Transactions of the Korean Nuclear Society Autumn Meeting
Changwon, Korea, October 24-25, 2024

Deep Metric Learning-based Multi-abnormal Event Diagnosis Approach in Nuclear Power Plants

Seung Gyu Cho, Seung Jun Lee*
Ulsan National Institute of Science and Technology, 50, UNIST-gil, Ulsan, 44911
**Corresponding author: reisi-fard.1@osu.edu*

***Keywords :** Deep metric learning, convolutional neural network, multi-abnormal events, nuclear power plant,

1. Introduction

In order to operate nuclear power plants (NPPs) safely and efficiently, there are thousands of components, hundreds of indicators, and safety and non-safety systems. NPP operators monitor plant variables, identify operational conditions and follow operating procedures as necessary. Abnormal operating procedures are well designed, but numerous changing plant variables, alarms, and limited time can cause human error for operators.

Abnormal event diagnosis studies using artificial intelligence (AI) have been actively conducted to reduce human errors that may occur in abnormal situations. To illustrate, there are two distinct approaches to abnormal event diagnosis: a gated current unit-based method utilizing the two-stage structure of the abnormal operating procedure and a convolutional neural network (CNN)-based approach employing a two-dimensional image of power plant variables [1, 2].

However, the majority of studies have concentrated on the diagnosis of a singular abnormal event. The occurrence of two abnormal events simultaneously, or what is referred to as a multi abnormal event, results in fluctuations in variables that may exhibit a spike, decline, or a cancellation of the initial changes. This makes it more difficult for operators to diagnose the correct abnormalities. Studies have been conducted for the diagnosis of multi abnormal events, but the limitations have been clear. Given the inherent difficulty in training all multi-abnormal events, a methodology was investigated with the objective of enhancing the training of the one-vs-rest classifier by focusing on the additional training principal multi abnormal events [3]. In a separate study, a CNN-based methodology for multi-abnormal events diagnosis was investigated. This methodology was developed by the key variables of each individual abnormal event were selected using machine learning techniques [4].

In this work, we introduce a generalized deep metric learning-based multi-abnormal event diagnosis approach, supplementing the limitations of previous studies. The proposed methodology trains only a single-abnormal event to diagnose even multi-abnormal events and does not need to separately select the characteristics of each single abnormal event. Deep metric learning is a technique that enables the extraction of discriminative features from input data and their mapping to embedding vectors. This approach allows for the detection and diagnosis of untrained multi-abnormal events by utilizing features that diverge from the previously trained embedding vector.

The remainder of the paper is organized as follows: Chapter 2: Explanation of deep metric learning and detection and diagnosis methods employed for multi-abnormal event. Chapter 3: Experimental Setup. Chapter 4: Results and Conclusions

2. Methodology

2.1 Deep metric learning

Deep metric learning is a technique that enables the extraction of features from the input data set and the mapping of those features to embedding vectors. This process serves to reduce the variation observed within a given class of data points while simultaneously increasing the variation observed between different classes. In this study, a deep metric learning using triplet loss was designed [5]. The triplet loss function defines three points for training: the anchor, positive, and negative inputs. The objective is to minimize the distance between the anchor input and the positive input, and to maximize the distance between the anchor input and the negative input. The loss function can be obtained by equation (1) where x_i^a, x_i^p, x_i^n are anchor, positive, and negative inputs, respectively, while α denotes margin. The Euclidean distance is employed to calculate the distance between the inputs.

$$(1)\quad L = \sum_i^N [\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2] + \alpha$$

2.2 Framework of multi-abnormal events diagnosis

In the context of this study, a multi-abnormal event is defined as the occurrence of two single-abnormal events. The number of multi-abnormal events is calculated using a combinatorial approach, based on the number of single-abnormal events. For example, the number of complex abnormal events for 24 single abnormal events is 276. The volume of data is too large to train on all the complex abnormal events, and it is challenging to obtain data from real power plants. Additionally, in contrast to the well-researched domain of multi-label classification, techniques such as partial object detection are not applicable to avoid training multi-abnormal data. This is due to the fact that the variables are globally altered by single-abnormal events.

