KUMP Lab

A Study on the Prediction of Operating Time of Medical Linear Accelerator Using Machine Learning and Data of TG-100 Based on Risk Assessment

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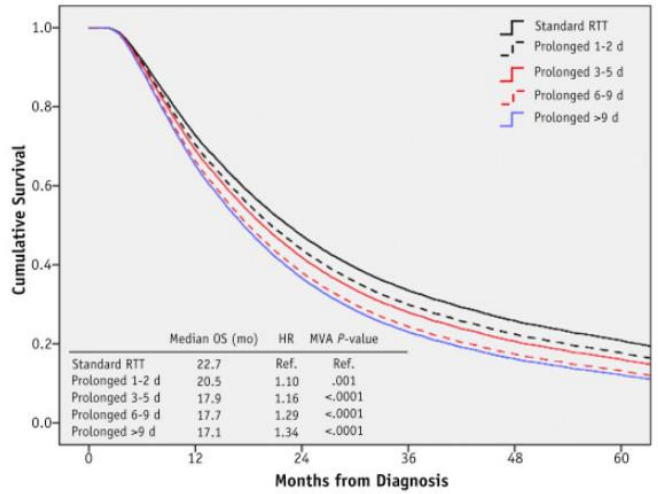
Motivation

Unexpected Medical linear accelerator Failure

❖ Delay treatment time due to downtime

❖ According to reports, The delay in treatment time affects the patient's survival rate



✓ Median Overall Survival

prolonged (Radiation Treatment Time) vs standard (Radiation Treatment Time) (18.6 vs 22.7 months, *P*<.0001)

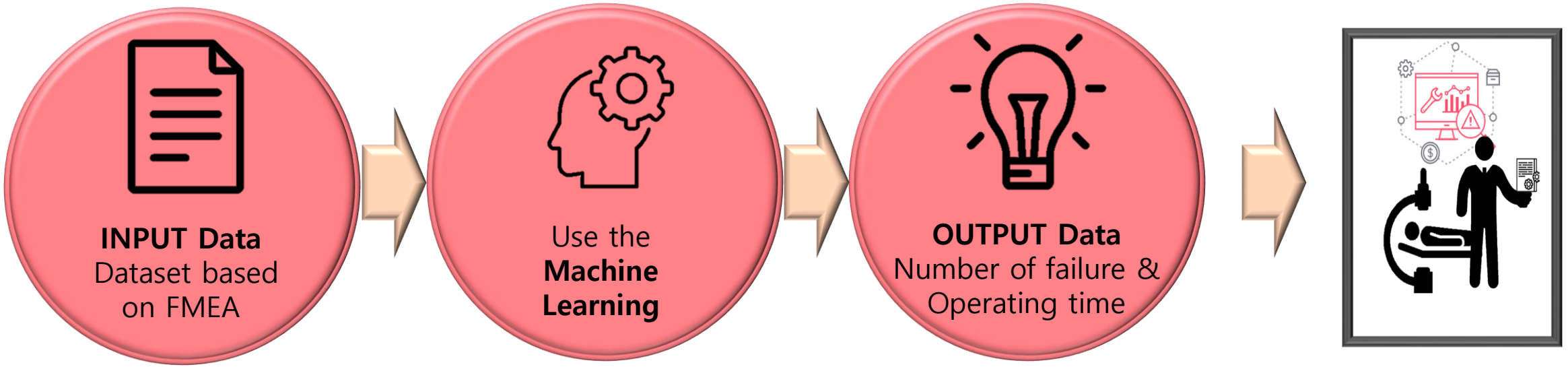
(standard Radiation Treatment Time vs prolonged 1-2 days, 20.5 months, P=.009; prolonged 3-5 days, 17.9 months, *P*<.0001; prolonged 6-9 days, 17.7 months, *P*<.0001; prolonged >9 days, 17.1 months, *P*<.0001)

❖ Configure dataset based on FMEA (Failure Mode Effects Analysis) that can be machine-learning for the medical linear accelerator failure predictions

