포항가속기연구소
POHANG ACCELERATOR LABORATORY

11TH INTERNATIONAL WORKSHOP ON RADIATION SAFETY AT SYNCHROTRON RADIATION SOURCES ( RADSYNCH23)

# Predicting 3D Radioactivity Distribution in Large-scale Structures Using Machine Learning Techniques

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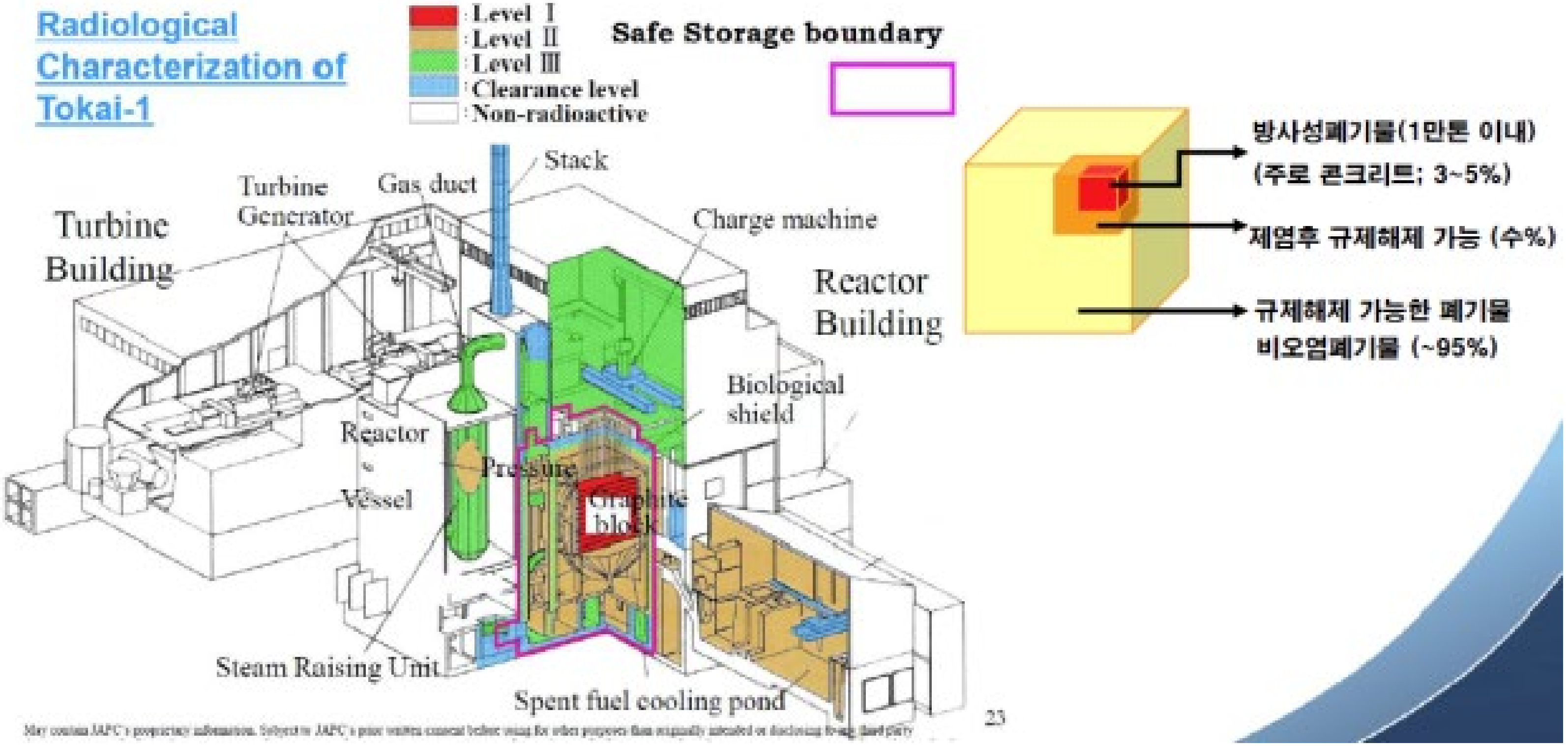
# Outlines

- **Introductions**
- **Methods**
  - Convolutional Neural Network (CNN)
  - Data generation for machine learning
- **Results**
  - Comparison of machine learning model
- **Future works**
- **Conclusions**

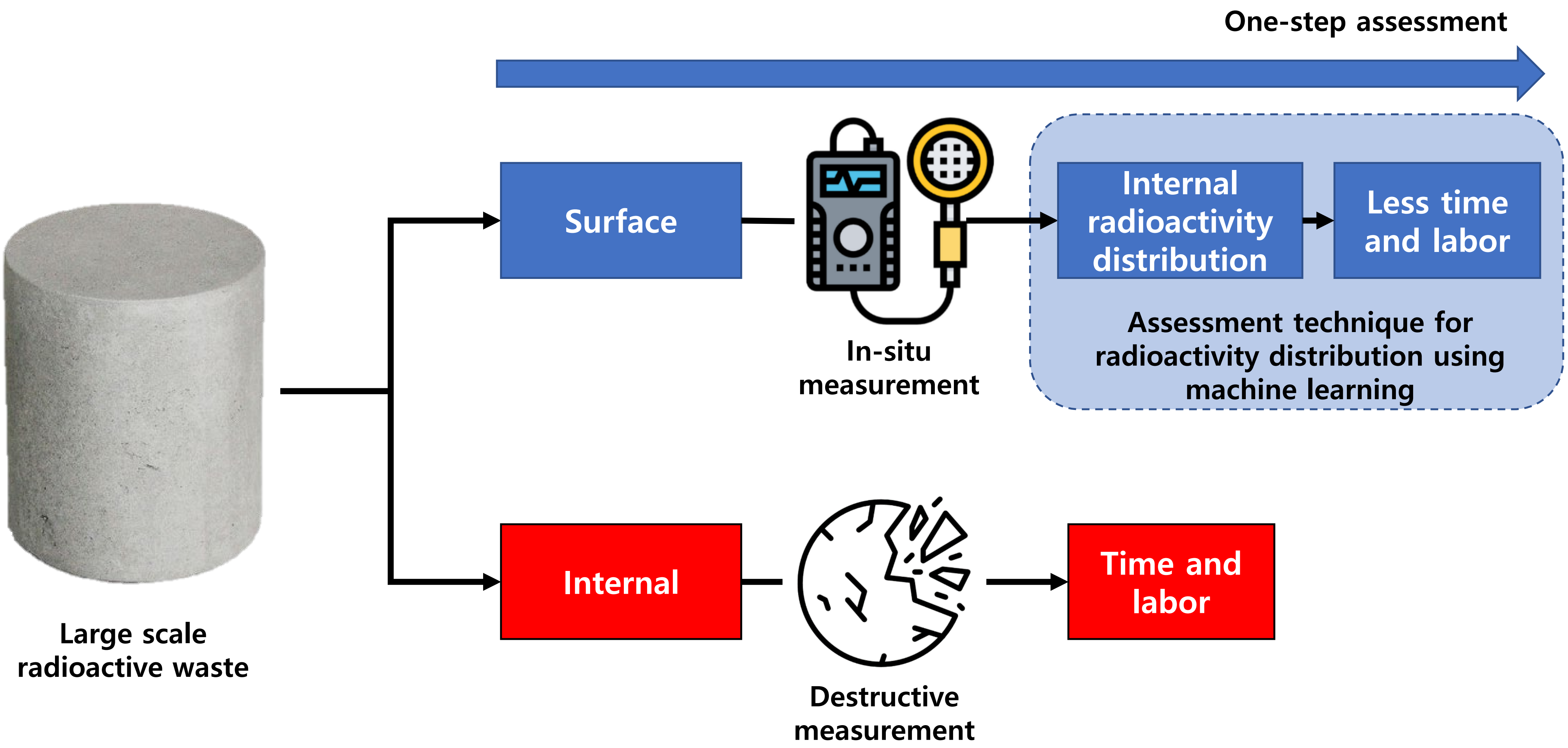
# Introductions

- The radioactive wastes are generated during decommissioning of nuclear facilities
- The amount of concrete block is dominant, and its activated part is small.
- Classification and disposal of radioactive wastes are important.
  → direct related with the cost of decommissioning