Therefore, instead of solving the traditional multi-label classification problem, we focused on the characteristics of the multi-abnormal event, which is a global change in plant variables. Fig. 1 illustrates the generation of one- and two-dimensional embedding vectors through the application of deep metric learning. It is notable that each multi-label is positioned between the single labels.

The training framework for multi-abnormal event diagnosis is shown in Fig. 2. Following the training of deep metric learning, the average value of the embedding vectors for each label is taken as the representative vector. In the test phase of Fig. 3, we employ the Mahalanobis distance to detect multi-abnormal events and utilize the Euclidean distance to diagnose both single- and multi-abnormal events. As the multi-abnormal events are untrained data, the Mahalanobis distance, which utilizes the covariance between the embedding vector and the representative vector, increases. Nevertheless, the Mahalanobis distance using covariance is not an optimal approach for diagnosis. The covariance is vulnerable to contamination in the case of multi-abnormal events, which are defined as a combination of single-abnormal events. This inherent limitation restricts the diagnostic accuracy of the covariance. Therefore, the Euclidean distance is utilized for diagnosis.

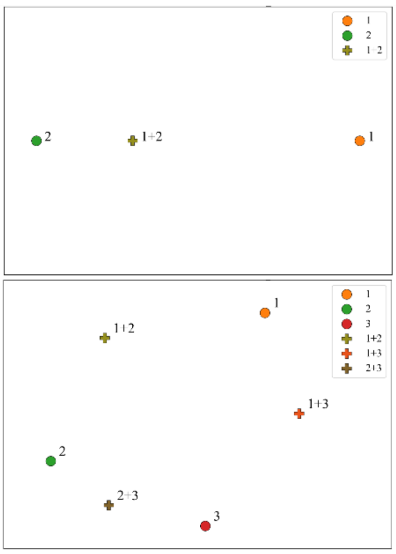

Fig. 1. Distribution of embedding vectors by label: one-dimensional embedding vectors (top), two-dimensional embedding vectors (bottom).

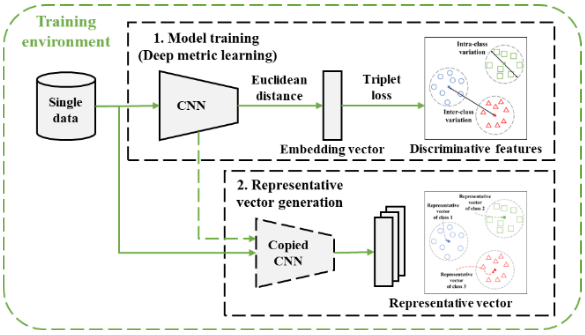

Fig. 2. Training framework of multi-abnormal event diagnosis.

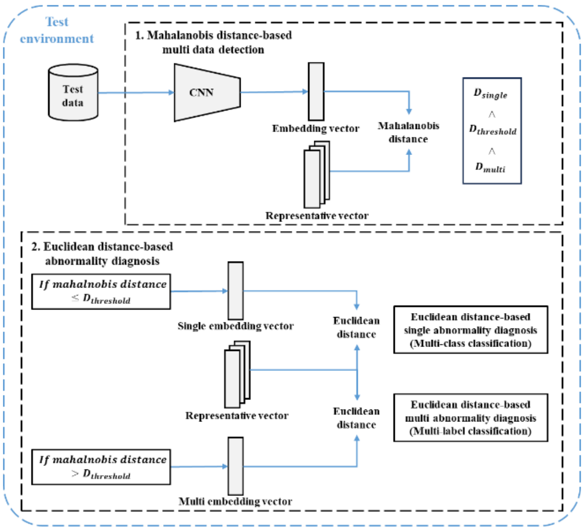

Fig. 3. Test framework of multi-abnormal event diagnosis.

