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Prediction of radiation level change of nuclear power plant using LSTM model

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1. Introduction

Nuclear power plants (NPPs) and disposal facilities monitor radiation level changes around their premises in order to detect any release of radioactive material early on and respond swiftly to protect both workers and residents. In the event of an abnormal release of radioactive material, radiation levels increase rapidly and various meteorological changes, such as rainfall, snowfall, or temperature, can cause fluctuations in radiation exposure around NPPs. Currently, past radiation measurement data and meteorological conditions such as precipitation are used as criteria to make decisions in the event of an accident.

Currently, different methods are being explored for predicting changes in radiation dosage using data processing technology. These studies aim to predict dose levels based on various measurement variables, identify disparities between actual and predicted doses, and determine the occurrence of accidents. Nevertheless, due to regional disparities, applying the same research outcomes to predict dosage levels is challenging.

In this study, we aimed to predict radiation dosage levels by utilizing deep learning techniques and past-measured data, instead of analyzing correlations with multiple variables. To assess the accuracy of our model, we compared the predicted data with actual data and analyzed the discrepancies. Additionally, we examined how varying the number of learning data affected the accuracy of our model.

2. Material and Methods

2.1 Data collection

For this analysis, 10-minute average radiation data was obtained from Korea Hydro & Nuclear Power (KHNP). The radiation data was measured at Kori Nuclear Power Plant (NPP). Table 1 and Figure 1 summarize the measured radiation data from 2012 to 2021.

Table 1

	Average	*Std.*	*Min*	*Max*
Kori NPP [nSv/h]	*114.4*	*7.2*	*83.5*	*183.0*

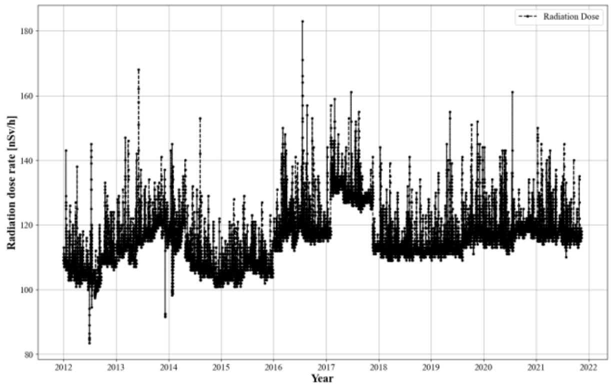

Figure 1. 2012 ~ 2021 radiation data in Kori NPP

2.2 LSTM model

This study used the Long Short-Term Memory (LSTM) model to predict radiation dosage levels. The LSTM model is a Recurrent Neural Network (RNN) well-suited for learning time series data. Other deep learning algorithms based on Artificial Neural Network (ANN) include Deep Neural Network (DNN), Convolutional Neural Network (CNN), Deep Belief Network (DBN), Deep Q-Network (DQN), among others.

The LSTM model is an algorithm designed to address the issue of degrading learning ability over time in RNNs. It has recently been widely used in stock price prediction research due to its effectiveness. Moreover, a study has confirmed that the performance of the LSTM model is superior to that of the traditional time series technique ARIMA model [2].

The LSTM model has a similar chain structure to the RNN, but its repeating module consists of four layers that communicate with each other, instead of just one tanh layer [3]. In an LSTM cell, the state is primarily divided into two vectors: ht, which can be viewed as a short-term state, and ct, which can be viewed as a long-term state, as shown in Figure 2.

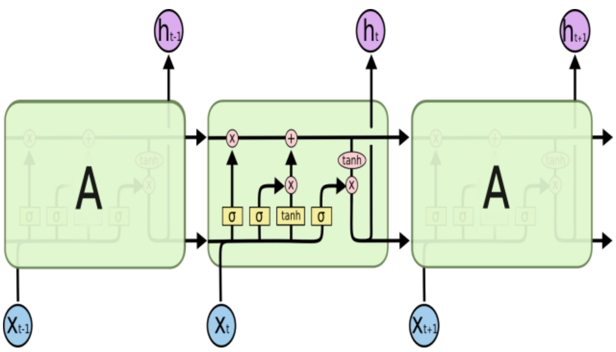

Figure 2. Architecture of LSTM model

The LSTM model consists of five steps: Cell gate, Forget gate, Input gate, Cell state update, and Output gate. The Cell state plays the role of allowing information to flow without changing. The Forget gate determines which information is discarded using a sigmoid layer in the cell state. The Input gate determines which new incoming information is stored in the cell state. First, the values to update are decided using a sigmoid layer, and then a new candidate vector is created in the tanh layer. Once the information to discard and update from the previous gate is decided, the update is carried out during the Cell state update process. The Output gate determines which information is exported to the output. First, the input data is fed into the sigmoid layer to determine the output information. Then, the Cell state is fed into the tanh layer, multiplied by the output of the sigmoid layer, and exported to the output.

In this study, the LSTM model was trained using varying amounts of data. Typically, larger training datasets lead to better predictive accuracy. In this study, the accuracy of the model's predictions for the target data (i.e., the radiation dose in 2021) has been evaluated based on the amount of training data used. Table 2 summarizes the radiation doses measured for each period, as well as in 2021.

