# Comparison of Diagnosis Model for Classifying Multi-Abnormal Events in Nuclear Power Plants

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## 1. Introduction

A nuclear power plant (NPP) is an electric power generation system consisting of dozens of systems and hundreds of components. In any problem with one of these components, operators should control it to prevent it from causing an accident. For this, the operators diagnose the abnormal event and carry out the appropriate abnormal operating procedure (AOP). However, it is burdensome for operators to recognize the entire plant state in a given time. For supporting this, artificial intelligence (AI) technology to diagnose such abnormal events has been studied recently.

However, an NPP should be able to ensure safety in all given situations. Therefore, a support system to be applied to real NPP should be able to prepare for more diverse situations. To satisfy these needs, we need to consider the occurrence of one or more abnormal events simultaneously in this diagnostic model. However, there are hundreds of abnormal situations. Therefore, it is impossible to train the model about all combinations of abnormal events due to a lack of data and computing memory problems. To solve this problem, this study purposed a model that can have high performance for multi-abnormal scenarios despite training only a single abnormal scenario. We considered feature selection in the proposed diagnostic algorithm and applied various model types to achieve the best performance. As a result, we improved the diagnostic performance with more than 96% accuracy for 10 multi-abnormal scenarios through feature selection with computing variance and a one-dimensional convolutional neural network (CNN) model set with two channels.

## 2. General Model

### *2.1 Datasets*

The amount of actual data on NPP abnormalities is insufficient to train the model. Therefore, in this study, abnormal event data were produced using the simulator for a generic pressurized water reactor from the Western Services Corporation [1]. We selected five single abnormal scenarios as shown in the following Table I to train the model. In addition, to evaluate the diagnostic performance of the multi-abnormal event, a total of 10 multi-abnormal scenarios consisting of a combination of two abnormal events in the below table were selected. For each scenario, 49 datasets were produced. One dataset consists of 60 second time steps for 681 parameters information.

Table. I: Scenario description

| State | Description |
|---|---|
| SGTL | Steam generator tube leak |
| CHRG | Charging line break |
| LTDN | Letdown line leak inside a containment |
| CDS | Loss of condenser vacuum |
| CWS | Circulating water tube leak in a condenser |

### *2.2 2-Channel Convolutional Neural Network*

Prior studies have attempted to apply various models such as deep neural network, recurrent neural network, and CNN to support abnormal state diagnosis. We evaluated single and multi-abnormal events, respectively, with a model trained for 50 epochs on a 2-channel based CNN, in which the model showed high diagnostic performance at single abnormalities among prior studies [2]. The filter inside a convolution layer has high performance in learning image data, and final classification is performed by the fully connected layer (FC layer). Fig. 1 below shows the structure of a 2-channel CNN. The first channel has information about the current state, and the second channel has information about the change compared to the state 5 seconds ago.

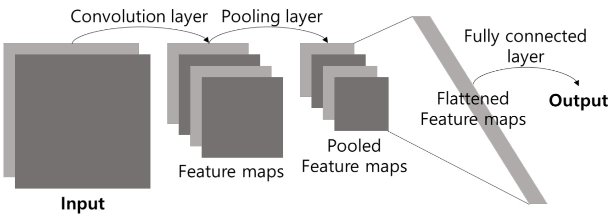


Fig. 1. 2-dimensional CNN structure with 2-Channel input

* Model Information
- Convolution layer :
  2 layers with 16 filters of 3*3 kernel size
- Activation function of convolution layer :
  ReLU [3]
- Activation function of FC layer : sigmoid
- Loss function / Optimizer :
  binary crossentropy / Adam [4]

### *2.3 Problem Recognition*

The model showed that it trained with very high performance on single abnormalities as below Table II.

Table. II: Training results of the general model

| | Accuracy (%) | Logloss |
|---|---|---|
| Training datasets | 99.93 | 0.0019 |
| Validation datasets | 99.99 | 0.0001 |

We evaluated the model using 10 multi-abnormal scenarios created by the combination of 5 single abnormal scenarios learned. About 0.5 thresholds for the prediction, the model diagnosed both events that occurred only 30.71% test data. It is a low performance to be applied for a diagnostic model at an actual NPP. Therefore, we need to improve the diagnostic performance for such situations occurring in multi-abnormal events.