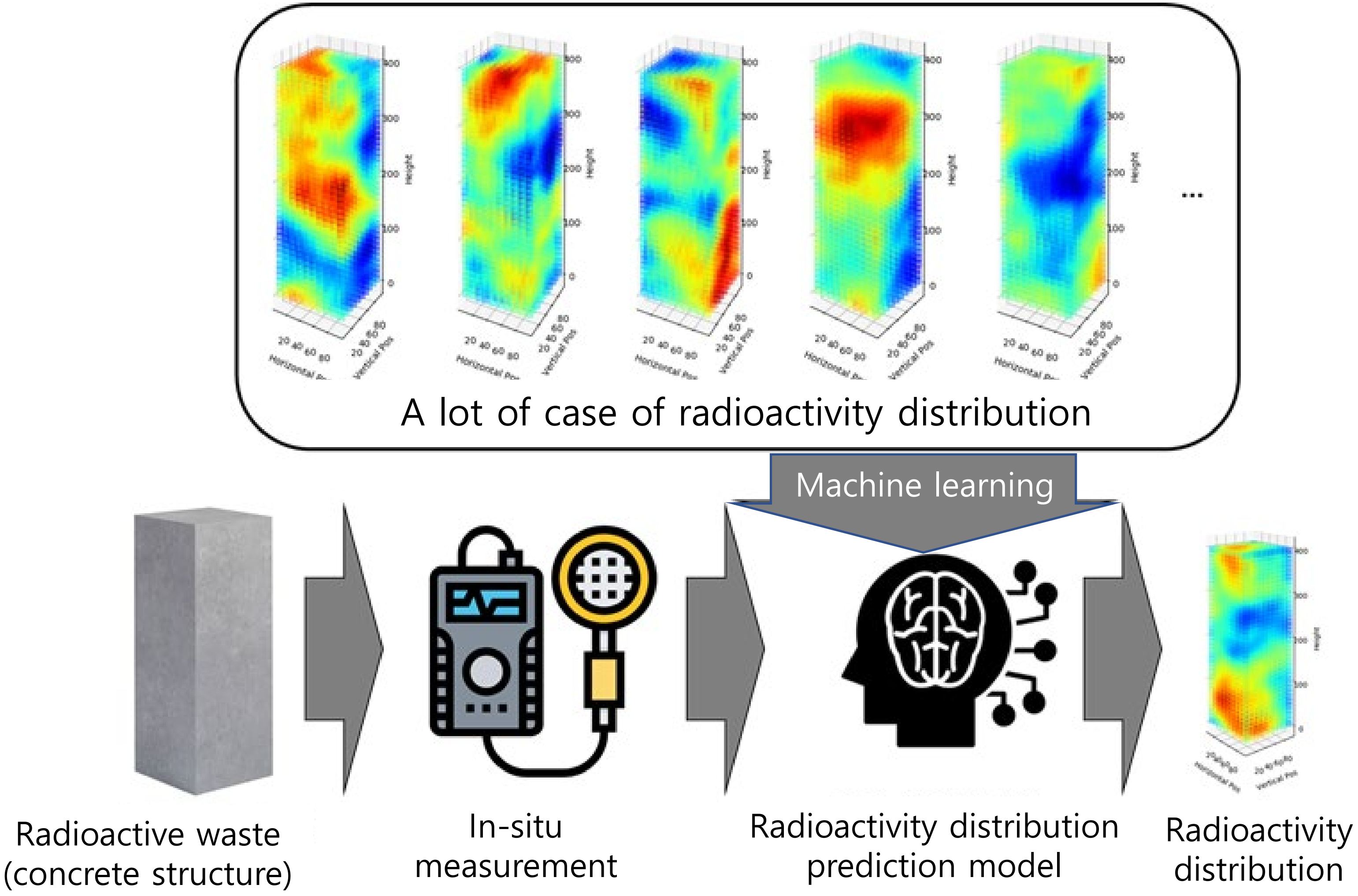
# Introductions





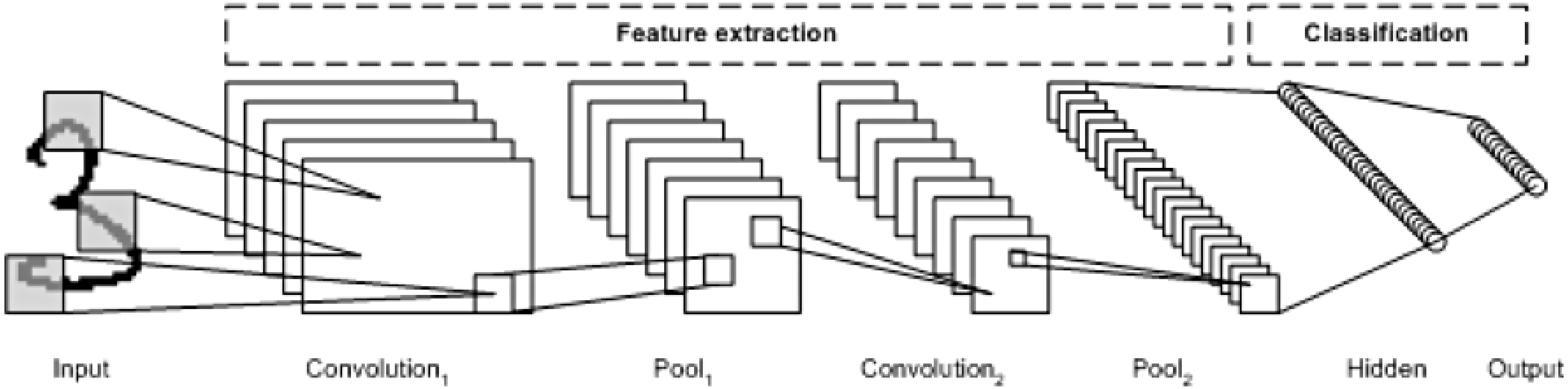
# Introductions

- **The concept of distribution assessment with machine learning**



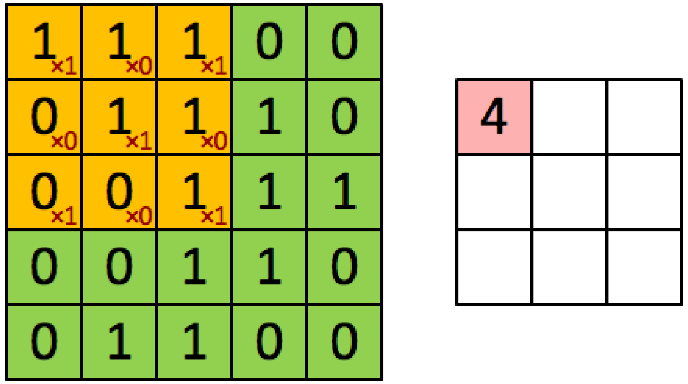
# Introductions

- **Convolutional Neural Network (CNN)**




**Learning with keeping spatial information of image**

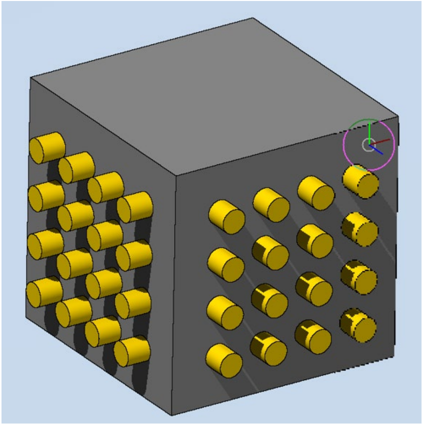
- ➢ Maintaining the shape of the input/output data of each layer
- ➢ Effective recognition of features with adjacent images while maintaining spatial information of images Image feature extraction and learning with multiple filters
- ➢ Pooling layer that collects and enhances the features of the extracted image
- ➢ Since the filter is used as a shared parameter, the learning parameter is very small compared to general artificial neural networks.




Image

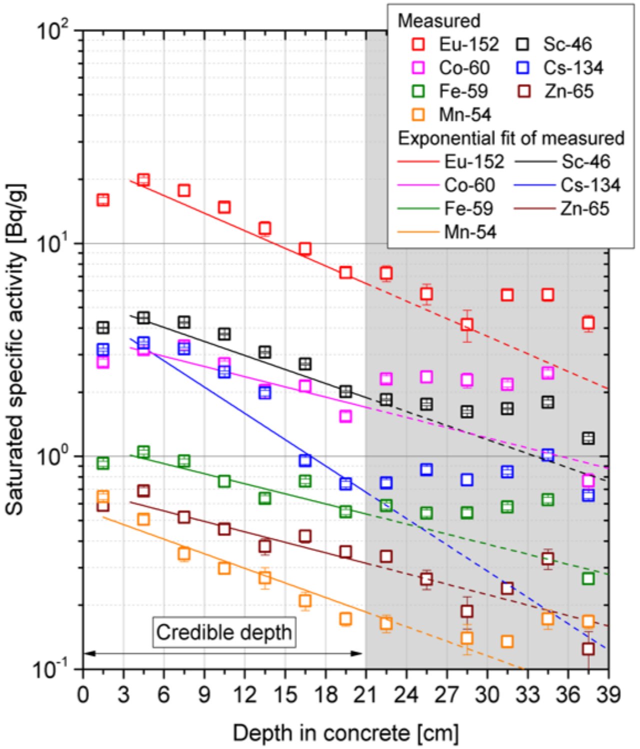
Convolved Feature

- **Learning data generation for feasibility test**



< Concrete structure and detector with using FLUKA 4-1.1>

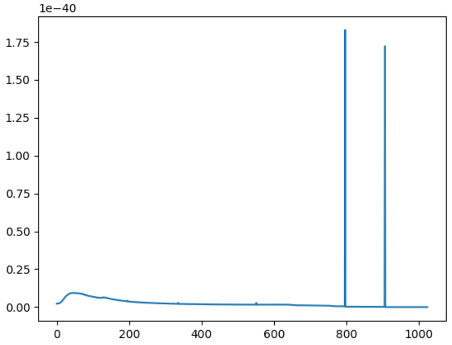
- Length of a side : 50 cm
- Material : concrete
- The number of detector: 16 per side surface (total 64)
- Radius of detector: 2.5 cm
- Height of detector: 5 cm



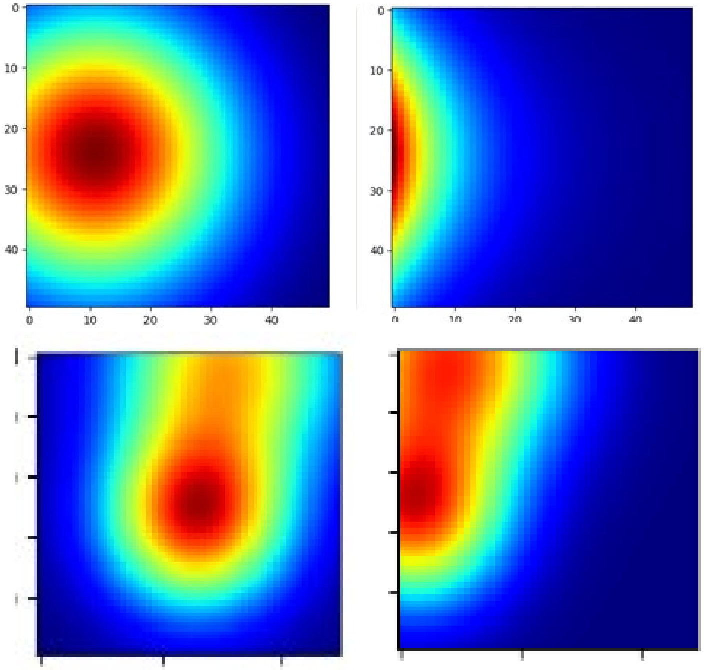

<Internal distribution of radionuclides in concrete structure>

$$f(x,y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{(x,y)-\mu}{\sigma}\right)^2}$$

<Surface distribution: Gaussian distribution>

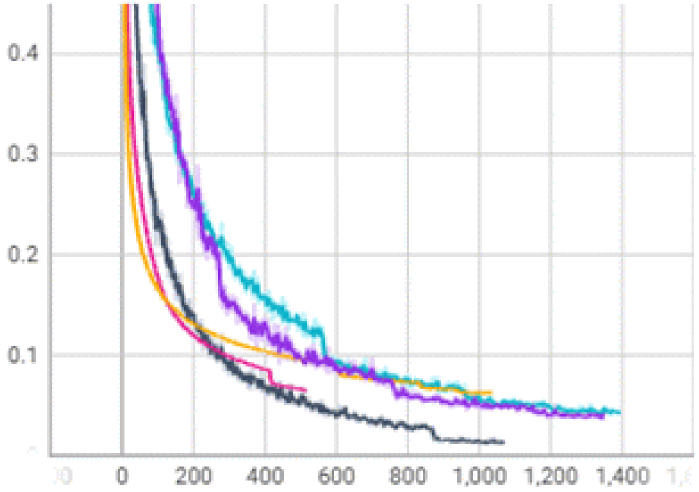


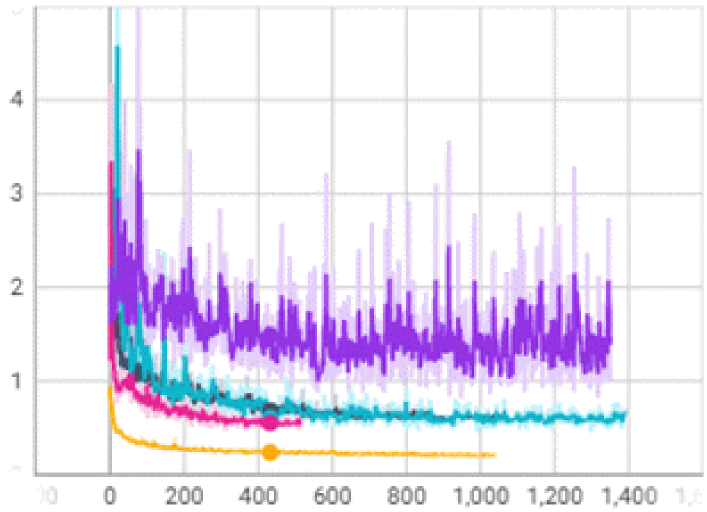
< Co-60 energy spectrum (1.17, 1.33 MeV) )>



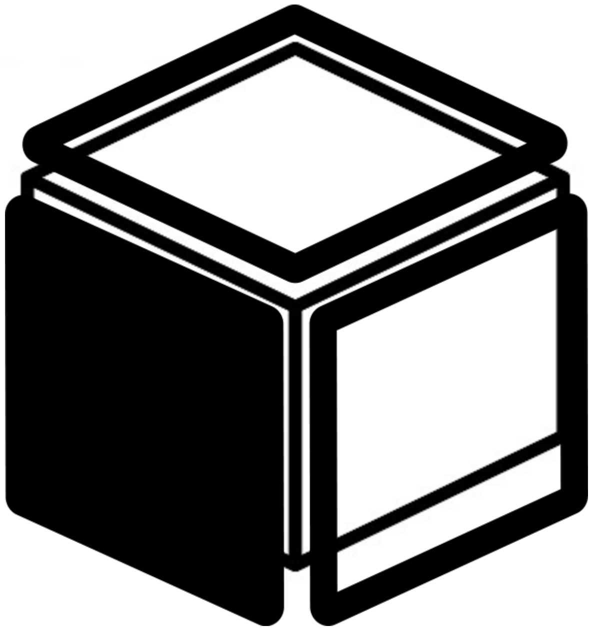
< The examples of source distribution; one source (up), two sources (down), XY view (left), YZ view (right)>

- **Learning circumstance (GPU) and Epoch**
  - Machine learning is conducted on GPU based PC
  - Two RTX 3090 launched PC : 20,992 cores.
  - The data for machine learning generated by simulation is divided by 8 (training) : 1 (validation) : 1 (test)




<Loss change derived by increasing the number of epochs using machine learning data (left) and loss change derived by increasing the number of epochs using validation data (right)>