Table 2. Summary of dose data for each period analyzed

	Average	***Std.***	***Min***	***Max***
2012-2020	*114.1*	*7.4*	*83.5*	*183.0*
2016-2020	*117.8*	*6.5*	*109.0*	*183.0*
2018-2020	*114.8*	*3.8*	*109.0*	*161.0*
2020	*117.4*	*3.1*	*111.0*	*161.0*
2021	*117.4*	*2.7*	*111.0*	*150.0*

3. Results

Figures 3 to 6 show a comparison between the actual and predicted radiation doses for 2021 using different amounts of training data. Figure 3 shows the results using one year of measured data, Figure 4 shows the results using three years of measured data, Figure 5 shows the results using five years of measured data, and Figure 6 shows the results using nine years of measured data.

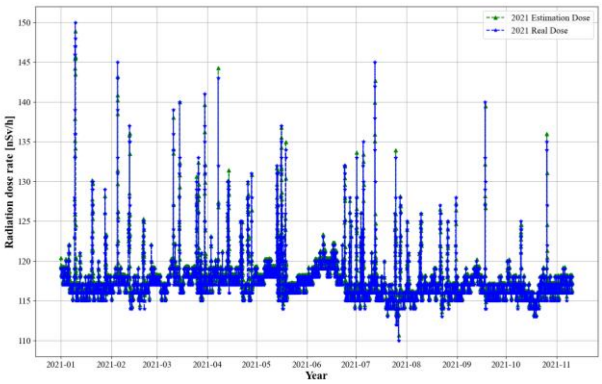

Figure 3. LSTM model trained on 9-year data and compared with actual dose

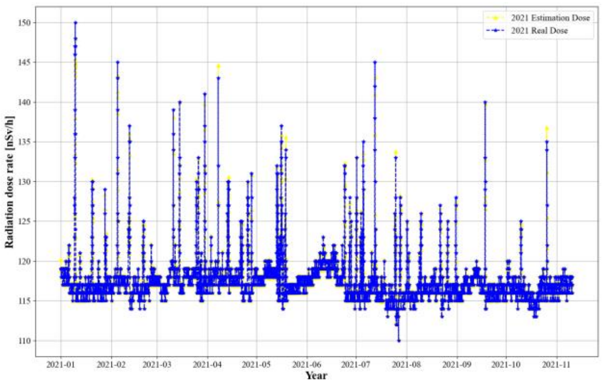

Figure 4. LSTM model trained on 5-year data and compared with actual dose

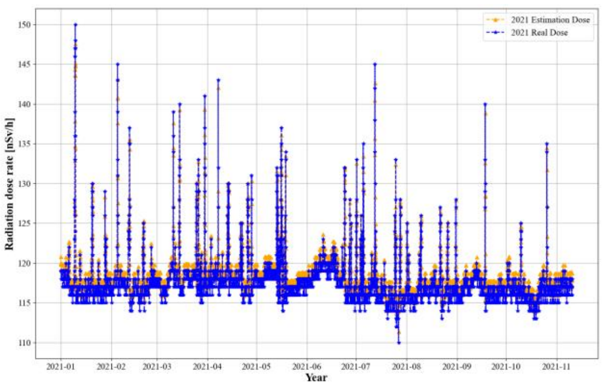

Figure 5. LSTM model trained on 3-year data and compared with actual dose

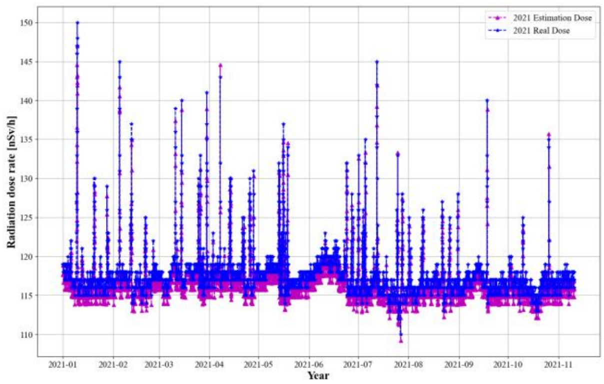

Figure 6. LSTM model trained on 1-year data and compared with actual dose

Generally, using 9 years of data for training can expect to produce the best results. However, according to the results in Table 3, it was confirmed that training with 5 years of data resulted in a similar model to the one trained with 9 years of data.

Table 3. Comparison of prediction performance results by analysis target period

	MAE	***MSE***	***RMSE***	R^2
2012-2020	*0.768*	*1.666*	*1.291*	*0.775*
2016-2020	*0.642*	*1.548*	*1.244*	*0.791*
2018-2020	*1.097*	*2.334*	*1.528*	*0.685*
2020	*1.296*	*2.897*	*1.702*	*0.609*

4. Conclusion

Based on the results of this study, it can be concluded that the LSTM model can be a useful tool for predicting radiation doses around nuclear facilities. By using historical data to train the model, it is possible to accurately predict radiation doses in the future. Additionally, it was found that training with 5 years of data is sufficient to obtain accurate predictions, rather than training with a larger amount of data.
This study provides valuable insights for developing effective models to predict changes in radiation around nuclear facilities. In the future, it will be important to continue to improve the accuracy of the model while also considering the appropriate amount of training data and the speed of calculation for quick response in the event of an emergency.

Acknowledgments

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