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A COMPARATIVE STUDY ON THE DIFFERENCE OF INCIDENT SURFACE DOSE PREDICTION MODEL BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract

Background/Objectives By predicting the quantitative amount of effective dose through machine-learning of the models of the artificial neural network program, the predicted data values between each model are compared and evaluated, and the ESD values derived from actual imaging and the data showing the most similar predicted values are compared. Therefore, practical accuracy and clinical utility were verified and evaluated.
Statistical analysis: Position the phantom upright on the detector face in the chest PA position, and take three shots with each combination of tube voltages 90, 100, 110, 120 kVp tube currents 5,8, 10, 12.5 mAs, SID 180, and 200 cm. The center line was taken with a vertical incidence on the mid-plane at the height of the 6th spine, and the dosimeter position was measured at 4 locations, including the 6th thoracic vertebrae, breast, thyroid gland, and upper abdomen (liver point). After that, after data mining the data values obtained through shooting, it is written in Excel, an artificial intelligence prediction program, and applied to Orange 3.0, an artificial neural network program, to obtain prediction data using data mining.
Findings: A total of 5 algorithms kNN, ,Tree, SVM, Random Forest, and Linear Regression were used. As for the accuracy of the evaluation model, the smaller the mean square error (MSE), the root mean square error (RMSE), and the mean absolute error (MAE) are, the better the model is. Therefore, the model with the best predictive power was analyzed in the order of Tree, Random Forest, Linear Regression, kNN, and SVM.
Improvements/Applications: The SVM was analyzed as not suitable for use as a model for using the ESD prediction rate, but since this is a data value that does not reflect the sensitivity of the variable, if the amount of data set is increased, it is expected that the utilization value will increase sufficiently in the future.

Keywords: Artificial intelligence (AI) , Entrance surface dose (ESD), Exposure dose, Data mining, Machine learning(ML).

1. INTRODUCTION

As medical technology has developed and public interest in health has increased, the exposure of the public to medical radiation is increasing, due to the diversity of health and medical examinations. Recently, the National Council on Radiation Protection (NCRP) report indicated an increase in the annual medical radiation exposure dose in the United States from 0.53 mSv in the 1980s to 3.0 mSv in 2006[1].

.In response to the increase in medical radiation exposure of the public due to the increase in the use of domestic and international diagnostic medical radiation, it is recommended to set a diagnostic reference level (DRL) for radiation safety management at the national level and to maintain exposure below this level[2].

.It has been established that reducing radiation exposure that does not contribute to the patient's clinical purpose in the process of radiation utilization can be achieved by focusing on using minimum doses within an appropriate range. However, it is difficult to quantitatively evaluate the effective dose due to differences in dose expression methods for each examination, such as general radiography, computed tomography, fluoroscopy and interventional procedures, equipment differences in hospitals, and differences in individual examiners[3].

.Thus, this study aimed to predict the radiation exposure dose by considering differences depending on the examination.

Currently, in South Korea, the most commonly used systems to monitor medical radiation exposure are; VUNO, which analyzes medical imaging and diagnostic data using artificial intelligence (AI) technology to determine the presence or absence of pulmonary lung lesions in a patient through AI medical data analysis; and Lunit, which diagnoses and interprets medical data through deep learning technology for pulmonary diseases and breast cancer from chest and breast X-rays[4]. In addition, machine learning and data mining are widely used in research in the medical/biological field for disease prediction and identification[5]. Data on this was investigated and showed that the higher the awareness and reliability of AI for medical use, the higher the expectation of use in health care[6]..

Chest radiography is the most commonly performed radiography procedure, as the chest is the location of many major organs. Although chest radiography using X-rays is a useful diagnostic method for diagnosis and treatment, the International Commission on Radiological Protection (ICRP) has published guidelines to manage patient dose, as this technique can have harmful effects on the human body[7]. Hen performing chest radiography, there is concern about secondary exposure in critical organs, such as the thyroid and breast, which are highly sensitive.

Therefore, this study aims to present an optimal algorithm model by comparing the accuracy and predictive power of the model used for prediction by measuring entrance surface dose (ESD) values at four points that could replace surrounding tissues during chest radiography, learning by machine learning (ML), and predicting ESD values at each point.

2. Materials and Methods

2.1. Equipment and Materials

For the imaging equipment, "AccuRay-650R" of DK Medical System, a diagnostic X-ray system, was used. For dose measurement, a PSD dosimeter (UNFORS, Sweden) and Phantom (PH-2B-2), (Kyoto Kagaku, Japan) were used.