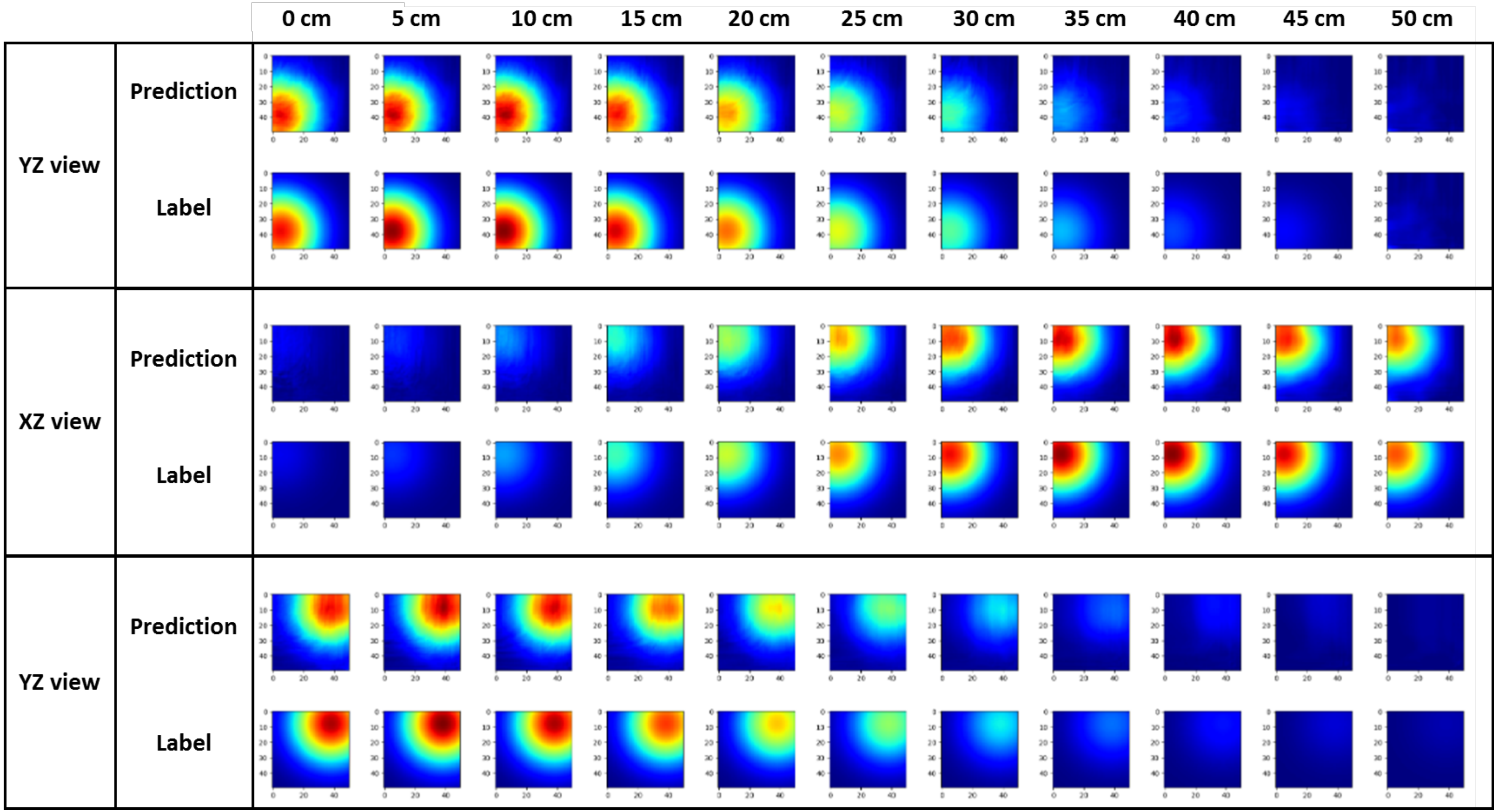


< The method for checking the result: section by each axis>

# Methods



- **Assessment result with 1 source distribution (MSE: 2.33E-06)**



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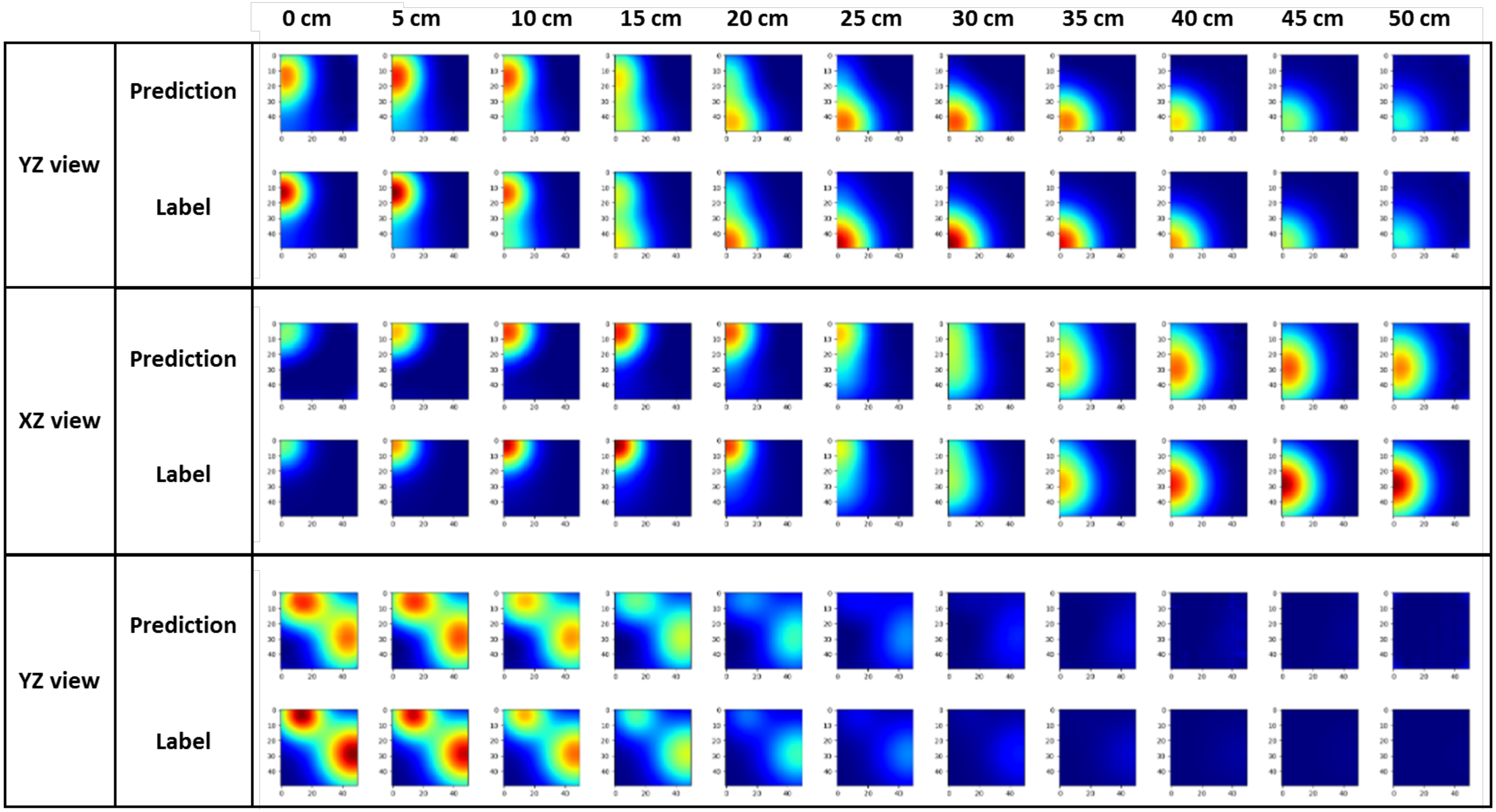
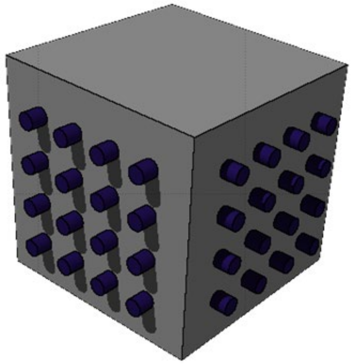
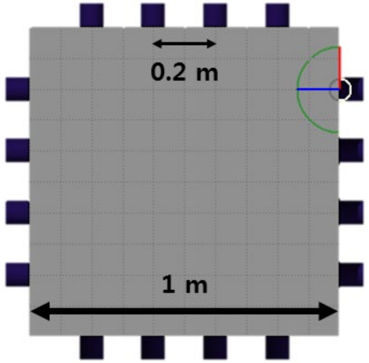
- **Assessment result with 2 source distribution (MSE: 6.84E-06)**



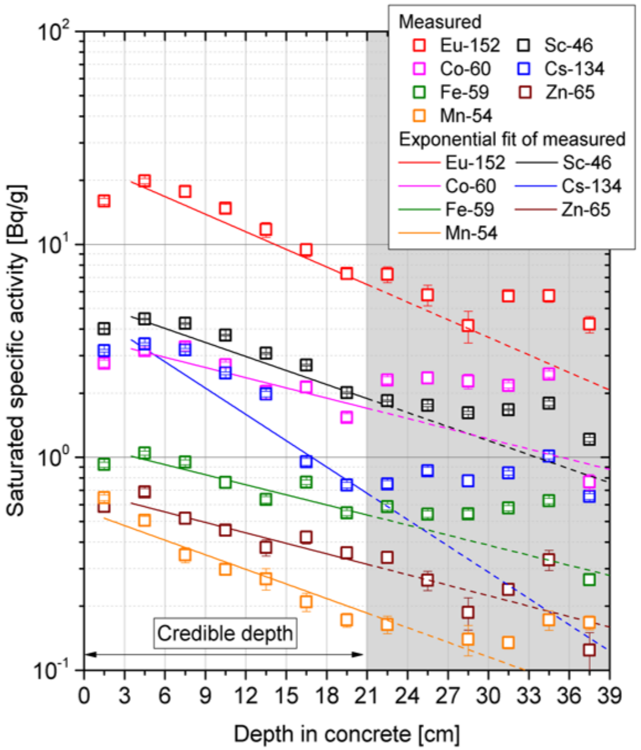
- **Machine learning data**






< Concrete structure and detector with using FLUKA 4-1.1>

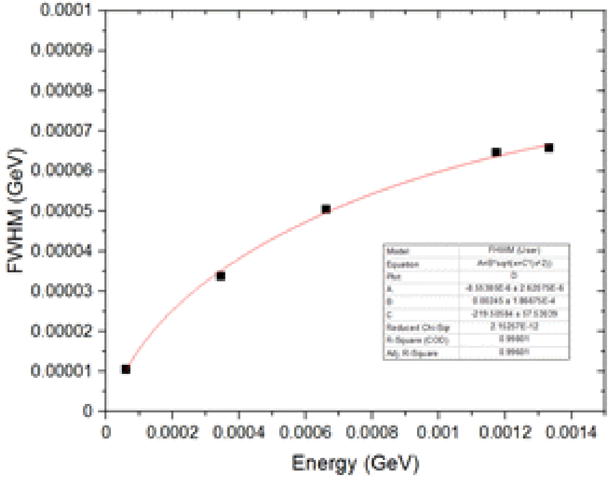
- ➢ Length of a side : 100 cm
- ➢ Material : concrete
- ➢ The number of detector: 16 per side surface (total 64)
- ➢ Radius of detector: 2.5 cm
- ➢ Height of detector: 5 cm

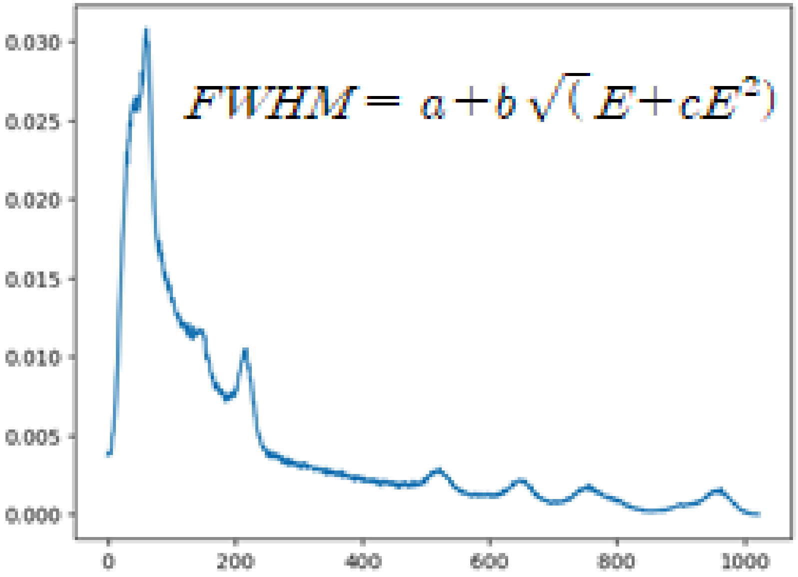



<Internal distribution of radionuclides in concrete structure>

$$f(x,y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{(x,y)-\mu}{\sigma}\right)^2}$$

