# Examination on Deep Learning Approach to Nuclear Proliferation Risk Modeling

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## 1. Introduction

Why do countries develop nuclear weapons while others do not/cannot? This question has been a major concern for scholars in the recent 20 years. Several studies have examined what factors cause nuclear proliferation. However, while scholars have focused on finding significant determinants of proliferation risk, they have not sought to enhance the ability to predict proliferation levels in a country. As Bell [1] pointed out, variables identified as significant determinants of nuclear proliferation have failed to offer a strong prediction ability.

Therefore, this study has sought to examine the possibility of improving the ability to predict and classify proliferation levels of a country. We apply a deep learning algorithm, specifically Multilayer Perceptron (MLP) to improve the prediction efficiency in classifying a proliferation level of a country. This preliminary research will have implications for the study of proliferation and nuclear security.

## 2. Methods and Results

In this section, we discuss some of the techniques used to develop neural networks and the results of the model.

### *2.1 Dataset*

The proliferation timeline of a country defined by Bleek [2] is used in this study. Bleek [2] updated the proliferation behavior of a country from prior works. Bleek [2] defined proliferation level as 4: No interest, Explore, Pursue, and Acquire. He presented that 31 countries have at least explored the nuclear program. Therefore, in this preliminary study, we only use 30 countries' proliferation timelines from 1945-2000 (We did not include the West Germany case in this study).

A number of studies have identified the determinants that could explain the cause of proliferation, such as domestic environment, economic capability, and nonproliferation norms. In this preliminary study, about 37 features identified as significant determinants from the previous studies were first selected to support developing a deep learning algorithm [3-7]. The specific model features are described in Table I.

Table I: Model Features

| Category | Variables |
|---|---|
| ***Economic Capability*** | GDP per capita |
| | GDP |
| | Industrial Capacity |
| | CINC |
| ***Nuclear Fuel Cycle Capability*** | Uranium ore production |
| | Uranium conversion capability |
| | Uranium enrichment capability |
| | Uranium oxide fuel fabrication capability |
| | Mixed oxide fuel fabrication capability |
| | Wet spent fuel storage facility |
| | Dry spent fuel storage facility |
| | Spent fuel reprocessing capability |
| | Zirconium alloy processing capability |
| | Zircaloy tube fabrication capability |
| | Heavy water production capability |
| | Power reactor capacity |
| | Number of fast reactors |
| | Number of heavy water research reactors |
| | Number of graphite research reactors |
| | Number of light water research reactors |
| | Number of other types of research reactors |
| | Latency Level |
| ***Nuclear Assistance*** | Sensitive Nuclear Assistance |
| | Civilian Nuclear Assistance |
| | Cumulative total number of civilian nuclear assistance |
| ***Security/ Threat Environment*** | Disputes |
| | Rivalry |
| | Allies |
| | Percentage of democratic countries |
| ***Domestic Environment*** | Polity score |
| | Trade ratio |
| | Liberalization |
| | IAEA membership |

| | |
|---|---|
| ***Nonproliferation Norms*** | NPT membership |
| | Safeguard |
| | Additional Protocol |

*2.2 Multilayer Perceptron*

A multilayer perceptron (MLP) is one of the neural networks in deep learning algorithms. It consists of three main layers: input, hidden, and output. We set a total of 6 layers in this preliminary model: 1 input layer, 4 hidden layers, and 1 output layer.

Since the proliferation level is defined as 4 (No interest, Explore, Pursue, and Acquire), We use Softmax function in the output layer. Consequently, we use the cross-entropy loss function for calculating the loss score.

The preliminary model uses 1511 time-series data points from 30 countries. 80% of the study observations were randomly selected and used as training datasets, while 20% of the observations were used as testing datasets. To run the model, we set batch number as 16, and epoch number as 300. The summary of the model specification is shown below.

Table II: Model Description

| Specification | Model |
|---|---|
| Batch | 16 |
| Epoch | 300 |
| Model | Multilayer Perceptron |
| Layer number | 6 |
| Model feature number | 37 |
| Output label function | Softmax |
| Loss function | Cross Entropy Loss |
| Optimizer | Adam |
| Total observation | 1511 (30 countries) |
| Training set | 80% of total observation |
| Test set | 20% of total observation |

*2.3 Results*

The average classification accuracy using the model is calculated through the classification results of testing data. This study achieves a classification average accuracy of 82% and a loss score of 58.08. From the results, it is also noticeable that the average classification accuracy between the 250 and 300 epochs is about 87% accuracy in the testing set. This result shows that the classifiers using the MLP model distinguish the levels of proliferation with high efficiency.

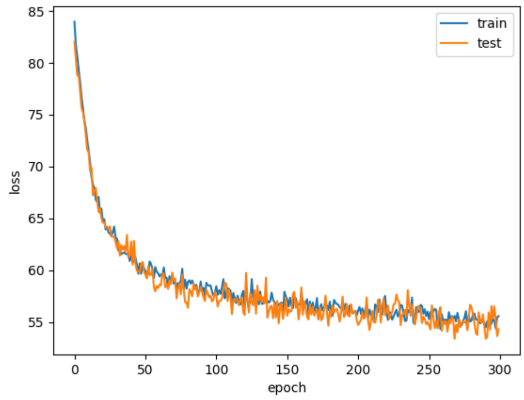


Fig. 1. Loss curve for MLP model in classification for nuclear proliferation risk

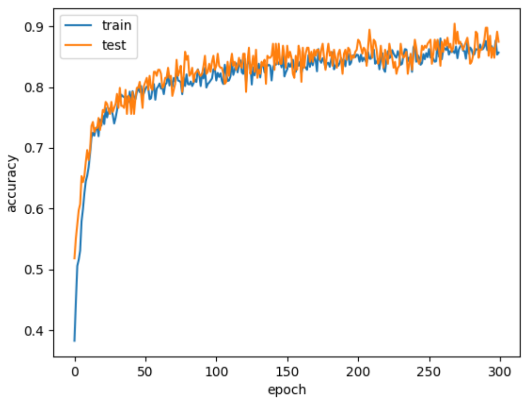


Fig. 2. Classification accuracy for MLP model in classification for nuclear proliferation risk.

## 3. Conclusions

This study examines the deep learning algorithm approach to classifying the proliferation risk. From the preliminary results, we show that the neural network model performs well enough to predict the country's proliferation risk level. This preliminary result provides a possibility of solving the tentative ability to predict proliferation previous researchers have proposed. Therefore, this study suggests the implementation of a deep learning approach to predicting the country's nuclear program level in the future.

This preliminary study has limitations. This model uses only 30 countries that at least have experienced the exploration of nuclear programs. Therefore, future work should be encouraged to apply more countries and features to overhaul the classification model accuracy.

## REFERENCES

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