## 3. Proposed Model for Multi-Label Classification

The general neural network derives a prediction biased to one label from the data corresponding to the out of distribution by the activation function of the FC layer [5]. Therefore, the model shows the output with one label even though it should be diagnosed with two or more labels when diagnosing multi-abnormal data that is outside the learned range. To solve this problem, we proposed the training and diagnosis algorithm which is following Fig.2.

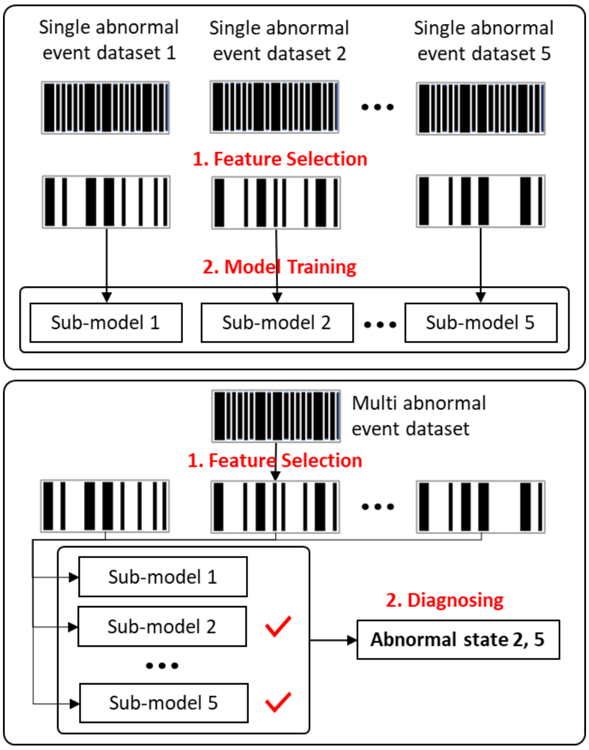


Fig. 2. Training and diagnosis algorithm of a proposed model

The overall model consists of a set of sub-models for diagnosing each single abnormality. To train and diagnose one sub-model, preprocessing is performed so that the data consists only of parameters whose changes by the corresponding abnormal state are clear.

### *3.1 Feature Selection*

We tried to improve the performance by selecting a feature specialized for a single abnormal event targeted by the submodel. The feature selected for one sub-model should be able to show a large change for the target event and relatively little change for other events. Therefore, we calculated the variation value of the overall parameter for each abnormal event. And, the parameters with the maximum variation value in the target event were selected.

### *3.2 Sub-model*

Each sub-model diagnoses only the occurrence of one abnormal event. That is, it performs only binary classification, so the model does not require a complex structure compared to the general model in Section 2. Therefore, to select an appropriate model, the following model types were applied as sub-models and the results were compared. Submodels 3, 4, and 5 all used CNN structure. Sub-model 3 uses one-channel data having only the current state information for input. Sub-models 4 and 5 use two-channel data that has two types of information, the current state, and the change, for input as in Section 2. However, sub-models 3 and 4 use a one-dimensional convolutional neural network, unlike the model proposed in Section 2.

* Sub-model 1 Information
- Model type : Support vector machine (SVM)
- Kernel type : Linear

* Sub-model 2 Information
- Model type : Artificial Neural Network
- Dense layer : 1 layer with 100 nodes
- Activation function of dense layer : ReLU
- Activation function of last layer : softmax
- Loss function / Optimizer :
  categorical crossentropy / Adam

* Sub-model 3,4,5 Information
- Model type : Convolutional neural network
- Convolution layer :
  1 layer with 16 filters of 3 or 3*3 kernel size
- Activation function of convolution layer : ReLU
- Activation function of FC layer : softmax
- Loss function / Optimizer :
  categorical crossentropy / Adam

## 4. Results

### *4.1 Application of Feature Selection*

From the results shown in Fig. 3, we confirmed that the diagnostic accuracy for multi-abnormal events increased by 18.8% in the model trained with the data of only selected parameters compared to the model trained with the data of all parameters. This result is a 60.48% improvement over the 30.71% accuracy shown in the general model in Section 2. The proposed algorithm shows improved performance compared to the general model and has higher performance when feature selection is additionally conducted.

