Feasibility Study on Classification of Nuclear Threat Types Using Machine Learning with Ratios of Xe Isotopic Activity

Sang-Kyung Lee [a*], Sang Woo Kim [b], Yu Yeon Cho [b], Chang Ho Shin [a], Ser Gi Hong [b]
[a] *Innovative Technology Center for Radiation Safety, Hanyang Univ., 222 Wangsimni-ro, Seongdong-gu, Seoul 04763*
[b] *Dept. of Nuclear Engineering, Hanyang Univ., 222 Wangsimni-ro, Seongdong-gu, Seoul 04763*
[*] *Corresponding author: sangkyung@hanyang.ac.kr*

1. Introduction

Neighboring countries have not given up on nuclear programs such as nuclear tests and the operation of research reactors. One of the detection methods for nuclear threats is to measure radioactivity and targets radioactive xenon, an inert gas produced by nuclear fission that does not occur naturally. Among the radioactive Xe isotopes produced by fission, the nuclides that can be detected are ^{135}Xe, ^{133}Xe, ^{133m}Xe, and ^{131m}Xe, considering the half-life. However, a process for distinguishing sources from measured radioactive Xe information has not been established [1]. This study aims at determining whether the machine learning model is applicable to predict the type of nuclear threat from the radioactivity ratio of four radioactive Xe.

2. Methods and Results

The machine learning models used in this study are Logistic regression, Support Vector Machine, and K-Nearest Neighbors. Python was used as the computer language, and modules in the scikit-learn package were mainly used in relation to machine learning. For learning the machine learning model, six types of radioactivity ratios (^{135}Xe/^{133}Xe, ^{133m}Xe/^{133m}Xe, ^{135}Xe/^{133m}Xe, ^{135}Xe/^{133m}Xe, ^{133m}Xe/^{133m}Xe, ^{133}Xe/^{133m}Xe) were used as input information. The sources of radioactive Xe predicted from these ratios were two nuclear tests (Pu bomb, U bomb) and four reactors (IRT-2000, MAGNOX, PWR, and CANDU).

2.1 Xe Activity Data for Machine Learning Models

Radioactivity data of Xe applied for learning were generated in ORIGEN/SCALE and SERPENT codes [2]. Radioactivity data of radioactive xenon was generated by changing various conditions related to nuclear tests and reactors. The data for nuclear reactors were generated by considering the nuclear fuel assembly types, initial composition (i.e. uranium enrichment), burnup, specific power, the time interval between cycles, number of nuclear cycles, and cooling time after shutdown. Data for nuclear test were generated by considering the initial composition, nuclear weapon yield, and fractionation time of the nuclear bomb according to the specifications given by gun type for highly enriched uranium nuclear bombs and imposition type for nuclear weapons-grade plutonium nuclear bombs. In order to classify using machine learning from the data generated in this way, analysis and selection of the Xe radioactivity ratio data and selecting the data must be preceded for effective use in learning.

According to the results of previous study [3], the difference in the separation time (i.e. fractionation time) of the parent nuclear species from their daughter ones in U bomb and Pu bomb had a significant effect on the Xe activity ratio change, while the reactor (PWR, CANDU, IRT-2000, MAGNOX) type had a slight effect on the Xe activity ratio change even though there were differences in composition and specific power. Therefore, 7,520 datasets generated under the following conditions were selected as data to be used for the machine learning model:

· Pu bomb (2,560 sets)
  - ^{239}Pu content: 93 w/o
  - Nuclear weapon yield: 50 kt
  - Fractionation time: no frac., 1h, 10h, full frac.

· U bomb (2,560 sets)
  - Enrichment: 90 w/o
  - Nuclear weapon yield: 20 kt
  - Fractionation time: no frac., 1h, 10h, full frac.

· PWR (600 sets)
  - Fuel assembly type: 17×17
  - Enrichment: 4.5 w/o
  - Specific power: 40 MW/t

· IRT-2000 (600 sets)
  - Enrichment: 36.15 w/o
  - Specific power: 557 MW/t

· MAGNOX (600 sets)
  - Enrichment: 0.71 w/o
  - Specific power: 0.5 MW/t

· CANDU (600 sets)
  - Enrichment: 0.71 w/o
  - Specific power: 19.5 MW/t

For the entire selected data set, training data and validation data were combined for 70% and the remaining 30% were divided into test data, and the ratio of each category was maintained the same for all the cases. As limited data set was used, model learning and model modification were conducted using the K-fold cross validation without separating the trained data and validation data.