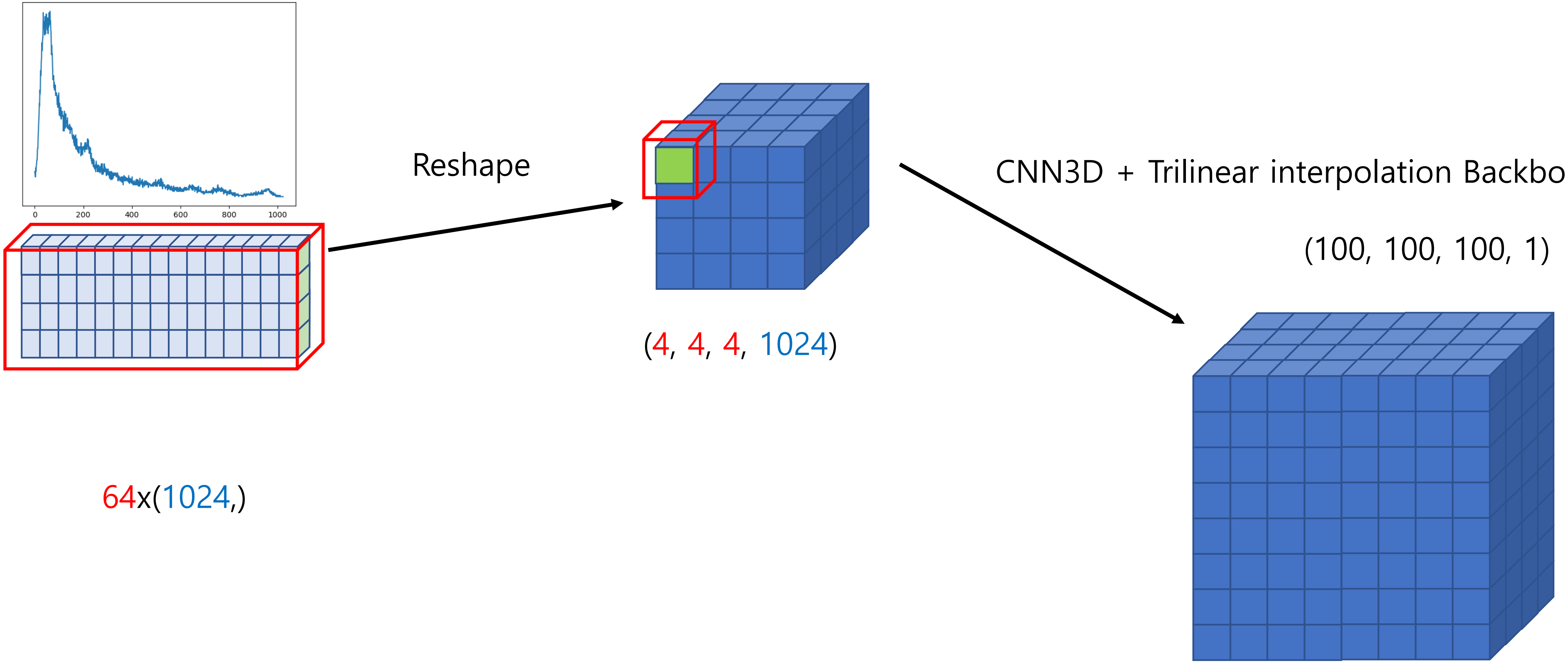
<Surface distribution: Gaussian distribution>



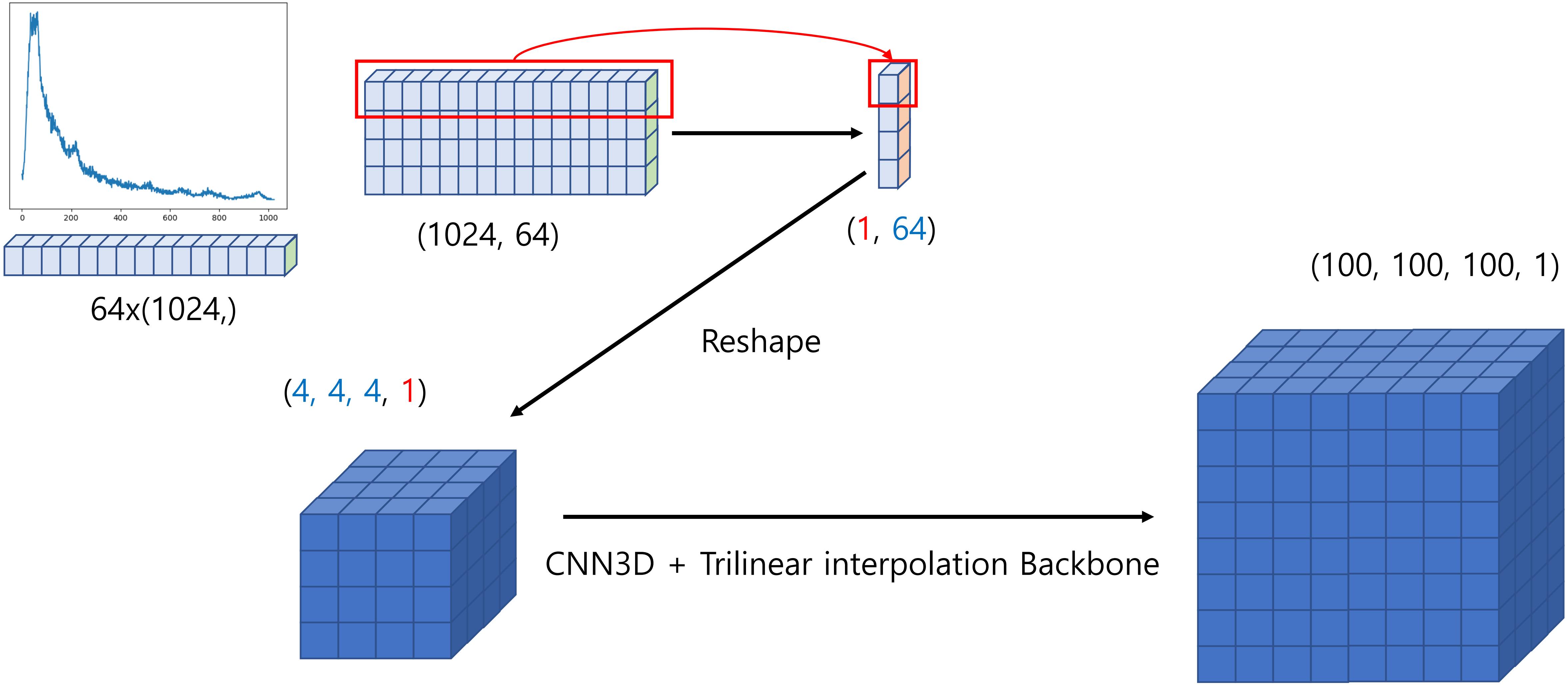
# Methods

- **Whole spectrum data directly (passthrough)**



# Methods

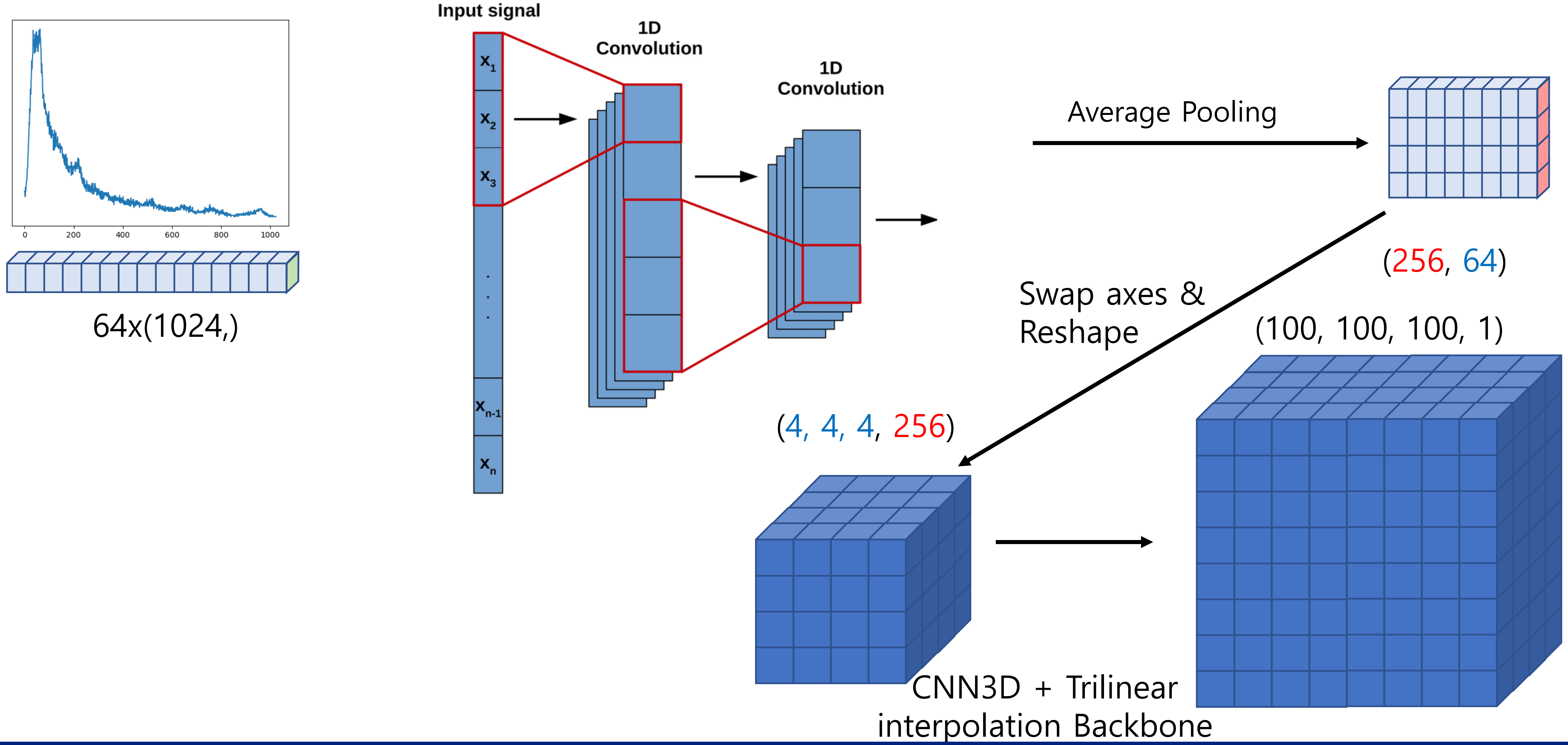
- **Summing whole spectrum data (simple sum)**



# Methods



- **Learning the shape of spectrum (CNN 1D)**



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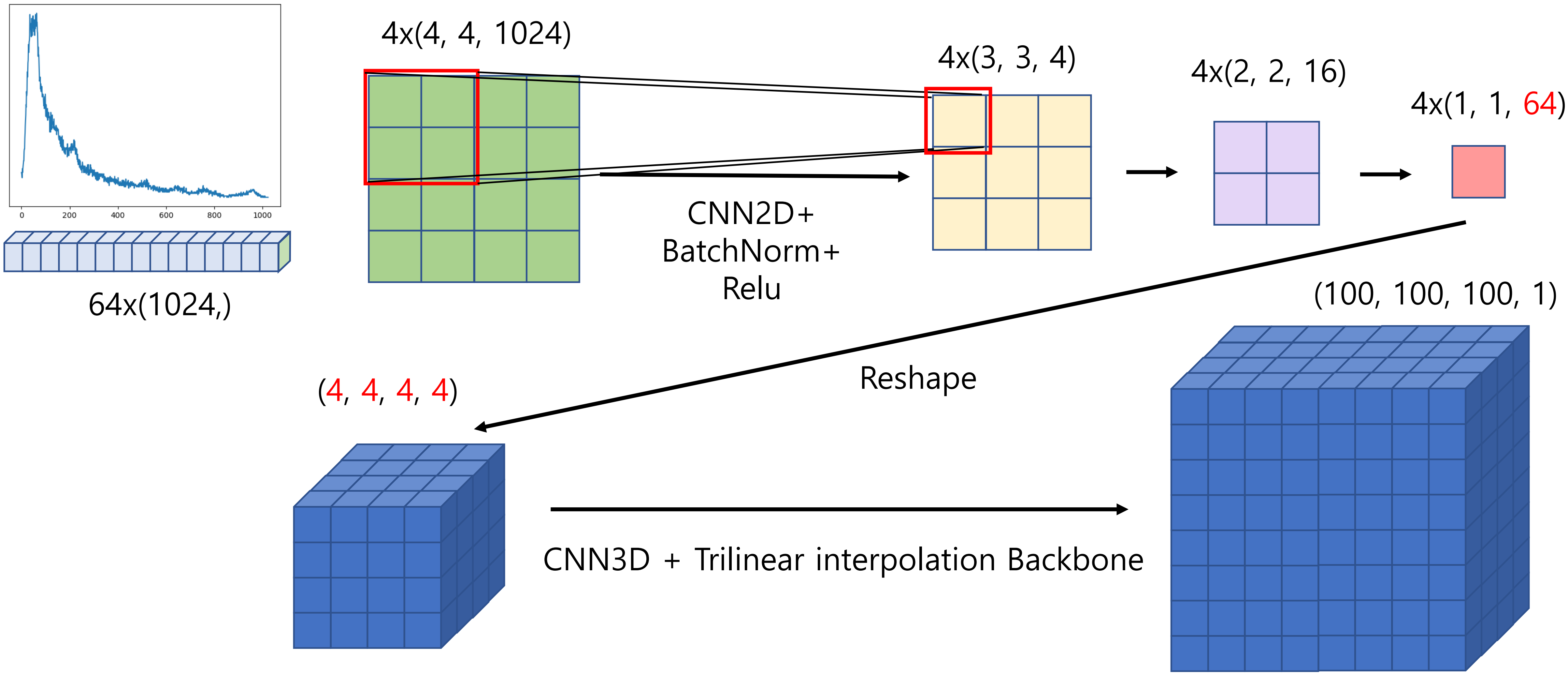
- **Learning the relation between each side detector (CNN 2D)**

