Determination of Thorax Exposure Factors in Conventional X-rays Imaging using the Artificial Neural Network Method

Donni Maulana Sipa and Jamrud Aminuddin
Department of Physics, Faculty of Mathematics and Natural Science, Universitas Jenderal Soedirman, Purwokerto, Indonesia

Keywords: X-ray, Exposure Factor, Neural Network.

Abstract: The application of artificial intelligence in the medical field is indispensable for providing optimum results. Conventional X-ray imaging is the fastest, most common and least expensive diagnostic imaging system available. However, an effective X-ray examination depends on the range of radiation given to the subject. The radiation from an X-ray primarily depends upon X-ray tube current (mA), tube voltage (kVp) and exposure time(s); these parameters define the dosage. X-ray radiation has a negative impact on the human body; this danger is not visible, but X-ray radiation can damage human cell tissue. This work aims to explore and analyze X-ray exposure parameter levels to the thorax with an artificial neural network, which helps to diagnose exposure of the tissue that is being irradiated. By entering distance, weight and height into the software, radiographers will get the optimum exposure factor settings for the patients' thorax. The subjectivity of exposure factor settings from radiographers can be objective, and optimum exposure settings for patients can result in lower radiation with a good, detailed image, thereby reducing the impact of X-ray radiation.

1 BACKGROUND

A radiograph from X-ray imaging is produced based on the suitability of the exposure factor chosen by a radiographer. The exposure factor is chosen based on the region of examination, the patient's body weight, projection position, distance from X-ray to the patient and the patient's physical condition (Carlton et al., 2019). If the value of the exposure factor is too high or too low, the radiograph will yield a shadow, which has no diagnostic information, and the inappropriate exposure factor also triggers a high radiation value. In other words, the image on X-ray film will be over-bright or over-dark, making it difficult to read by a doctor and giving the effects of excessive radiation to the patient (Gois et al., 2019).

The value of the exposure factor can be seen by the state of the patient; underweight patients and overweight patients have different exposure factor settings. Because of the differing patient surface areas, radiographers need to ensure that the value of the exposure factor is a match to the patient. Every X-ray device and every radiographer needs to have clear parameters for overweight or underweight patients; this makes the settings of exposure factor subjective by the radiographer itself (Elster, 2010).

Exposure factor calculation using fuzzy logic has been developed by Santoso et al., (2016). Fuzzy logic succeeded in calculating the optimum exposure factor. Instead of using fuzzy logic, however, we employed the use of an artificial neural network. Therefore, the aim of this work is to explore and analyse X-ray exposure parameter levels to the thorax with an artificial neural network, which helps to diagnose exposure of the tissue being irradiated.

2 METHOD

2.1 Exposure Factor

A good image depends on the exposure factor. Image quality also represents the amount of radiation received by the patient during the imaging technique. Three main factors that determine the image quality are the kilovolt potential (kVp), which controls the penetrating power of the X-ray; the milliampere (mA), which controls the number of X-rays; and the exposure time (S), which controls the duration of exposure (Hiswara, 2002). These combinations will decide the contrast sensitivity, detail and noise of the radiograph. Variables from imaging techniques must

Sipa, D. and Aminuddin, J.
Determination of Thorax Exposure Factors in Conventional X-rays Imaging using the Artificial Neural Network Method.
DOI: 10.5220/0009388100330037
In *Proceedings of the 4th Annual International Conference and Exhibition on Indonesian Medical Education and Research Institute (The 4th ICE on IMERI 2019)*, pages 33-37
ISBN: 978-989-758-433-6

be precise so the radiograph from X-ray imaging yields a good image with minimum radiation; this also decreases the risk of X-rays radiation (Lampignano and Bontrager, 2014).

2.1.1 Kilo Volt Potential

Energy from X-rays is controlled by a voltage regulator. The potential difference setting usually has the keV (kilo electron volt) or kVp (kilo Volt potential) label. These are the important parts that regulate the potential difference between anode and cathode. The higher value of the potential difference, the more energy is produced by X-rays (Omura, 2018). The high energy produced is contrary to the contrast of the radiograph—the higher the energy, the lower the image contrast.

2.1.2 Milliampere

Besides the potential difference, the current also influences the imaging technique. This setting has the label mA (milliampere); this represents how much filament flows. The higher value of the mA (the tool will get hotter) that is flowed through the filament, the more electrons available in the 'space charge' to accelerate through the target; the result is a high flux of photons when energy flows. The effect of the current is quite linear. To duplicate X-rays from the tube, it can be done by doubling the previous tube current settings. Changing the amount of current will affect the blackness of the radiograph but it doesn't affect the contrast (Plaats, 1965).

2.1.3 Exposure Time

The final setting is the exposure time. With the *s* (second) label, the exposure time is often associated with regulating the tube current. The combination of current and exposure time is often called mAs, or milliAmpere second. For example, a 100-mA current setting and a 0.5 s exposure time is the same as 50 mAs, as is a 50-mA current and 1 s exposure time; the result is the same: 50 mAs. The combination of these two factors is directly proportional to the effect on the film (Sari and Fransiska, 2018). To produce a darker radiograph, the value of mAs must be increased; and to produce a brighter image, the value of mAs must be reduced.