2.2 Logistic Regression

Logistic regression is a stochastic model proposed by Cox [4] in 1958 that uses regression (a technique of finding the correlation between independent and dependent variables) to predict the probability of a data belonging to a particular category as a value between 0 and 1 and classify it as the most likely category. The basic logistic function is the sigmoid function, and its parameter was estimated using cross entropy as a cost function as the maximum likelihood estimation. The results obtained using test data in Fig. 1 show that the accuracy for the entire test data was 73%, with the highest probability of accurately classifying Pu bomb at 89.97%, and the lowest probability of accurately classifying PWR at 13.89%. It is also noted that the classification of 5MW Yongbyon reactor (designated as MAGNOX) has high probability of 79.44%

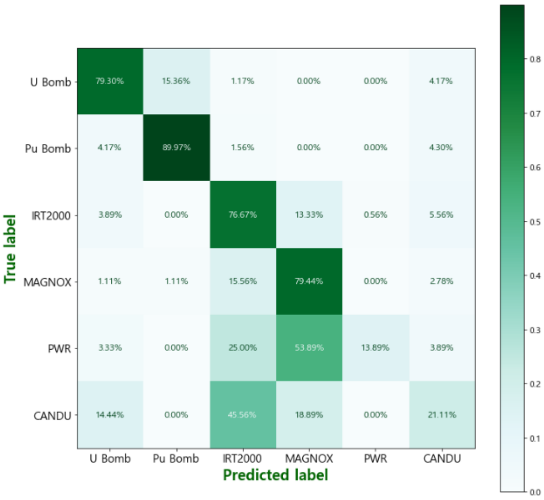

Fig. 1. Results of nuclear threat classification test using Logistic Regression.

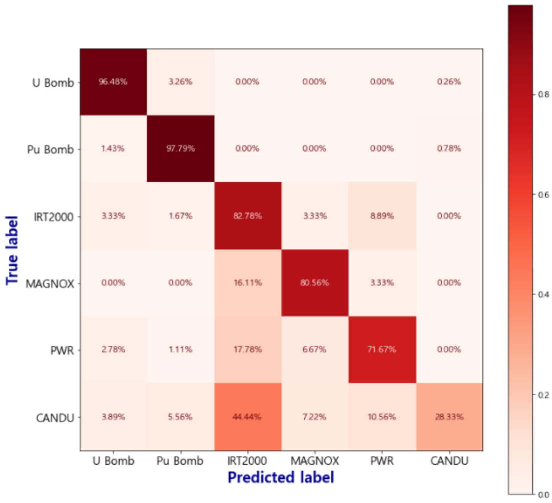

Fig. 2. Results of nuclear threat classification test using Support Vector Machine

2.3 Support Vector Machine (SVM)

Developed by Vapnik, SVM is a supervision learning technique that allows classification to be performed by designing a hyperplane with a maximum margin between the decision boundary and the learning data [5]. Basically, it is used for binary classification, but using the One-versus-the Rest or One-versus-One strategy can also be applied to the multiple classifications required in this study [6]. For a data set that cannot be linearly separated by an SVM, a mapping operation from a low-dimensional space to a high-dimensional space must be performed using a kernel function. In this study, the process of finding the optimal function and hyper parameter among the following four kernel functions [7] was performed, and the accuracy of the validation data was the highest using Radial basis function.

· Linear function

$$K(x, x_i) = < x, x_i >$$

· Polynomial function

$$K(x, x_i) = (\, r + \gamma \cdot < x, x_i >)^d$$

(d: degree of kernel function)

· Radial basis function

$$K(x, x_i) = e^{-\gamma \| x - x_i \|^2}$$

· Sigmoid function

$$K(x, x_i) = \tanh\,(\gamma \cdot < x, x_i > + \gamma)$$

The predicted results using test data in Fig. 2 show that the overall accuracy is 87%, with the highest probability of accurately classifying Pu bomb at 97.79%, and the lowest probability of accurately classifying CANDU at 28.33%. Also, the probabilities of classification for U bomb and 5 MW Yongbyon reactor are significantly improved in comparison with the logistic regression cases.