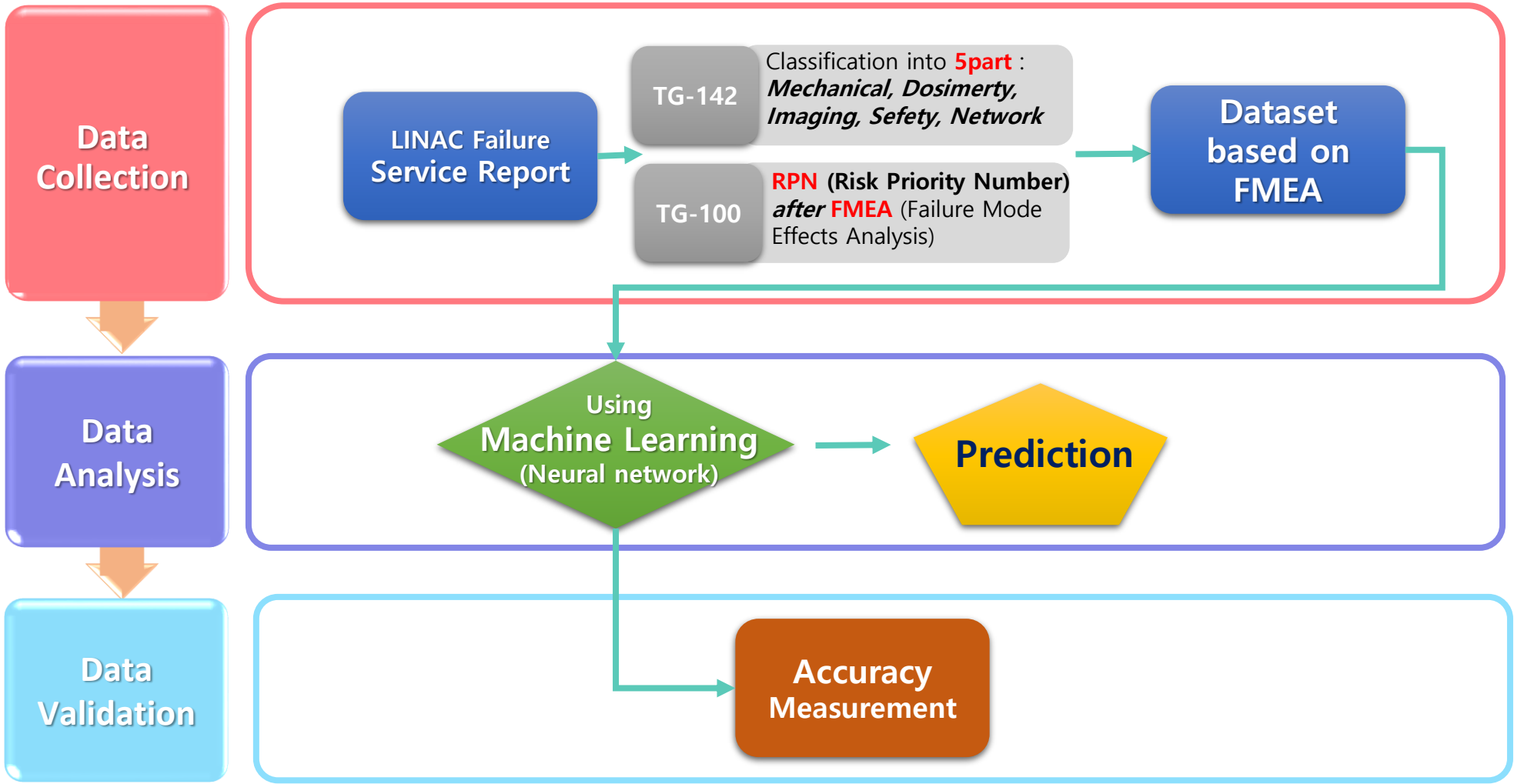
Ref. Radiation Treatment Time and Overall Survival in Locally Advanced Non-small Cell Lung Cancer, radiation oncology, 2017

Purpose

Predict the number of failures and operating time of the medical linear accelerator



Scheme of this study to predict number of failures and operating times of the medical linear accelerator



Dataset based on FMEA for machine learning

❖ Dataset based on FMEA for machine learning

Treatment date	Part	Cause of failure[#]	Quality control[#]	Downtime[h]	Total dose[cGy]	Total MU	Total patient[#]	Number of failures[#]	Accumulative number of failures[#]	O	S	D	RPN
		Step 1					Step 2				Step 3		

✓ Step 1
- Collection of failure service report (Hardcopy data) for the medical linear accelerator in 9 years.
- The causes of failure are classified into 5 parts (Mechanical, Dosimetry, Imaging, Safety, Network) by reference to the TG-142 report.

✓ Step 2
- Add the Total dose, Total MU, total patient, number of failures and accumulative number of failures indicating the use of the medical linear accelerator

✓ Step 3
- The risk priority number (RPN) value for the cause of failure was derived after FMEA (Failure Mode Effects Analysis) by referring to the TG-100 report.