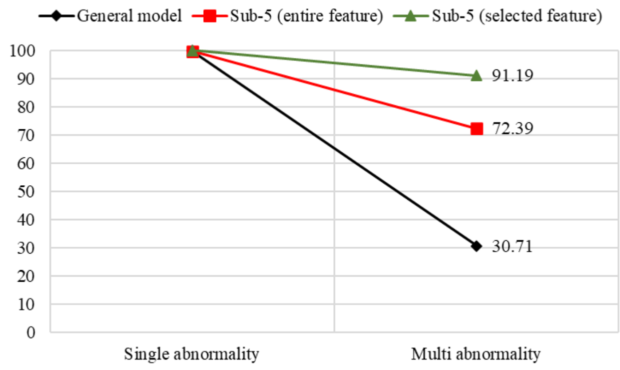


Fig. 3. Accuracy comparison by feature selection

### *4.2 Comparison about Sub-model type*

We compared the results by the submodel candidates to be used together with feature selection in the proposed algorithm as shown in Table. III below. The proposed model showed improved results compared to the Section 2 model for all multi-abnormality cases. Overall, models consisting of submodel with CNN type had higher accuracy in diagnosing the inclusion of specific abnormalities.

Table. III: Accuracy for multi-abnormality data involving specific abnormalities

| Model type | Sub-1 | Sub-2 | Sub-3 | Sub-4 | Sub-5 |
|---|---|---|---|---|---|
| SGTL | 79.11 | 72.17 | 85.03 | 92.91 | 84.91 |
| CHRG | 92.33 | 85.03 | 91.54 | 98.53 | 97.14 |
| LTDN | 84.58 | 76.96 | 88.94 | 96.51 | 88.28 |
| CDS | 90.06 | 60.12 | 82.89 | 96.24 | 87.18 |
| CWS | 95.35 | 87.64 | 94.88 | 99.34 | 98.42 |
| Total acc. | 88.29 | 76.38 | 88.66 | **96.71** | 91.19 |

In Fig. 4 below, Submodel 1, that is, SVM which is for binary classification only, showed an accuracy of 88.29%. However, for single abnormal data, its performance decreased by about 3%. However, Submodel 4, which 2-dimensional CNN with 2-Channel input is used as a sub-model type, showed to diagnose multi-abnormal events with the highest performance of 96.71% while maintaining classification performance for single abnormal events. This is a 66% improvement in multi-abnormality diagnostic accuracy compared to the previous model in Section 2.

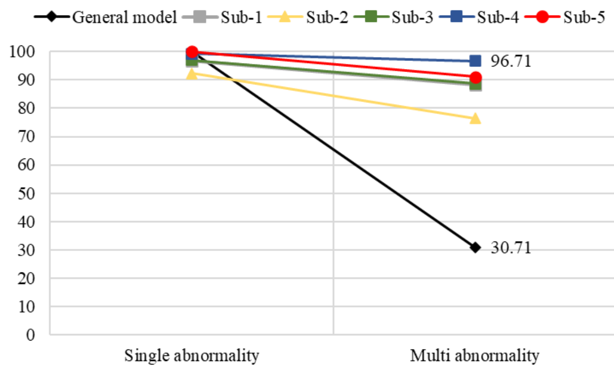


Fig.4. Accuracy comparison by submodel type

## 5. Conclusions

Since an NPP is a system in which safety should be the top priority, it should be able to relieve all possible events and accidents. In this study, an improved diagnostic model was proposed to consider the case where two abnormal events occurred at the same time. The 2-channel CNN sub-model set trained with parameter data selected through variance was able to diagnose multi-abnormal scenarios with very high accuracy while maintaining diagnostic performance for single abnormal scenarios.

We used only one intuitive method of feature selection to create training data specialized for a specific event. However, the model can expect a higher diagnosis performance by applying more diverse feature selection methods. In addition, we evaluated the multi-abnormality data created through the combination of five representative abnormal events. However, for applicating to actual NPP, evaluation of intensified cases such as a combination of two events that induce mutually related or contradictory changes in future work needs to perform.

## ACKNOWLEDGMENT

This work was supported by Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government (MOTIE) (No. 20211510100020, Development of operation supporting technology based on artificial intelligence for nuclear power plant start up and shutdown operation).

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