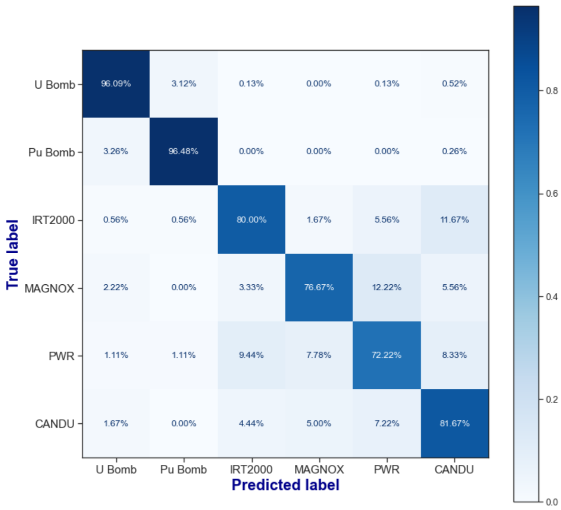

Fig. 3. Results of nuclear threat classification test using K-Nearest Neighbors

2.4 K-Nearest Neighbors (KNN)

KNN is a method of finding K data in order of distance from a given data and assigning categories of groups to which the largest number of data belongs. Since KNN is based on a nonparametric method, there is an advantage that classification performance is not greatly influenced by the distribution type of data. The following five distance measurement methods [8] were applied to KNN to select the distance measurement method and K value with high accuracy for validation data:

· Euclidean distance

$$d(A,B) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

· Manhattan distance

$$d(A,B) = |x_1 - x_2| + |y_1 - y_2|$$

· Mahalanobis distance

$$d(A,B) = \sqrt{(A-B)^T \Sigma^{-1} (A-B)}$$

(Σ: covariance matrix)

· Pearson correlation distance

$$d(A,B) = 1 - \frac{\sum_{i=1}^{n}(A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^{n}(A_i - \bar{A})^2 \sum_{i=1}^{n}(B_i - \bar{B})^2}}$$

(n: number of data)

· Spearman rank correlation distance

$$d(A,B) = 1 - \frac{6\sum_{i=1}^{n}(\mathrm{rank}(A_i) - \mathrm{rank}(B_i))^2}{n(n^2-1)}$$

As a result of the comparative analysis, applying the K value of 3 using the Manhattan distance method showed the best performance. From the results predicted using test data in Fig.3, the overall accuracy was 90%, with the highest probability of accurately classifying Pu bomb at 96.48%, and the lowest probability of accurately classifying PWR at 72.22%.

3. Conclusions

In order to develop a predictive model that can classify nuclear threats, three machine learning models have been applied. The prediction showed that KNN is relatively higher performances than other machine learning models, so it is suitable as prediction model of nuclear threat types. As there are various machine learning models in addition to the three machine learning ones used in this paper, it is necessary to find a model with better performance through further research.

Since the machine learning model was developed in the context of knowing all four types of radioactive xenon, there may be a problem in the substantive measurement situation in which only some radioactive xenon isotopes are detected. Therefore, further research must be needed for developing a predictive model that is possible even if information on some of the four radionuclides is not available.

Acknowledgment

This work was supported by the Nuclear Safety Research Program through the Korea Foundation Of Nuclear Safety (KoFONS) using the financial resource granted by the Nuclear Safety and Security Commission (NSSC) of the Republic of Korea. (No. 2103089).

REFERENCES

[1] Martin B. Kalinowski et. al. Discrimination of Nuclear Explosions against Civilian Sources Based on Atmospheric Xenon Isotopic Activity Ratios, Pure Appl. Geophys. 167 (2010) 517-539.

[2] B.T. Rearden et al., SCALE CODE SYSTEM, Oak Ridge National Laboratory, 2018, ORNL/TM-2005/39.

[3] G.H. Park, et al. Analysis and DB construction of radioactive xenon isotope characteristics for various types of nuclear threat in neighboring countries, Hanyang University, 2021, NSTAR-21PS52-371.

[4] D. R. Cox, The regression Analysis of Binary Sequences. Journal of the Royal Statistical Society, XX, p.215-232, 1958.

[5] C. J. Burges, A Tutorial on Support Vector Machines for Pattern Recognition. Data Mining and Knowledge Discovery, 2 (1998) 121-167.

[6] Bishop, Christopher M., Pattern Recognition and Machine Learning, Springer, 2006.

[7] A. Patle, SVM Kernel Functions for Classification. Advances in Technology and Engineering (ICATE), 2013 International Conference on 2013 Jan, pp.1–9, 2013.

[8] K. Chomboon et al., An Empirical Study of Distance Metrics for K-Nearest Neighbor Algorithm, Proceedings of the 3rd International Conference on Industrial Application Engineering 2015, pp.280-285, 2015.