The RPN is set as follows,

TG-100 RPN table

Rank	Occurrence (O)		Severity (S)		Detectability (D)
	Qualitative	Frequency in %	Qualitative	Categorization	Estimated Probability of failure going undetected in %
1	Failure unlikely	0.01	No effect		0.01
2		0.02	Inconvenience	Inconvenience	0.2
3		0.05			0.5
4	Relatively Few failures	0.1	Minor dosimetric Error	Suboptimal plan or treatment	1
5		<0.2	Limited toxicity or tumor underdose	Wrong dose, dose distribution, location, or volume	2
6	Occasional Failures	<0.5			5
7		<1	Potentially serious toxicity or tumor underdose		10
8	Repeated Failures	<2			15
9		<5	Possible very serious toxicity or tumor underdose	Very wrong dose, dose distribution, location, or volume	20
10	Failures inevitable	>5	Catastrophic		>20

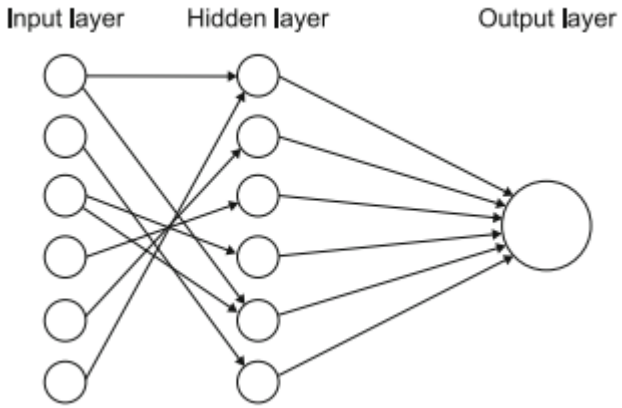
RPN table of Our Study

Rank	Occurrence (O) (based on Failure rate)		Severity (S) (based on Downtime)		Detectability (D) (based on A/S time)	
	Status	Frequency in %	Status	Frequency(h)	Status	Frequency(h)
1	No fault	>0.01	None	>0.1	Almost certain	>0.1
2	Very few failures	>0.5	Very slight	>0.5	Very high	>0.4
3	Relatively small failure	>2	Slight	>1.5	High	>0.8
4		>3.5	Very low	>3	A little high	>1.3
5		>5	Low	>5	Ordinary	>1.5
6	Intermittent fault	>7.5	Ordinary	>10	Low	>2
7		>10	High	>15	Very low	>2.5
8	Repetitive failure	>12.5	Very high	>20	Thinness	>5
9		>15	Warning Risk	>25	Very thinness	>10
10	Unavoidable failure	>20	Risk without warning	>40	Undetectable	>15

Ref. The report of Task Group 100 of the AAPM: Application of risk analysis methods to radiation therapy quality management, Med. Phys. 43 (7), 2016

Machine learning Algorithms used for this study

❖ Artificial Neural Network, ANN



- ✓ A general name for a computing system that is implemented based on the neural network of the human or animal brain.
- ✓ One of the detailed methodologies of machine learning, the neuron, is the form of several connected networks.
- ✓ Divided into different types by structure and function, the most common artificial neural network is a multilayer perceptron with multiple hidden layers between one input layer and output layer.

Ref. Renganathan V, Overview of artificial neural network models in the biomedical domain, Bratisl Med J, 120 (7), 2019

❖ Gaussian Kernel

$$G_{1D}(x;\sigma) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{x^2}{2\sigma^2}},\quad G_{2D}(x,y;\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}},\quad G_{ND}(\vec{x};\sigma) = \frac{1}{(\sqrt{2\pi}\,\sigma)^N} e^{-\frac{|\vec{x}|^2}{2\sigma^2}}$$

- ✓ The s determines the *width* of the Gaussian kernel.
- ✓ In statistics, when we consider the Gaussian probability density function it is called the *standard deviation*, and the square of it, s2, the *variance*.