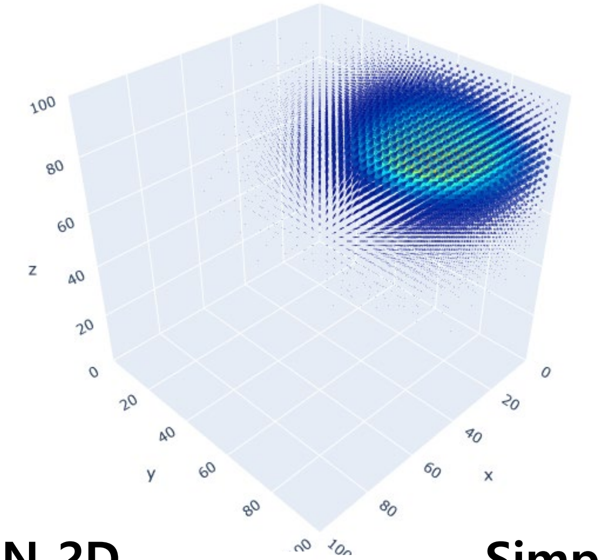


# Results

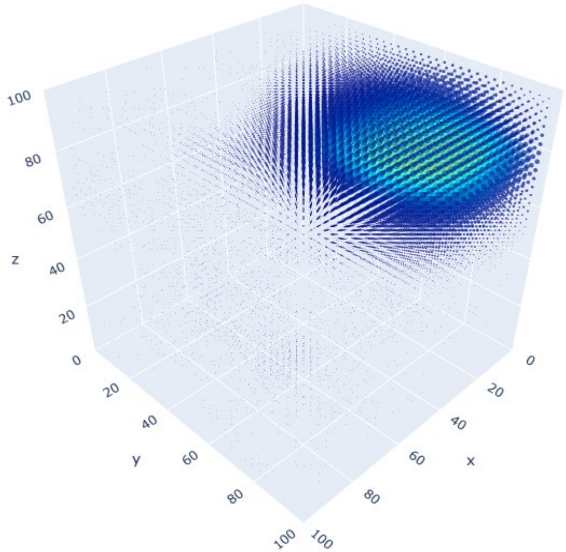


- **Overall distribution check**
  - Random case #1

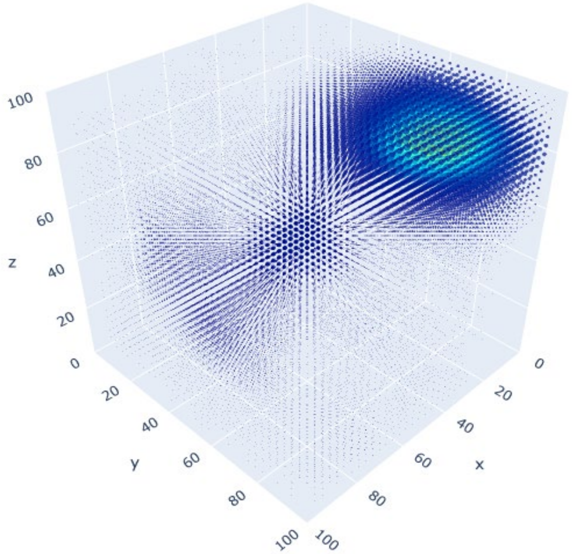
**Label distribution**



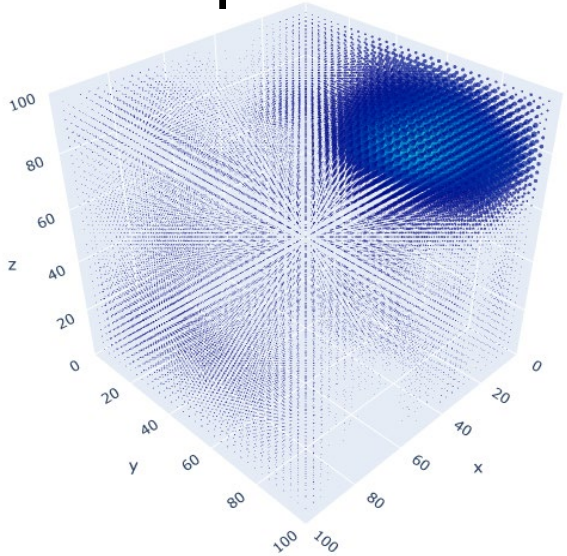

**CNN 1D**



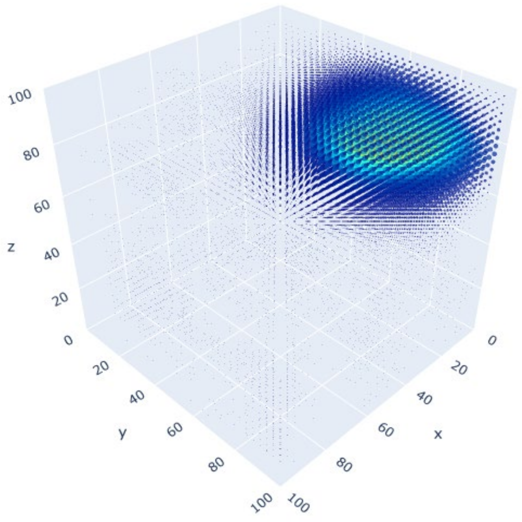

**CNN 2D**




**Simple sum**



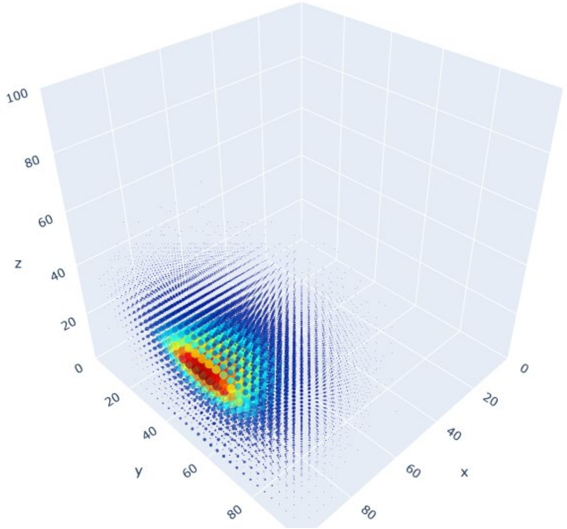

**passthrough**



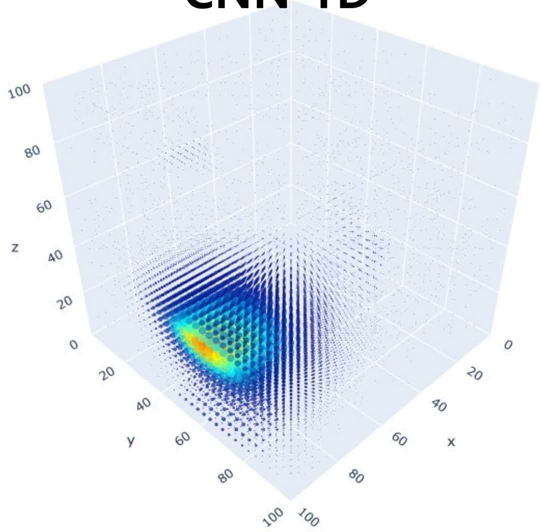
# Results

- **Overall distribution check**
  - Random case #2

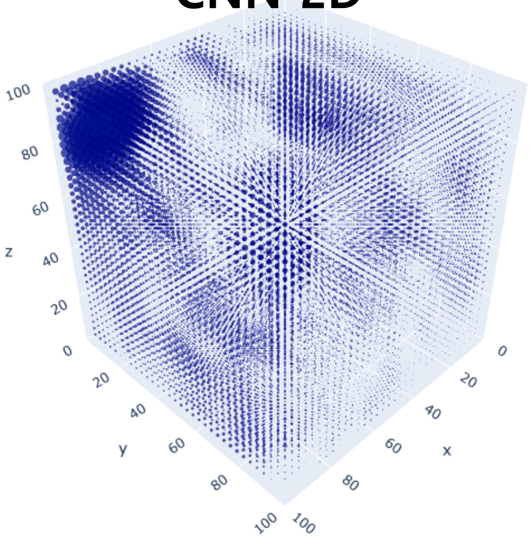
**Label distribution**



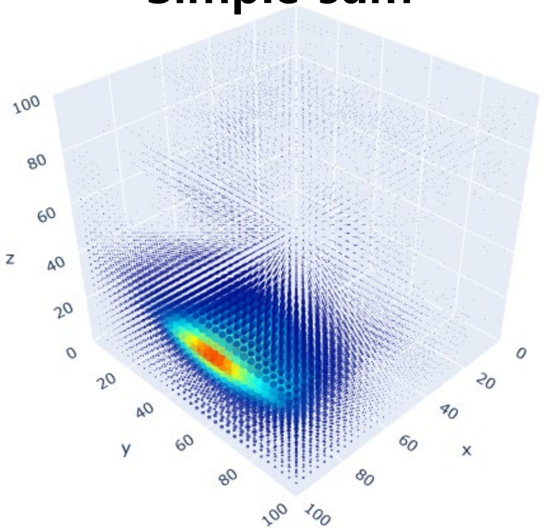

**CNN 1D**



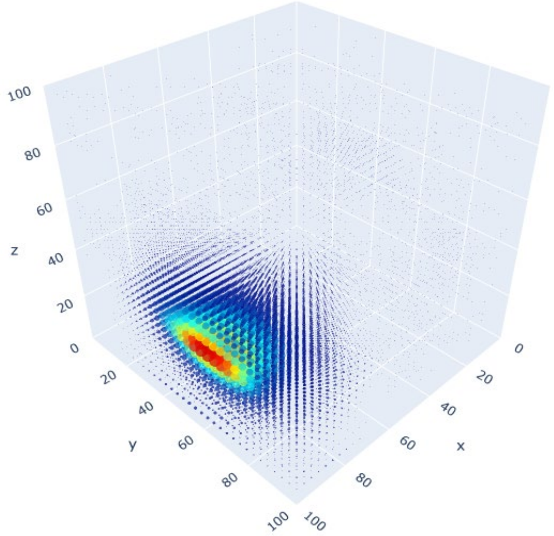

**CNN 2D**




**Simple sum**




**passthrough**



# Results

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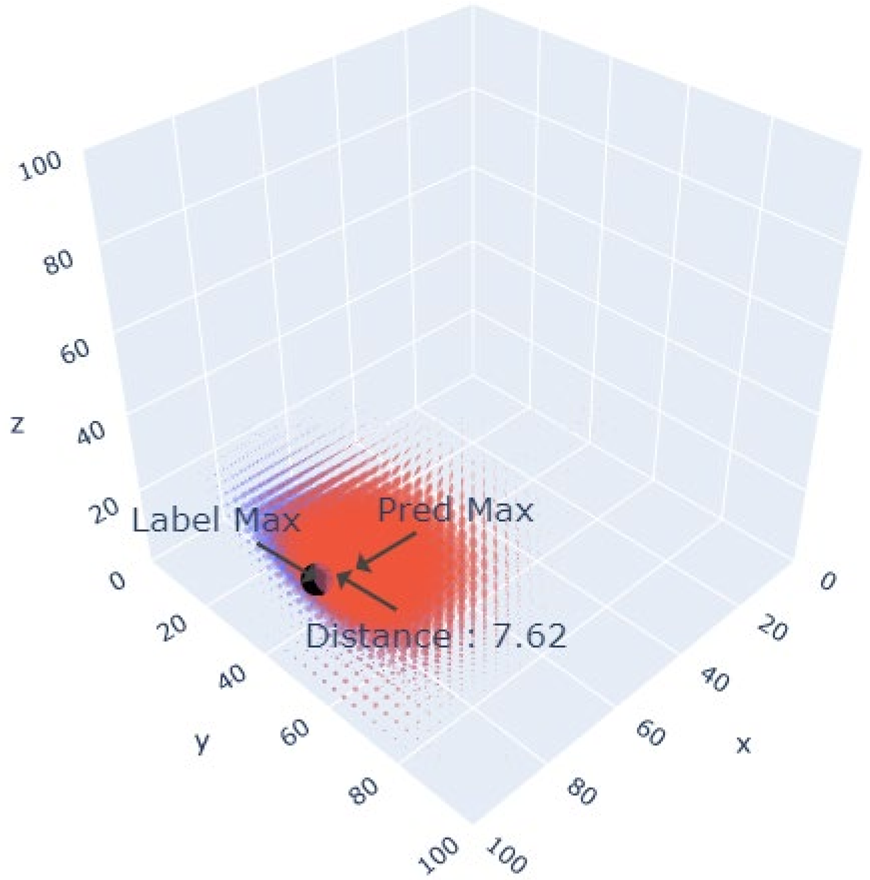
- The quantitively analysis for each machine learning result (CNN 1D, CNN 2D, passthrough, simple sum).
- 5425 data set for constructing evaluation model, 603 data set for evaluating result.
- Evaluation factor for machine learning result.
  - The location of maximum point of distribution
  - Intensity of maximum point
  - Sigma value for Gaussian distribution

# Results

- **Maximum point of distribution**
  - Distance between position distance of label data and prediction data.