2.2. STUDY METHODS

For imaging conditions, after fixing the radiation field to 14 × 17 inch, tube voltage, tube current, and focus film distance (FFD) were used as variables, and the incidence point was set perpendicular to the midplane at the height of the sixth thoracic vertebra to obtain ESD values. Chest PA has the characteristics of reducing the exposure dose due to the high voltage and the convenience of positioning. Hence, for dose measurement, the phantom was placed in front of the IR plane in the chest PA posture, and the ranges were set to tube voltages of 90 kVp, 100 kVp, 110 kVp, and 120 kVp, the tube current amounts of 5 mAs, 8 mAs, 10 mAs, and 12.5 mAs, and FFD of 180 cm and 200 cm. In order to minimize the error caused by the surrounding environment and equipment, ESD values were obtained by performing radiography three times based on a total of four dosimeter positions, sixth thoracic vertebrae, breast, thyroid, and the upper abdomen (liver point), for each condition. Using Orange version 3.27.0, an open software, as a machine learning algorithm, prediction models were created using Tree, Random Forest, SVM, linear regression analysis, and the kNN algorithm to identify and compare the prediction rate and accuracy[Fig.1].

[Fig. 1] *The dosimeter is measured in four locations*

The thoracic spine 6, breast, thyroid, and upper abdomen (liver point)

2.3. Machine-learning (ML)

In the classification depending on the purpose of the algorithm, the algorithms for classification and discrimination, and the estimation of the result values are defined as supervised learning, and the algorithms for association rules and clustering are defined as unsupervised learning. This study is utilizes supervised learning, and an algorithm to estimate result values is thus particularly suitable. The corresponding algorithms include Linear Regression analysis, decision tree analysis, k-nearest neighbor algorithm (kNN), support vector machine (SVM), and Random Forest. In the medical field, neural network, SVM, and decision tree analysis are most frequently applied among machine learning methods. Random Forest is highly utilized as a method with excellent predictive power. In particular, K-NN derives the prediction results using a simple data matching method based on similarity. Linear regression analysis is not complicated in the concept of an algorithm, and can be widely applied to various problems. Therefore, these models were used for comparison[Fig.2].

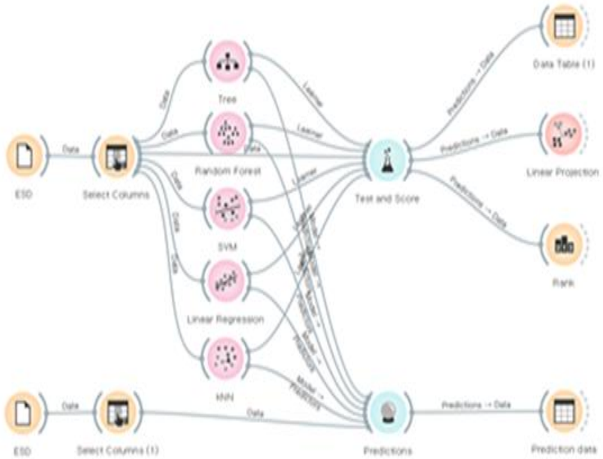

Fig. 2 *Predicted model <Model. Tree, Random Forest, SVM, Linear Regression, kNN>*

2.3.1 Random Forest

Random Forest is an algorithm that applies the CART algorithm for decision tree analyses and the bagging algorithm for ensemble models. The learning method is supervised learning of neural networks, such as MLP, RBF, and SVM. Since this model is based on CART, there is no distribution assumption, and there are few constraints as it is free from the types of target and input variables. In addition, this algorithm solves the over-fitting problem, which is the weakness of the decision tree analysis and improves the prediction accuracy, which is the strength of the ensemble model. As such, this model has the best predictive power, is helpful in dealing with missing value, requires no transformation of variables, and does not invovle over-fitting. However, the learning time is excessive, and if there are few records and variables in the dataset, the model's goodness of fit may not be high[8].

2.3.2 Linear Regression analysis

Linear Regression analysis is a method used to analyze the correlation between variables which models the relationship between independent and dependent variables. The relationship between two variables is called simple linear regression, but also involves multiple linear regression for several variables. Multicollinearity is a phenomenon in which a correlation occurs between independent variables, and interpretation of the regression coefficient is impossible at this time[9].

2.3.3 SVM

SVM is an analysis algorithm that can classify, discriminate and estimate, and corresponds to supervised learning. This algorithm is used to predict classification and discrimination when target variables exist, or to predict a continuous value (point estimation). This involves a method of classifying observations with two categories, and focuses on finding the optimal hyperplane that separates the given data into two groups. Although It has excellent predictive power, involves no assumptions about model calculation, and is free from variable types, it has the disadvantage that the model is sensitive depending on parameter C (unit cost) and kernel selection[10].