❖ How to Use Algorithms

- ✓ Using the Python Program
- ✓ Using Gaussian Kernel neural network
- ✓ Learning as a neural network algorithm using 90:10 Training vs Test set using neural network using Gaussian Kernel
- ✓ Using the accuracy measurement for the validation of machine learning

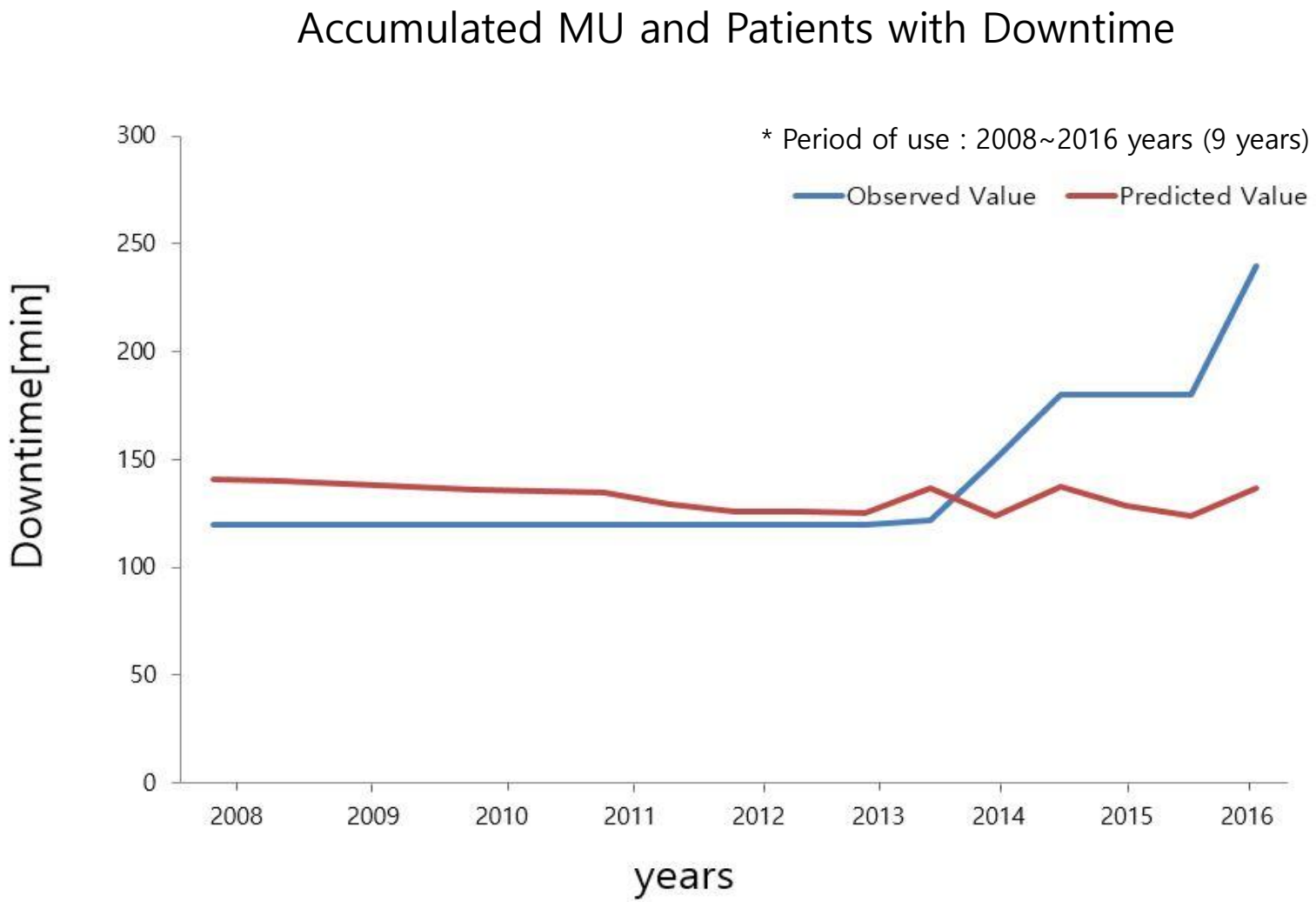
Average value of dataset based on FMEA for machine learning

✓ The dataset based on FMEA for machine learning consists of daily treatment date, total cause of failure, downtime, number of failures, accumulative number of failures, RPN (O/S/D), total dose, total MU and number of total patients in each QA part (Mechanical, Dosimetry, Imaging, Safety, Network).