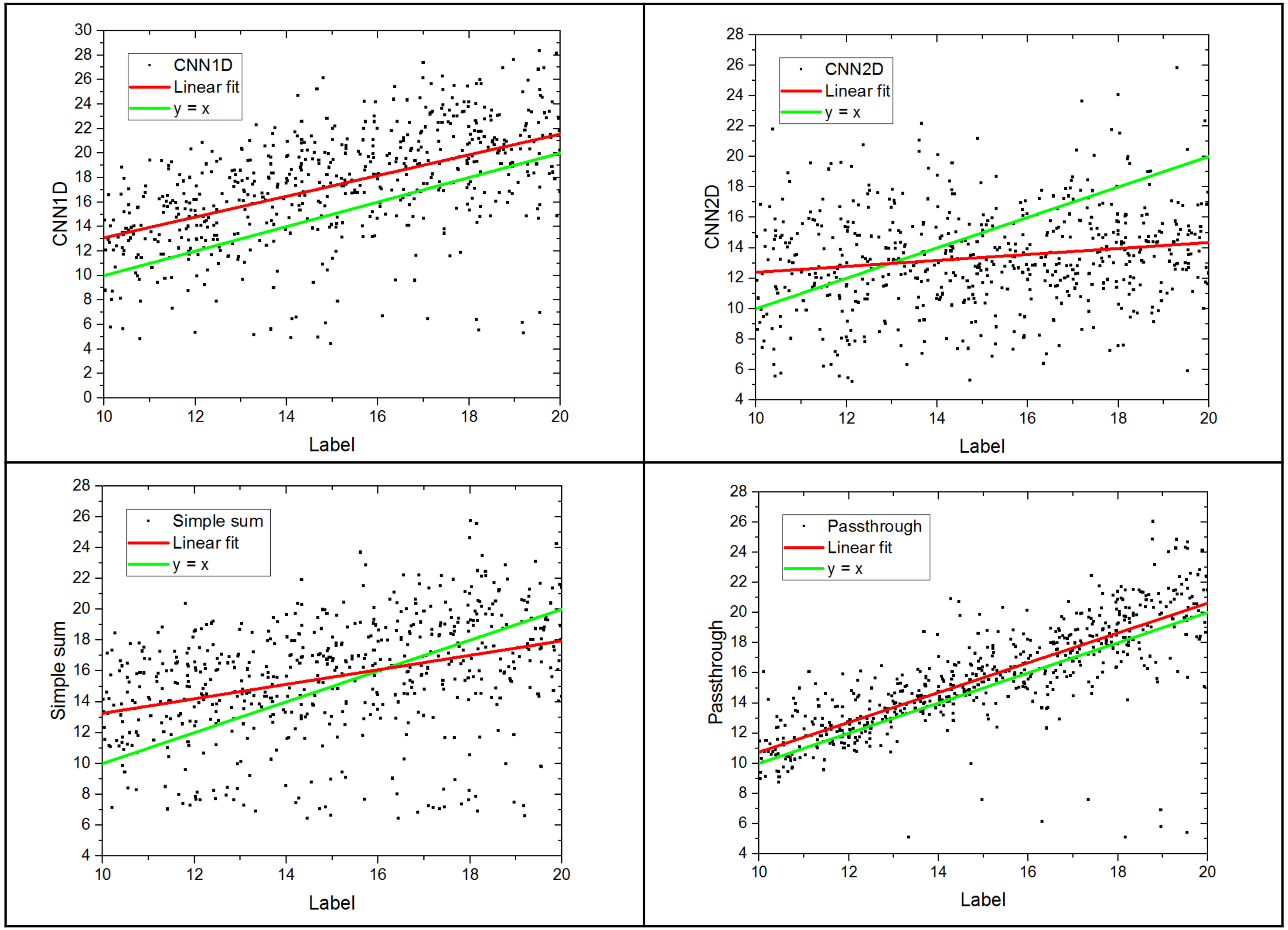

<Average distance and standard deviation between label data and prediction data>

| | Average [cm] | Std. |
|---|---|---|
| CNN 1D | 5.86 | 7.26 |
| CNN 2D | 21.46 | 23.47 |
| Simple S | 6.38 | 3.64 |
| **P.T.** | **2.72** | **1.94** |

# Results



- **Sigma value of Gaussian distribution**



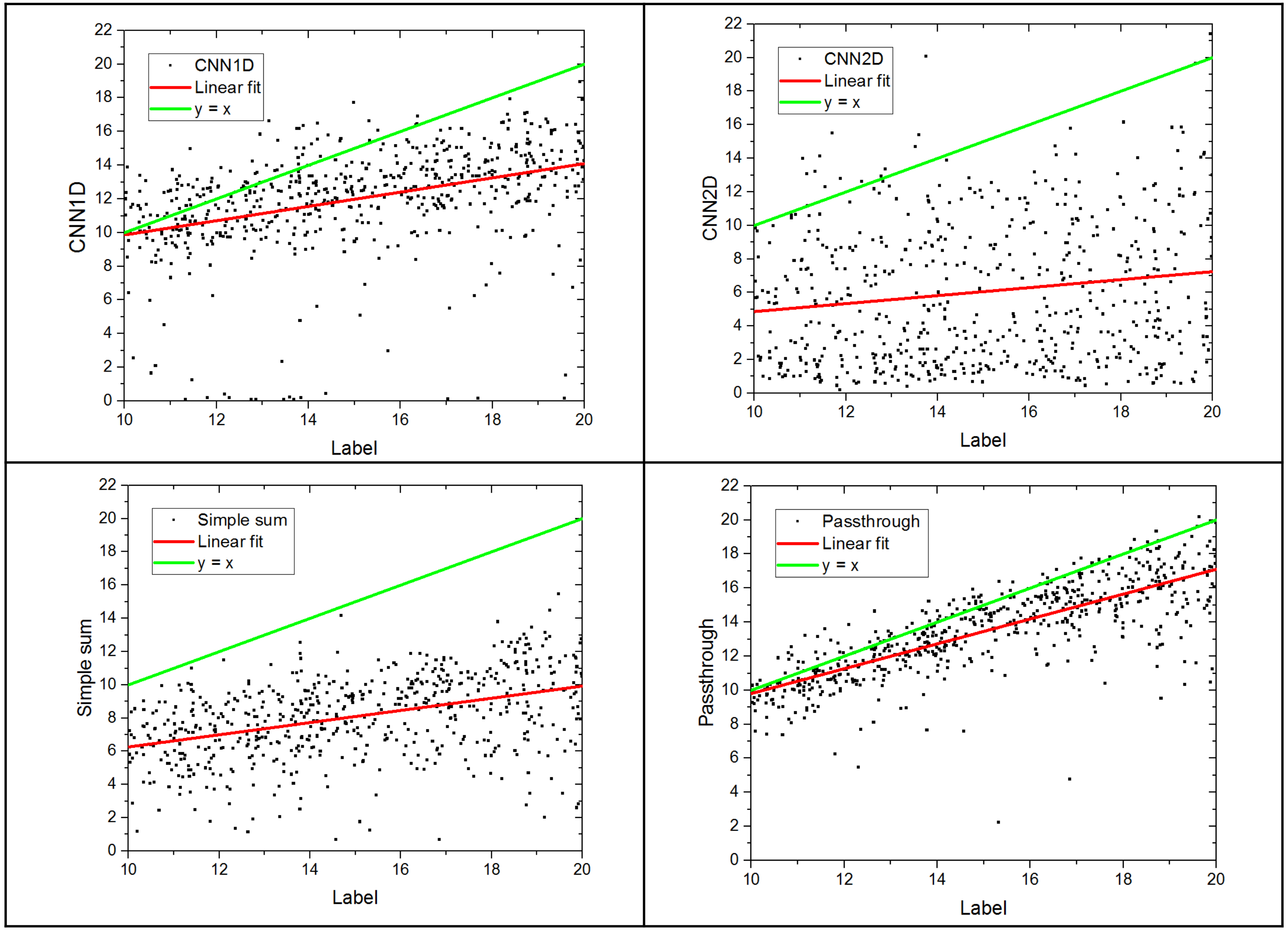

<Slope and $R^2$ value for linear fit curve>

| | Slope | $R^2$ |
|---|---|---|
| CNN 1D | 0.8461 | 0.2803 |
| CNN 2D | 0.1961 | 0.0293 |
| Simple S | 0.4704 | 0.1292 |
| **P.T.** | **0.9881** | **0.6226** |

# Results



- **Intensity of maximum point**




<Slope and $R^2$ value for linear fit curve>

| | Slope | $R^2$ |
|---|---|---|
| CNN 1D | 0.4235 | 0.1524 |
| CNN 2D | 0.2381 | 0.0193 |
| Simple S | 0.3663 | 0.1971 |
| **P.T.** | **0.7302** | **0.6121** |

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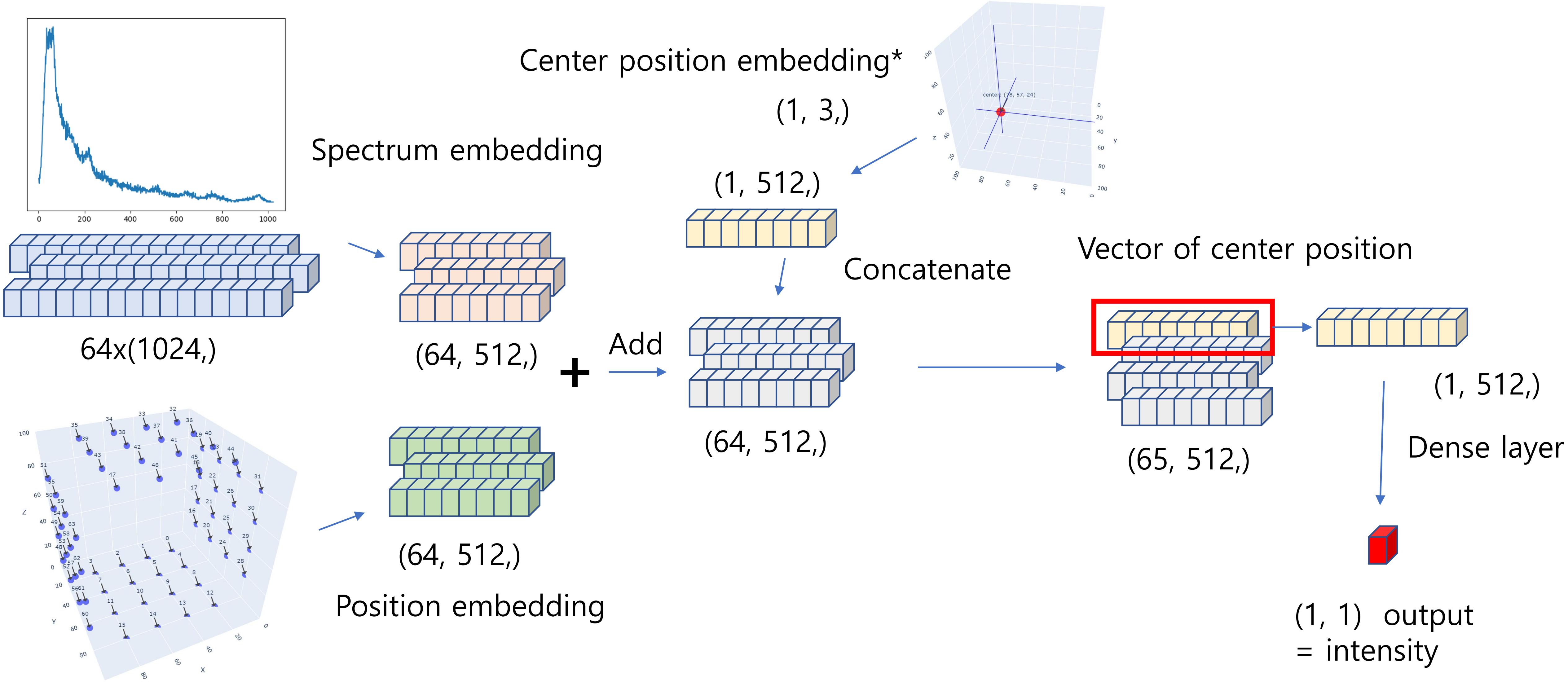
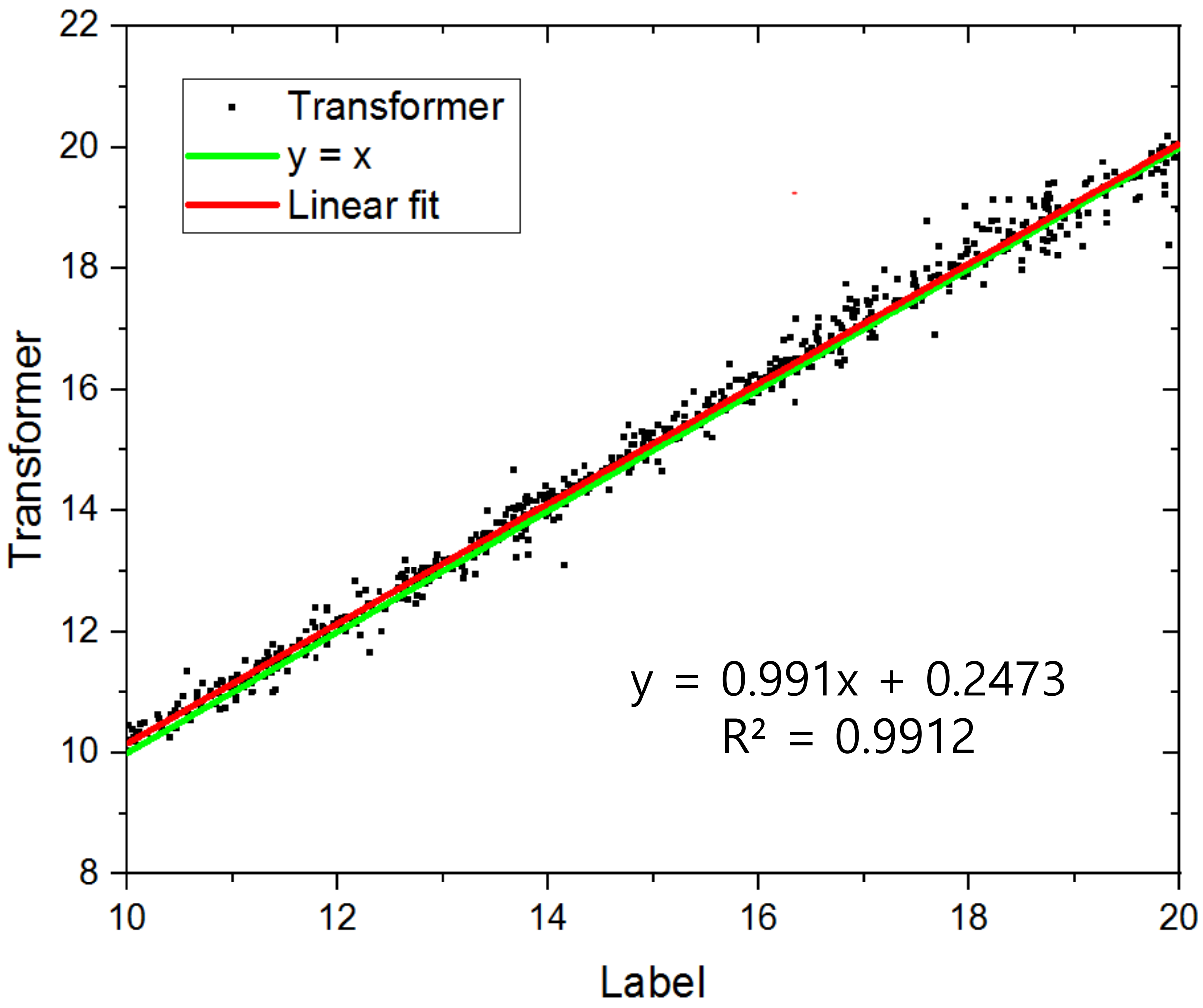
- **Transformer method**