3. Experimental settings

3.1 Data acquisition and preprocessing

All datasets are produced from the 3KEYMASTER simulator which is a 2-loop 1400MWe generic pressurized water reactor [6]. Each dataset is 60 seconds in duration and comprises 637 power plant variables, extracted using machine learning techniques. The number of labels generated by the simulator is one normal, 24 single abnormal data, and 276 generated by the combination calculation of single abnormal data. The single-abnormal labels are detailed in Table 1.

Table 1. Description of abnormal events.

Label	Description
Normal	Initial condition #2 middle of life cycle 100%
POSRV[VO]	Pilot operated safety relief valve leakage
RVHF[LK]	Reactor vessel head flange leakage
SGTL[TL]	Steam generator tube leakage
RCP[LC]	Loss of reactor coolant pump component cooling water (CCW)

RCP[LS]	Loss of injection seal water
PZR[VO]	Pressurizer spray valve failure open
VCT[LL]	Volume control tank level low
LTDN[LK]	Letdown line leakage
LTDN[VC]	Letdown line blocked
LTDN[LC]	Letdown temperature abnormal
CHRG[PP]	Charging pump abnormal stop
CHRG[VC]	Abnormal operation of the charging line valve
CHRG[LK]	Charging line leakage
CCW[LK]	CCW heat exchanger leakage
TCS[VC]	High pressure turbine control valve abnormally closed
MSIV[VC]	Abnormal main steam isolation valve
SBCS[VO]	Steam bypass control system valve failure open
HFH[TL]	High pressure feed water heater tube ruptured
LFH[TL]	Low pressure feed water heater tube ruptured
CST[LL]	Condenser storage tanks level low
CDS[LV]	Condenser vaccum degradation
MFW[VO]	Main feed water pump recirculation valve abnormality open
MFIV[VC]	Main feed water isolation valve closed
EWS[TL]	Secondary system essential service water leakage

The single-data set was generated with 50 data sets for each label, and the multi-data set was generated with 9 data sets for each label by combining two single malfunctions. Fig. 4 illustrates the methodology employed in the generation of the multi-abnormal event data set.

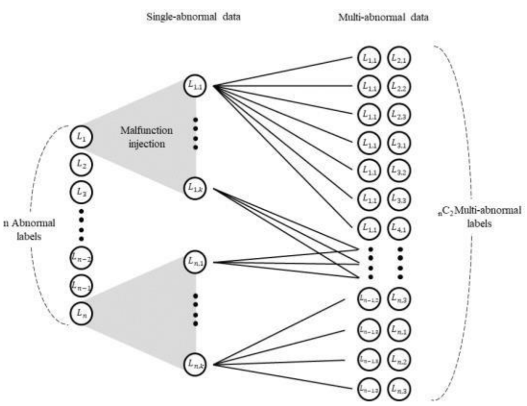

Fig. 4. Multi-abnormal data generation process.

3.2 Model development

The base model for deep metric learning employs a two-channel and two-dimensional CNN, with the second channel utilizing the difference from 10 seconds prior as the input data [7].

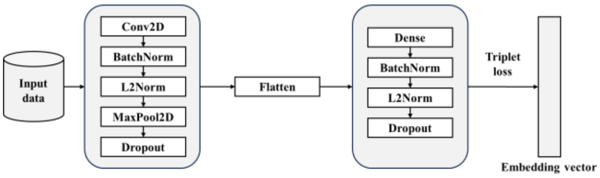

Fig. 5. Architecture of Deep metric learning.

4. Results

Table 2 illustrates the multi-abnormal event diagnosis accuracy. The accuracy of single-abnormal event diagnosis is 100%, the multi-abnormal event detection rate is 99.36%, and the multi-abnormal event diagnosis accuracy is 98.8%. The results indicated a tendency for diagnosing single-abnormal events, either with or without the detection of multi-abnormal events.

