the fundamental thermal hydraulic experiment of pool and flow boiling and spectrogram frequency analysis of the acoustic emission signal, the signal in a specific frequency range that can distinguish convection, nucleate boiling, CHF and transition boiling, and film boiling regime was derived. Using this, the real-time boiling regime classification technology based on CNN-ResNet algorithm was developed using the MATLAB platform. This result can be used to confirm the safety of the two-phase flow heat transfer system and can be used as a fundamental result necessary for real-time diagnosis and prediction of safety margin.

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