* Period of use : 2008~2016 years (9 years)

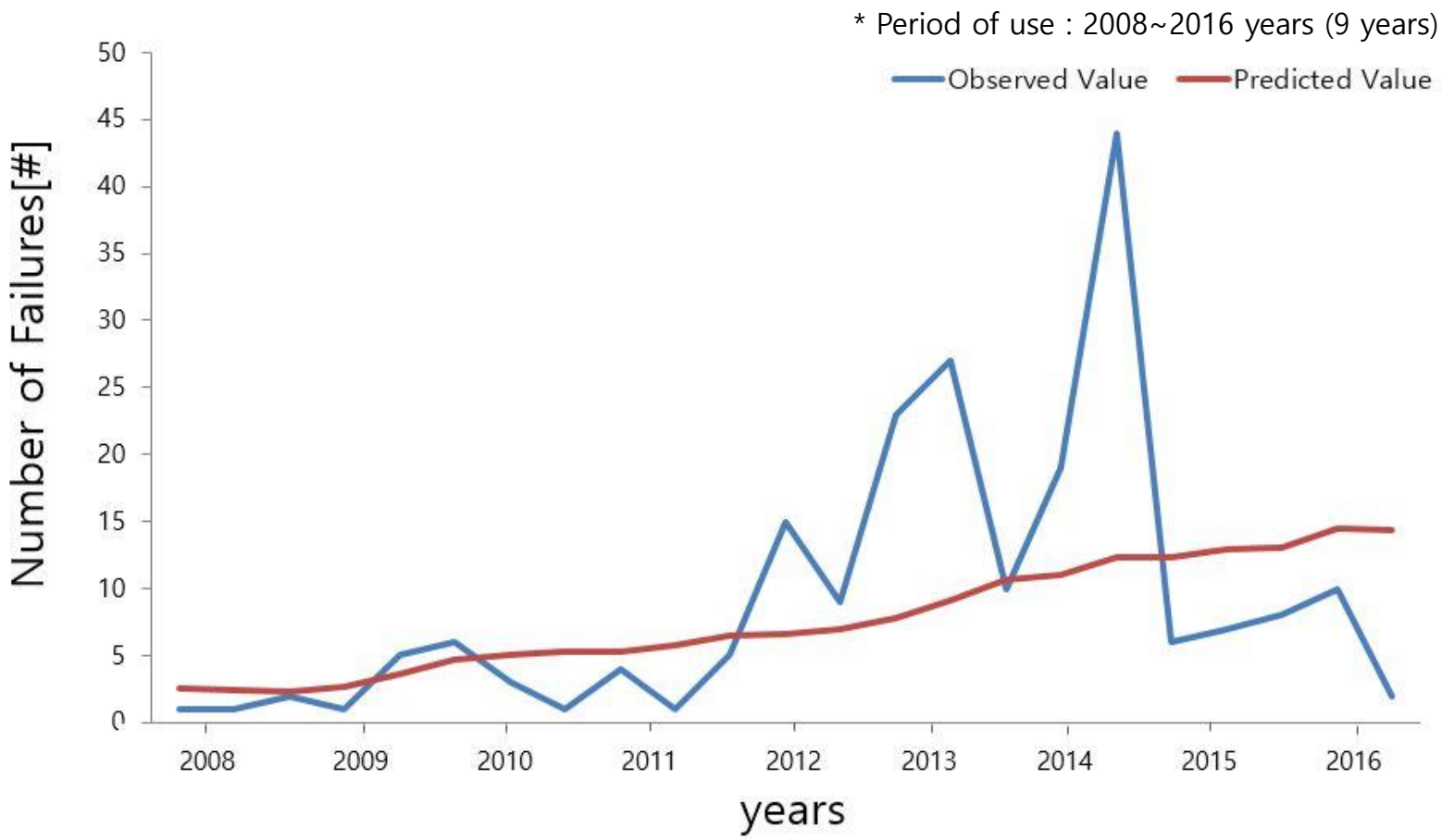
QA Part	Total cause of failure[#]	Total Quality control (QC)[#]		Total downtime[h]	Number of failures[#]	Accumulative number of failures[#]	O	S	D	RPN	Total dose [cGy]	Total MU	Total Patient[#]
		Replacement	Check, Control and Cleaning										
Mechanical	186	134	52	443	186	186	3.8	3.8	3.9	56	7425	12479	35
Dosimetry	18	11	7	122	18	18	2.1	7.6	7.2	115	6687	11248	32
Imaging	12	4	8	31	12	12	4.8	3	3.1	45	7677	13052	37
Safety	9	9	0	21	9	9	3	2.1	2.9	18	7668	13072	36
Network	4	3	1	60	4	4	2.8	7.3	7.3	149	3967	5971	17
Total	229	161	68	678	229	229	16.5	23.8	24.4	383	33424	55822	157

Artificial neural network prediction result for accumulated MU and patients with downtime