2.3.4 TREE

Decision tree analysis is an analysis method that classifies or predicts a group of interests by charting a decision rule. Since there is no parameter, parameter optimization is not required, and data with missing values is well processed. The model can be observed visually because the tree structure expresses the analysis process. Among other data mining techniques, it has the advantage that the analysis process can be easily understood and explained compared to regression analysis and neural networks. Decision tree analysis is used for classification or prediction and is more useful when an explanation of the analysis process is prioritized over the accuracy of the analysis[11].

2.3.5 kNN(k-Nearest neighbor)

The 'K-Nearest neighbor' algorithm identifies the 'K' nearest neighbors to a new data point in the training data and uses the most frequent class among these neighbors as a predicted value[12].

3. RESULTS

3.1. Prediction accuracy of algorithm models

To examine the accuracy and importance of predictor variables using the algorithms, cross-validation was analyzed by stratifying the Random Forest, Linear Regression analysis, kNN, Tree, and SVM. The accuracy of the evaluation model is evaluated as better if the mean square error (MSE), the root mean square error (RMSE), and the mean absolute error (MAE) are smaller, and the explanatory power index, R2, is closer to 1. Our analysis revealed that; kNN had an MSE of 8.471, RMSE of 2.910, and MAE of 2.478; Tree had an MSE of 1.848, RMSE of 1.359, and MAE of 0.802; SVM had an MSE of 27.932, RMSE of 5.285, and MAE of 3.699; for Random Forest, the MSE was 4.750, the RMSE was 2.179, and the MAE was 1.753; and for Linear Regression analysis the MSE was 6.771, the RMSE was 2.602, and the MAE was 1.889, which were analyzed low in the order of Tree, Random Forest, Linear Regression, KNN, and SVM. In addition, the R2 values of KNN, Tree, SVM, Random Forest and Linear regression analysis were 0.944, 0.988, 0.814, 0.968, and 0.955, respectively. Thus, the models were ranked in descending order as; Tree, Random Forest, Linear Regression, kNN, and SVM <Table 1>[Fig.3].

Table 1. *Results of model accuracy comparison*

Model	MSE	RMSE	MAE	R2
kNN	8.471	2.910	2.478	0.944
Tree	1.848	1.359	0.802	0.988
SVM	27.932	5.285	3.699	0.814
Random Forest	4.750	2.179	1.753	0.968
Linear Regression	6.771	2.602	1.889	0.955

3.2. Validation of algorithm model prediction rate

The results of the model predictive power verification in this study using the algorithms of kNN, Tree, SVM, Random Forest, and Linear Regression analysis are shown in Table?. Similar to the accuracy of the evaluation model, the smaller the mean square error (MSE), the root mean square error (RMSE), and the mean absolute error (MAE), and the closer the explanatory power index, R2, was to 1, the higher the reliability of the predictive power. As a result of the analysis, the MSE of kNN was 3.331, the RMSE was 1.825, and the MAE was 1.489; the MSE of Tree was 0.168, the RMSE was 0.410, and the MAE was 0.263; the MSE of SVM was 19.345, the RMSE was 4.398, and the MAE was 3.074; the MSE of Random Forest was 0.589, the RMSE was 0.768, and the MAE was 0.557; while the MSE of Linear Regression analysis was 6.295, the RMSE was 2.509, and the MAE was 1.806. Thus, the models were analyzed in the order of Tree, Random Forest, Linear Regression, KNN, and SVM. the R2 values of KNN, Tree, SVM, Random Forest and Linear regression analysis were were; 0.977, 0.999, 0.869, 0.996, and 0.957, respectively, indicating that the most predictive model was SVM, followed by Linear Regression, kNN, Random Forest, and Tree <Table.2> [Fig.3].