# Results



- **Intensity of maximum point with transformer model**




- **Passthrough**

  → position of maximum point

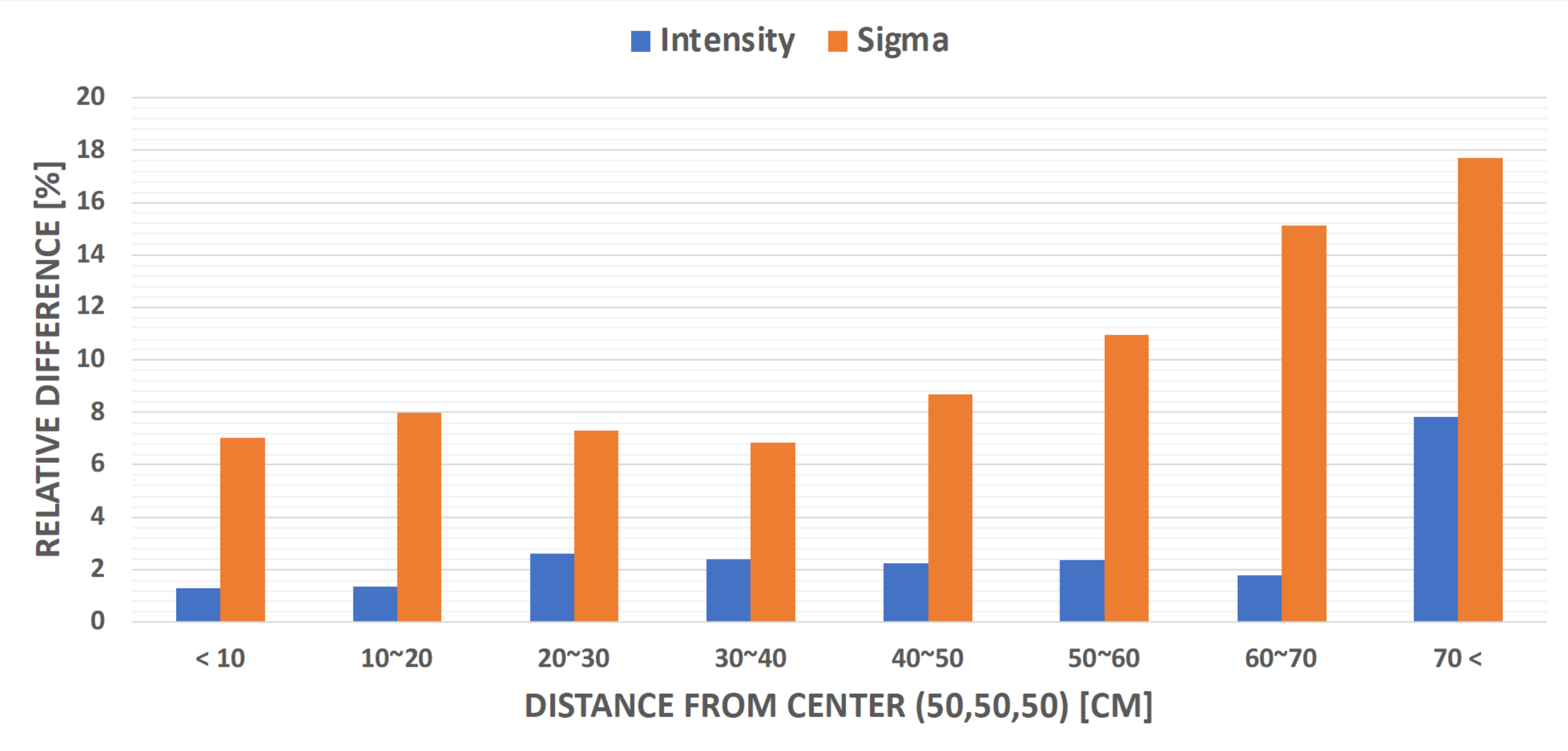
  → sigma value for distribution

- **Transformer**

  → intensity of maximum point

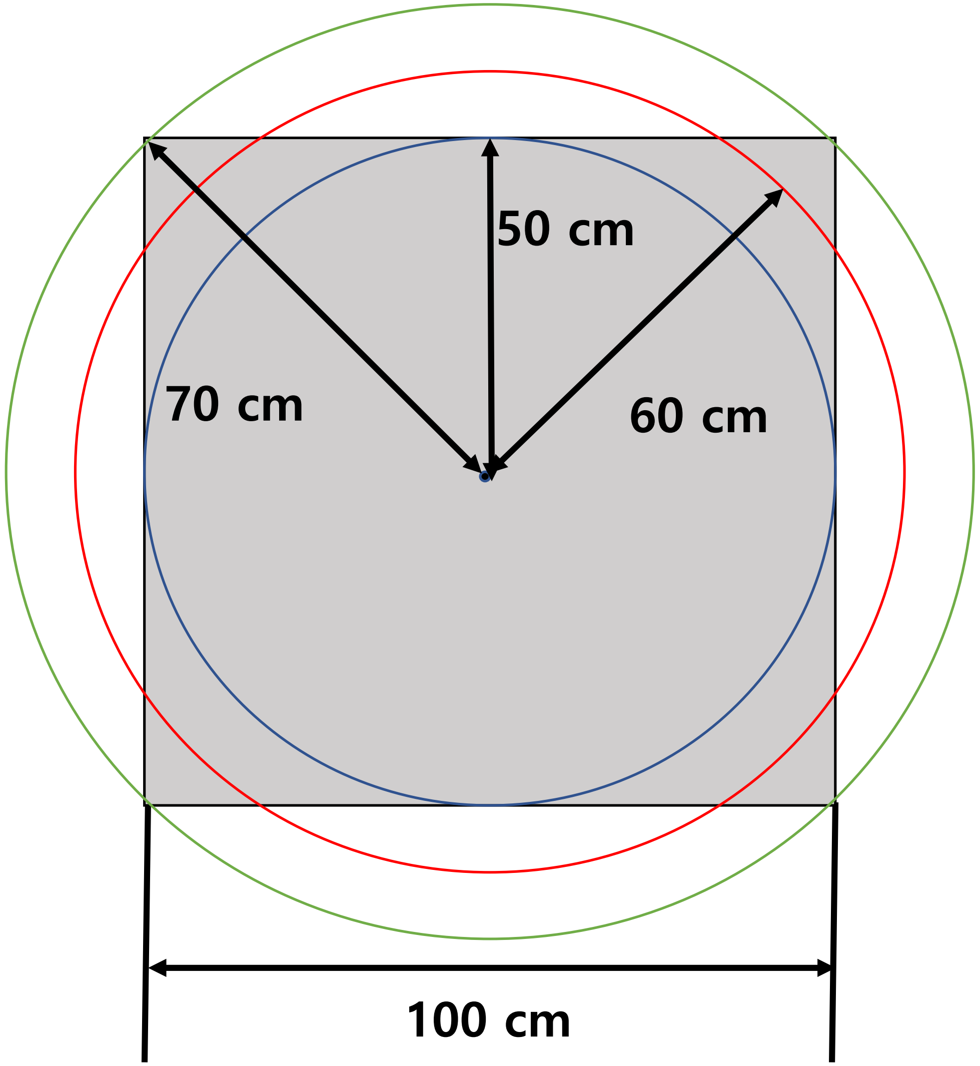
- **Prediction result with distance between center and maximum point of distribution**

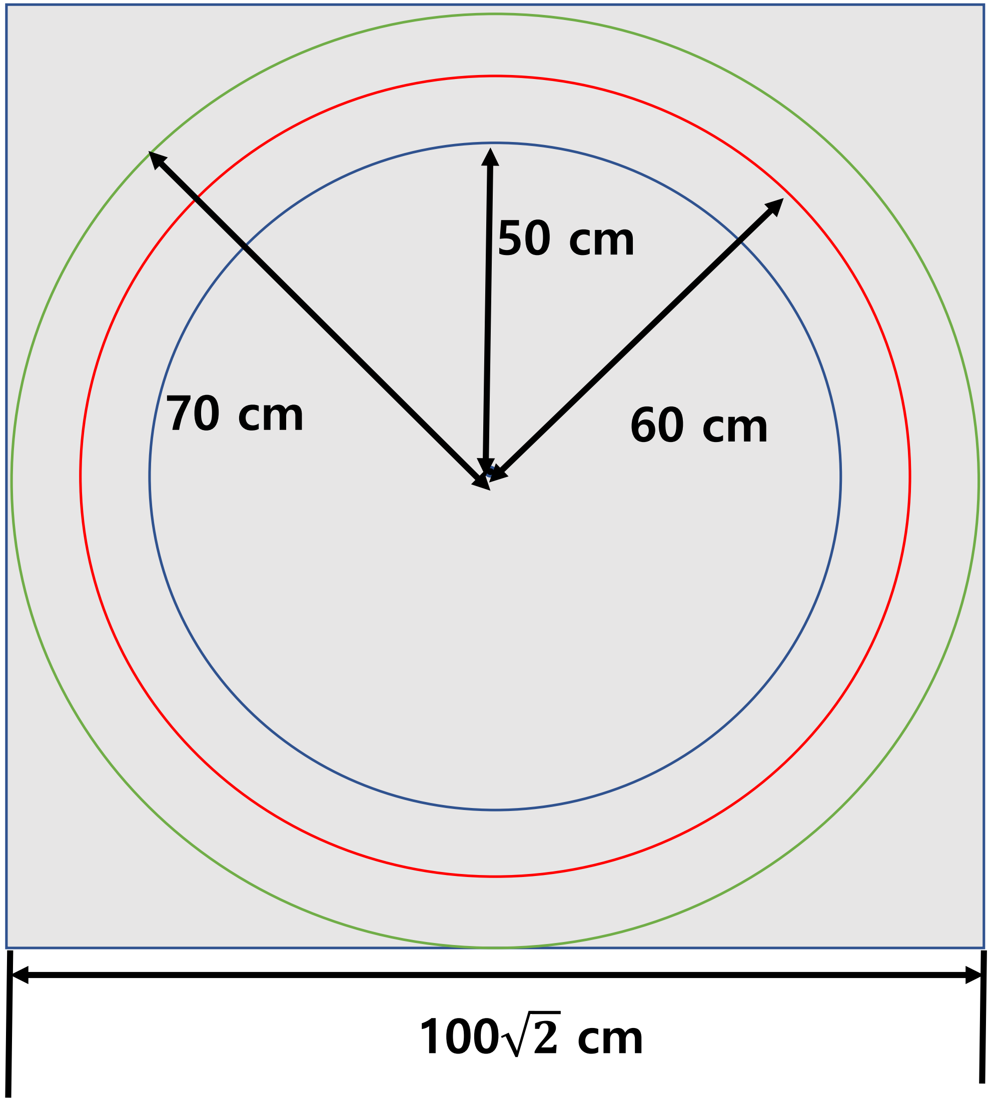
$$\text{Average relative difference} = \left(\sum_{i=1}^{n}\left|\frac{Label_i - Predictioni}{Label_i}\right|\right)/$$