Table 3 presents all cases of misdiagnosed multi-abnormal events. The most problematic case is the multi-abnormal event that occurs on the letdown line, and most of the case it is misdiagnosed as another letdown line multi-abnormal event. For instance, an LTDN[LK] + LTDN[VC] multi-abnormal event was incorrectly diagnosed as LTDN[LC] + LTDN[LC], but an LTDN[VC] + LTDN[LC] multi-abnormal event was incorrectly diagnosed as LTDN[LK] + LTDN[VC]. However, since misdiagnosed cases are also capable of system diagnosis, partial abnormal diagnosis results can be provided to operators.

Table 2. Results of multi-abnormal event diagnosis

Data type	Accuracy (%)
Single	100
Multi	98.8

Table 3. Description of misdiagnosis cases

Label	Accuracy (%)
LTDN[LK] + LTDN[LC]	22 (2/9)
LTDN[LK] + LTDN[VC]	33 (3/9)
LTDN[VC] + LTDN[LC]	56 (5/9)
CHRG[PP] + CHRG[LK]	67 (6/9)
CHRG[VC] + TCS[VC]	78 (7/9)
TCS[VC] + SBCS[VO]	78 (7/9)
POSRV[VO] + PZR[VO]	89 (8/9)
POSRV[VO] + LFH[TL]	89 (8/9)
SGTL[TL] + HFH[TL]	89 (8/9)
CHRG[VC] + CHRG[LK]	89 (8/9)

CHRG[VC] + MSIV[VC]	89 (8/9)
CCW[LK] + TCS[VC]	89 (8/9)

5. Conclusions

In this study, the deep metric learning method was applied to develop a generalized multi-abnormal event diagnosis approach. The data used in the experiment used a 2-loop 1400MWe generic pressurized water reactor, producing 1 normal, 24 single-, and 276 multi-abnormal labels. The multi-abnormal event diagnosis model trained only a single-abnormal event, and Mahalanobis distance was used for detection of multi-abnormal events and Euclidean distance was used for diagnosis. The experimental results of the multi-abnormal event diagnosis approach show a single-abnormal event diagnosis accuracy of 100%, a multi-abnormal event detection rate of 99.36%, and a multi-abnormal event diagnosis accuracy of 98.8%. Even in the case of misdiagnosis, a single-abnormal was diagnosed. This means that even when misdiagnosed, abnormal diagnosis information can be provided up to the system level.

Future studies will investigate whether the detection rate and diagnostic accuracy of multi-abnormal events are maintained even in noise-added data. This finding could serve as a basis for the diagnosis of generalized multi-abnormal events.

ACKNOWLEDGEMENTS

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. RS-2022-00144042)

This research was supported by the National Research Council of Science & Technology(NST) grant by the Korea government (MSIT) (No. GTL24031-000)

REFERENCES

[1] Kim, J. M., Lee, G., Lee, C., & Lee, S. J. (2020). Abnormality diagnosis model for nuclear power plants using two-stage gated recurrent units. Nuclear Engineering and Technology, 52(9), 2009-2016.

[2] Lee, G., Lee, S. J., & Lee, C. (2021). A convolutional neural network model for abnormality diagnosis in a nuclear power plant. Applied Soft Computing, 99, 106874.

[3] Cho, S. G., Choi, J., Shin, J. H., & Lee, S. J. (2023). Multi-abnormality attention diagnosis model using one-vs-rest classifier in a nuclear power plant. Journal of Nuclear Engineering, 4(3), 467-483.

[4] Shin, J. H., Cho, S. G., Koo, S. R., & Lee, S. J. (2024). Approach to diagnosing multiple abnormal events with single-event training data. Nuclear Engineering and Technology, 56(2), 558-567.

[5] Schroff, F., Kalenichenko, D., & Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 815-823).

[6] Western Service Corporation, 3KEYMASTER Simulator, Western Service Corporation, Frederick, MD, USA, 2013.

[7] Lee, G., Lee, S. J., & Lee, C. (2021). A convolutional neural network model for abnormality diagnosis in a nuclear power plant. Applied Soft Computing, 99, 106874.