	SVM	Linear Regression	kNN	Random Forest	Tree	ESD	자세	SID	관전압	관전류량	위치
1	18.21	10.19	13.91	13.29	12.84	12.72	PA	180	90	5.0	갑상선
2	18.21	10.19	13.91	13.29	12.84	13.09	PA	180	90	5.0	갑상선
3	18.21	10.19	13.91	13.29	12.84	12.72	PA	180	90	5.0	갑상선
4	18.87	14.73	14.35	14.76	15.32	15.32	PA	180	90	5.0	유방
5	18.87	14.73	14.35	14.76	15.32	15.69	PA	180	90	5.0	유방
6	18.87	14.73	14.35	14.76	15.32	14.94	PA	180	90	5.0	유방
7	18.48	15.92	15.16	15.29	15.79	16.14	PA	180	90	5.0	흉추 6번
8	18.48	15.92	15.16	15.29	15.79	15.79	PA	180	90	5.0	흉추 6번
9	18.48	15.92	15.16	15.29	15.79	15.44	PA	180	90	5.0	흉추 6번
10	17.14	10.37	13.58	13.44	13.16	13.52	PA	180	90	5.0	liver
11	17.14	10.37	13.58	13.44	13.16	12.81	PA	180	90	5.0	liver
12	17.14	10.37	13.58	13.44	13.16	13.16	PA	180	90	5.0	liver
13	22.73	20.32	22.22	20.78	20.72	21.09	PA	180	90	8.0	갑상선
14	22.73	20.32	22.22	20.78	20.72	20.72	PA	180	90	8.0	갑상선
15	22.73	20.32	22.22	20.78	20.72	20.36	PA	180	90	8.0	갑상선
16	25.08	24.86	22.86	23.47	24.16	24.28	PA	180	90	8.0	유방
17	25.08	24.86	22.86	23.47	24.16	24.66	PA	180	90	8.0	유방
18	25.08	24.86	22.86	23.47	24.16	23.54	PA	180	90	8.0	유방
19	24.90	26.05	23.24	24.50	24.92	25.06	PA	180	90	8.0	흉추 6번
20	24.90	26.05	23.24	24.50	24.92	25.02	PA	180	90	8.0	흉추 6번
21	24.90	26.05	23.24	24.50	24.92	24.67	PA	180	90	8.0	흉추 6번
22	22.09	20.50	20.74	20.83	20.75	20.63	PA	180	90	8.0	liver
23	22.09	20.50	20.74	20.83	20.75	20.99	PA	180	90	8.0	liver
24	22.09	20.50	20.74	20.83	20.75	20.63	PA	180	90	8.0	liver
25	27.08	27.08	27.74	26.11	25.69	25.45	PA	180	90	10.0	갑상선
26	27.08	27.08	27.74	26.11	25.69	25.81	PA	180	90	10.0	갑상선
27	27.08	27.08	27.74	26.11	25.69	25.81	PA	180	90	10.0	갑상선
28	30.44	31.62	28.71	29.64	30.76	30.64	PA	180	90	10.0	유방
29	30.44	31.62	28.71	29.64	30.76	31.01	PA	180	90	10.0	유방

Fig. 3 *Prediction results used by the Orange version 3.27.0*

Table 2. *Results of predictionl accuracy comparison*

Model	MSE	RMSE	MAE	R2
kNN	3.331	1.825	1.489	0.977
Tree	0.168	0.410	0.263	0.999
SVM	19.345	4.398	3.074	0.869
Random Forest	0.589	0.768	0.557	0.996
Linear Regression	6.295	2.509	1.806	0.957

4. DISCUSSION

Recently, machine learning and data mining have been widely used in medical research for disease prediction and identification[13], while study on a hypercholesterolemia prediction model using anthropometric information has also been reported[14][15]. Machine learning, a field of AI, is a big data-based AI learning method that uses algorithms to analyze large amounts of data, recognize patterns, and predict results.

Among the machine learning models used in this study, Tree considers one variable at a time as a subgroup classification. Thus, if the analysis involved multiple variables, it would have been difficult to understand the interaction between variables, resulting in a low predictive power of this model. On the other hand, if more variables and data are obtained, it is expected that Random Forest, which improves the predictive performance, will have good predictive power. Among the machine learning algorithm models used, Tree and Random Forest showed the best prediction and accuracy, which SVM showed the lowest accuracy. SVM was considered inappropriate for use as an ESD prediction rate utilization model. However, since this is a data value that does not reflect the sensitivity of variables, it is expected that the utilization value will increase sufficiently in the future if the amount of datasets is increased.

More variables and data could be obtained if radiography and PA are performed in various postures to increase the available variables, or if other general radiography equipment is used to increase the accuracy of the results. Thus, primary data for ESD prediction data based on AI algorithm modeling is expected to be valuable in the future.

If this is applied to increase the amount of data and variables in the algorithm and use an appropriate model for the amount, it could also be applied to applications. It is expected that the accurate exposure dose could be predicted not only for pediatric and general radiography, but also for imaging techniques using X-rays, such as computed tomography (CT). Therefore, patients can increase their awareness of the exposure dose by comparing the recommended dose value of ICRP 103 with the predicted value of the AI algorithm, thereby creating psychological stability by reducing anxiety about exposure. Furthermore, knowledge regarding clinical use could be useful to remind radiologic technologists of the importance of awareness.

5. CONCLUSION

This study measured the ESD values of four points in surrounding tissues during chest radiographing through experiments, and constructed an algorithm to present the optimal algorithm model for machine learning. The machine learning algorithm in the study used the algorithms kNN, Tree, SVM, Random Forest, and Linear Regression analysis, of which the highest model accuracy and prediction accuracy were observed in the Tree model. The most significant factors in the prediction of each model were tube current and voltage. In addition, since the Random Forest model does not show a significant difference between the model accuracy and the prediction accuracy, it was determined that the algorithm will be highly reliable for predictive utilization if the shortcomings of the Random Forest model could be compensated.

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