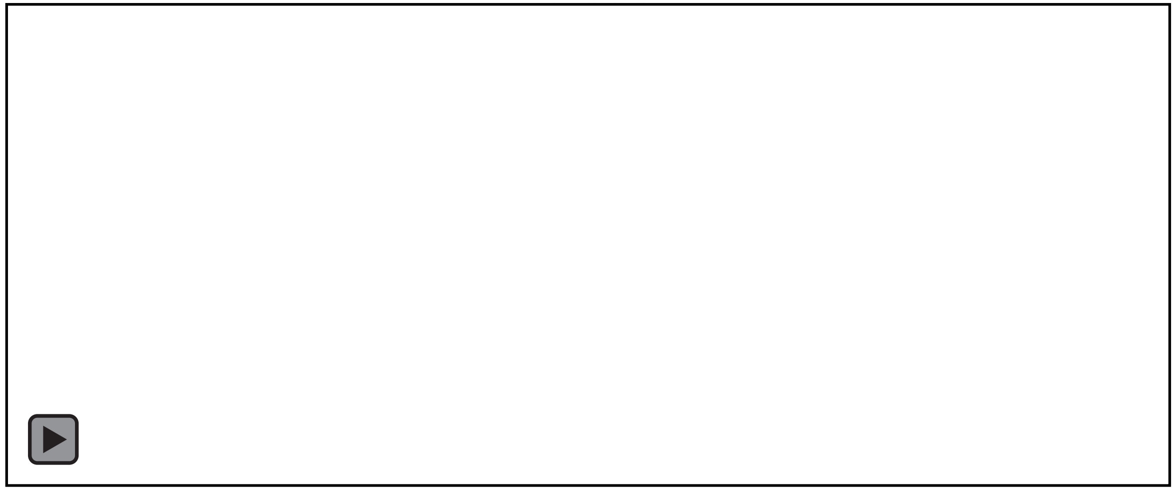
# Results

- **Learning the shape of spectrum (CNN 1D)**

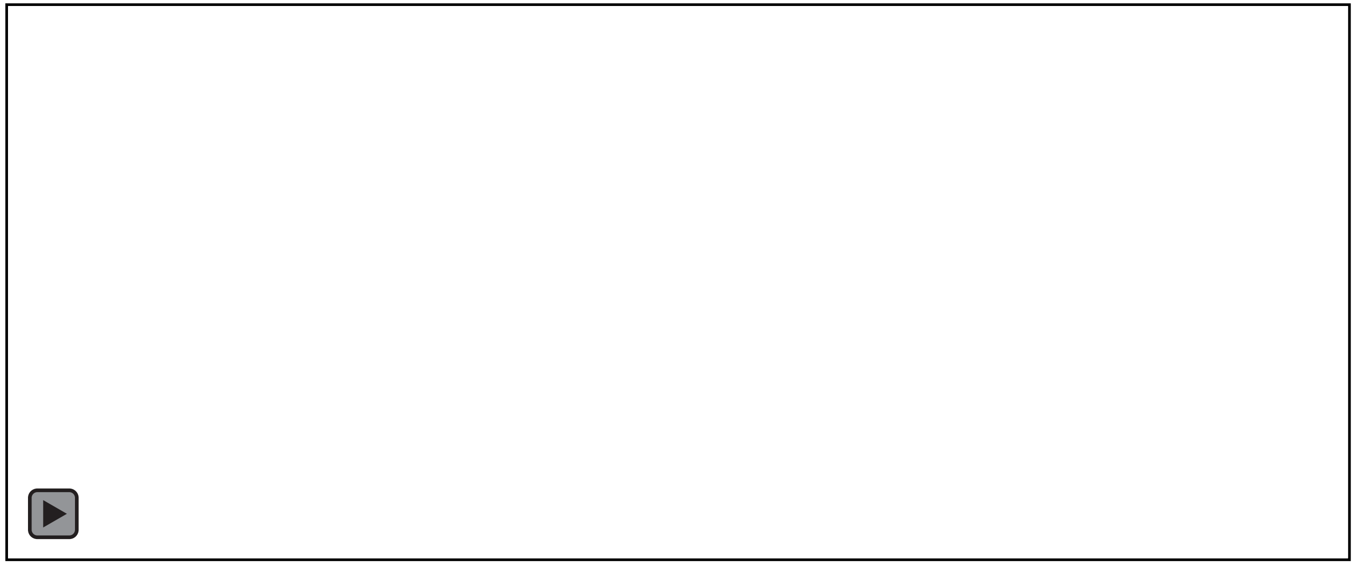


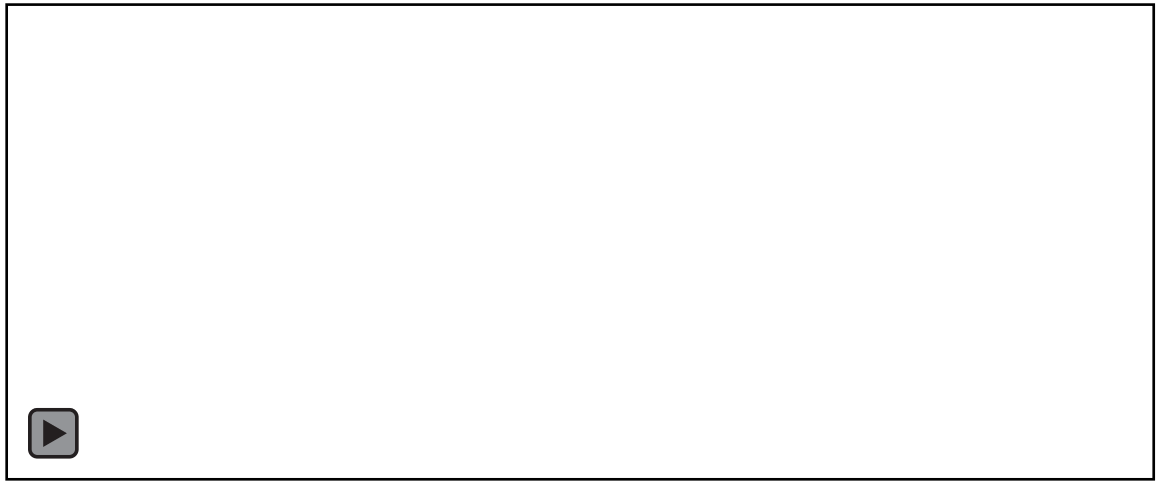



# Results

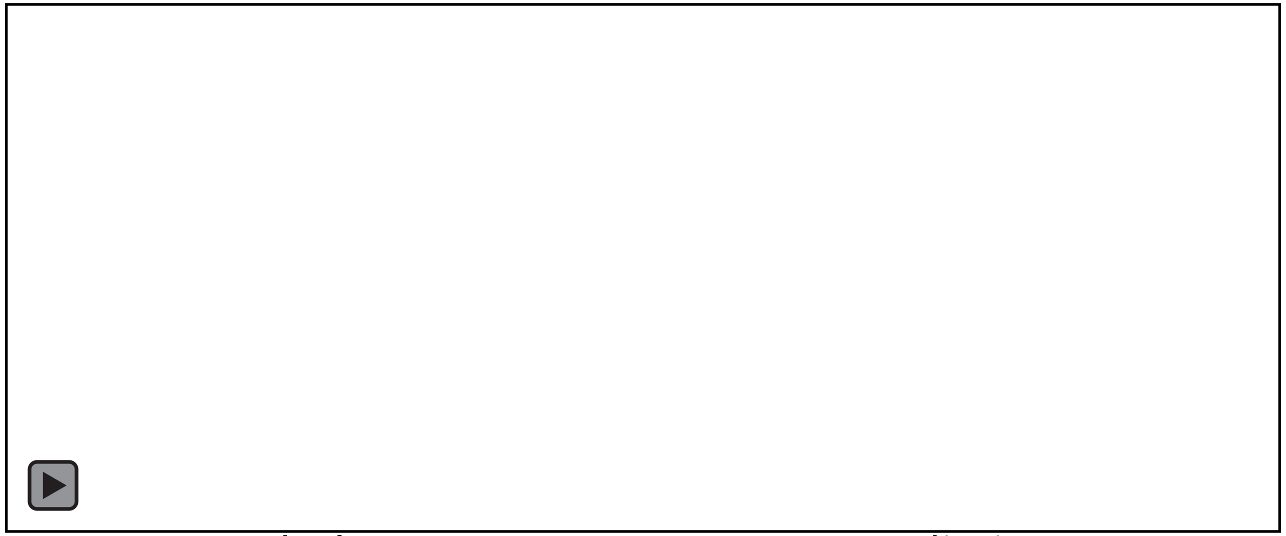


Label Prediction





Label Prediction



Label Prediction

# Conclusions

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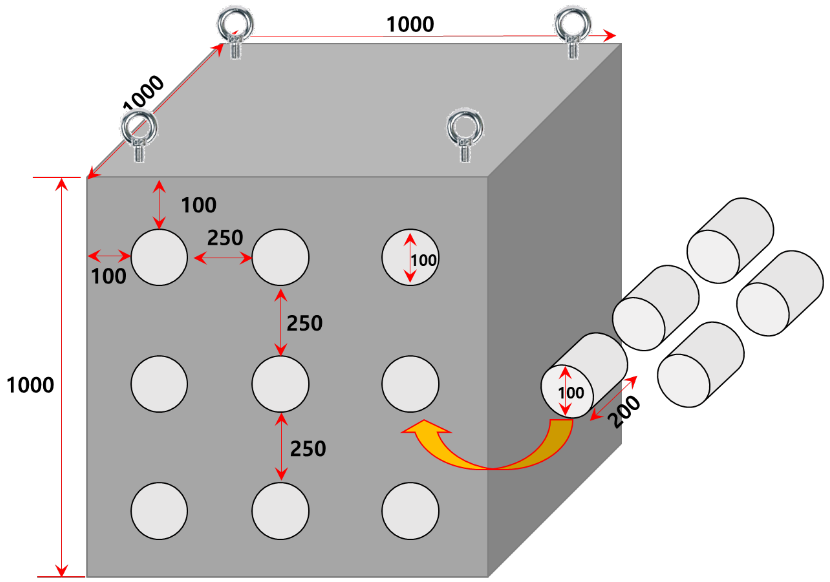
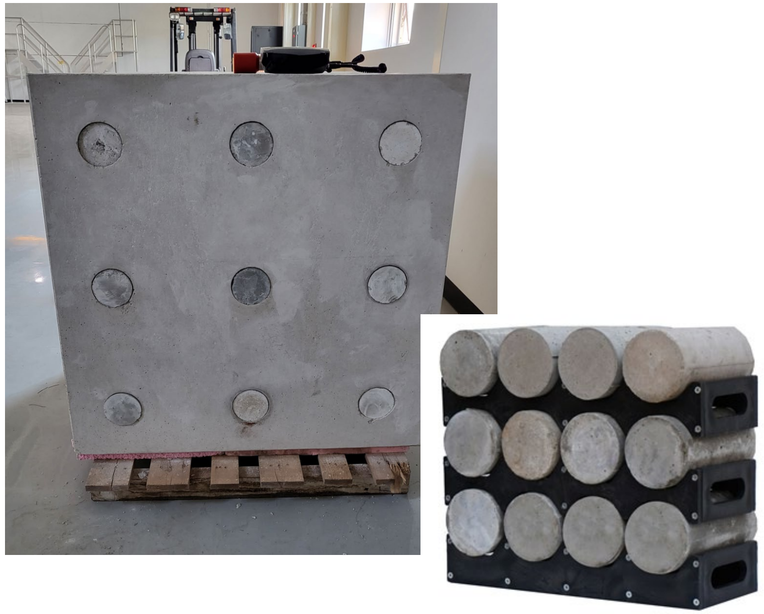
- The prediction of radioactivity distribution using machine learning is suggested.
- The intensity and distribution can be estimated within 10% relative difference.
- The real measured data will be applied using real concrete structure.



# Thank You for Your Attention!