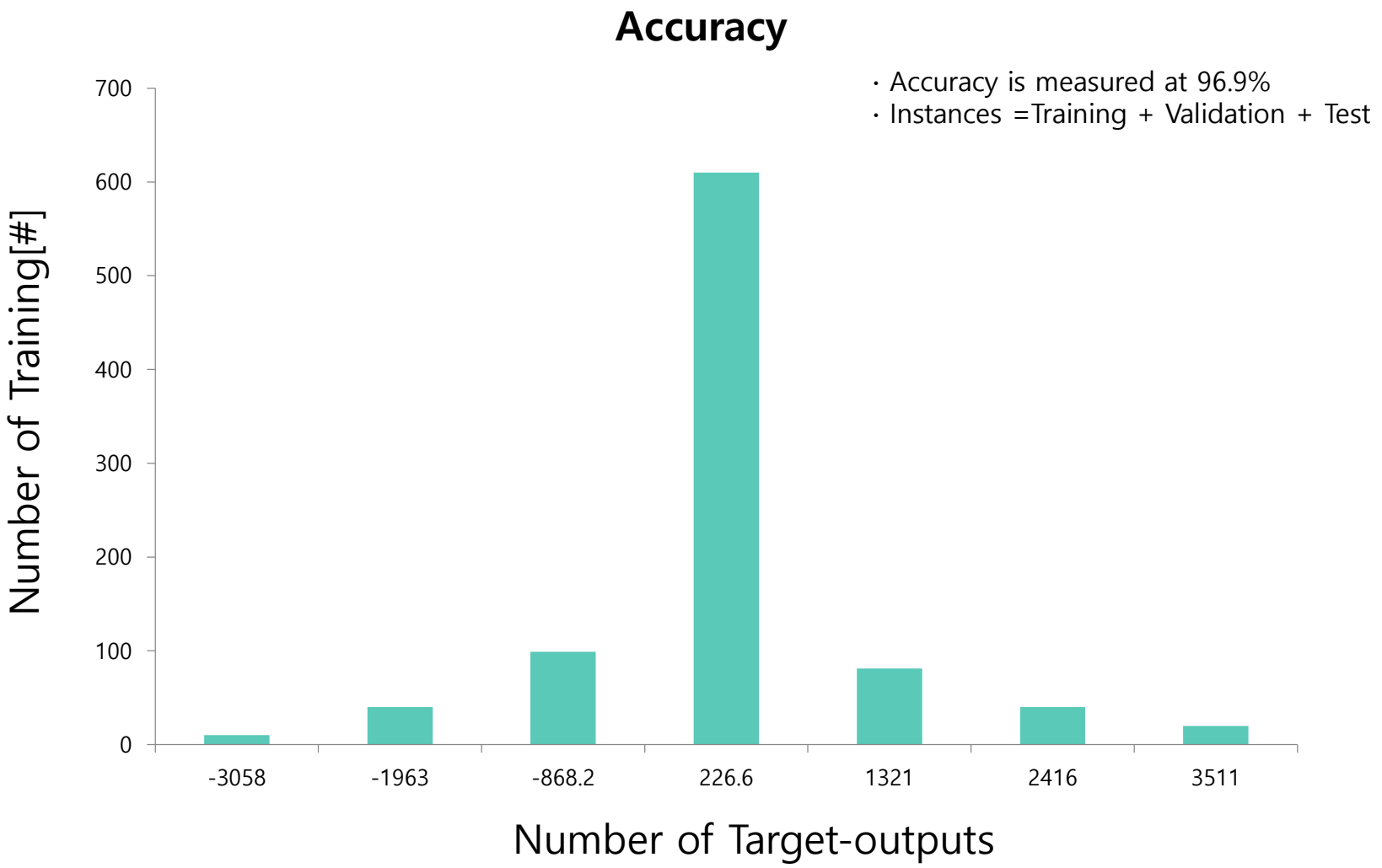


Artificial neural network prediction result for accumulated MU and patients with number of failures

Accumulated MU and Patients with number of failures



Accuracy measurement of machine learning



Conclusion & Discussion

- ✓ **Establish dataset based on FMEA use to machine learning**
- ✓ **It was possible to evaluate the predictability of the number of failures and operating time of the medical linear accelerator.**

Future study are :

- ✓ *Need to optimize dataset based on FMEA*
- ✓ *Need to select an appropriate M/L algorithm to predict operating time and number of failures of the medical linear accelerator*
- ✓ *Correlation analysis is required for each part in the future.*

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