2.2 Body Mass Index

BMI is a comparison between weight and squared height. The method of measurement is to measure his weight and height. Then the BMI can be calculated by:

$$\text{BMI} = (\text{weight (kg)}) / (\text{height (m)})^{\wedge} 2$$

To determine the nutritional status of children under five years of age (0–60 months) and children aged 5–19 years, the BMI value should be compared with the standard BMI value according to the Republic of Indonesia's Ministry of Health (2010). At this time, the index is most often stated with Z-scores or percentiles. Theoretically, the Z-score can be calculated in the following way:

$$\mathrm{Z-Score} = \frac{\mathrm{BMI - Mean\ of\ BMI\ from\ reference}}{\mathrm{Standard\ Deviation\ from\ reference}}$$

Classification is distinguished in the 0–60-month age group and also in the 5–18-year age group (Munish, 2015). Classification of BMI for ages 0–60 months is presented in Table 1, while BMI classification for children aged 5–18 years is presented in Table 2.

Table 1: BMI for newborn baby 0–60 months.

Category	Z-score value
Abnormal	Z-score < -3
Underweight	-3 ≤ Z-score < -2
Ideal	-2 ≤ Z-score < 2
Overweight	2 ≤ Z-score < 3
Obese	Z-score ≥ 3

Table 2: BMI for kids/teenagers 5–18 years old.

Category	Z-score value
Abnormal	Z-score < -3
Underweight	-3 ≤ Z-score < -2
Ideal	-2 ≤ Z-score < 2
Overweight	2 ≤ Z-score < 3
Obese	Z-score ≥ 3

In adults, measurement of nutritional status is done by using body mass index (BMI). BMI calculation is the same as above. The results are compared with the BMI threshold values according to the Indonesian Ministry of Health, and the boundary values are presented in Table 3. In adults the age factor is not considered when calculating BMI, because the height is usually relatively stable, so variations only occur in body weight (Baş Mor, 2018).

Table 3: BMI for adults.

Category	BMI value
Abnormal	BMI < 17.0
Underweight	17.0 ≤ BMI < 18.5
Ideal	18.5 ≤ BMI < 25.0
Overweight	25.0 ≤ BMI < 27.0
Obese	BMI ≥ 27.0

2.3 Linear Neural Network

A linear network can only solve linearly separable problems since its transfer function is linear. This allows their outputs to take on any value.

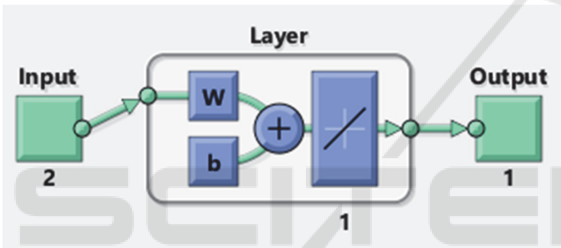

Figure 1: Layer in Neural Network.

Like the human brain, nerve tissue also consists of several neurons, and there are connections between these neurons. Figure 1 shows the structure of neurons in which neurons will transform information received through the output connection to other neurons.

By using the function newlind in Matlab toolbox as follows:

Net = newlind (P, T)

This returns a linear layer designed to output T given input P (MathWorks, 2019).

This reference data was obtained from Conventional X-rays device kVp and mAs sheet in a hospital, thus the data will be used as an input (P) for artificial neural network.

Table 4: Exposure Factor for Thorax in Neural Network.

		Exposure Factor				
Age	Projection	Abnormal	Underweight	Ideal	Overweight	Obese
		kV/mAS	kV/mAS	kV/mAS	kV/mAS	kV/mAS
Newborn baby	AP			55/2		
(0–2 y)	LAT			55/2.5		
Baby	AP			55/2.5		
(2–5 y)	LAT			55/3		
Kids/Teenager	AP	51/4	53/4	55/4	57/4	59/4
(5–18 y)	LAT	61/4	63/4	65/4	67/4	69/4
Adults	AP	61/16	63/16	65/16	67/16	69/16
(> 18 y)	LAT	71/20	73/20	75/20	77/20	79/20

3 RESULTS

Without using loss function and optimizer in the training of the linear neural network, the determination of X-rays that come out for overweight patients and with underweight patients is different. Overweight patients require higher doses because of the larger surface area and density of the body. Likewise, underweight patients will require a lower dose because of smaller surface area and body density.

To obtain a good-image quality, optimal X-ray output settings are needed with the patient because the higher the X-ray output settings, the greater the dose received by patients.

4 CONCLUSIONS

An artificial neural network program can be used to determine the thorax exposure factor in the conventional X-ray devices. By entering body weight and body height, this program calculates the optimum value of exposure factors that can be used to the patient.

The output of this program is the value of kVp and mAs. Compared to the reference, the value of kVp and mAs is under the predetermined range, which means the software can determine the optimum exposure factor. Optimum exposure factors yield a minimum dose of radiation and good image quality.

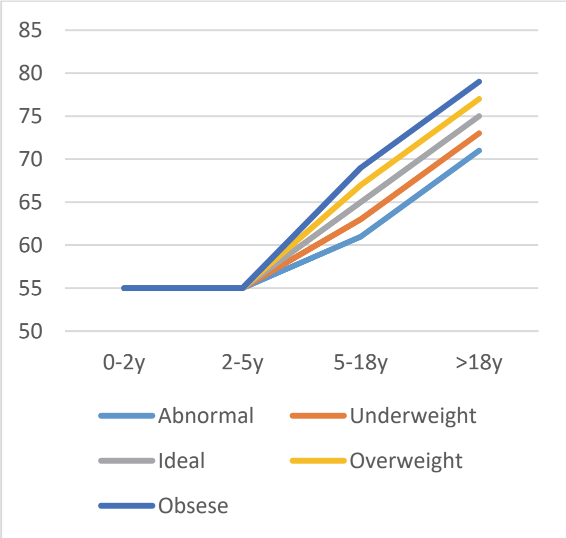

Figure 2: Thorax AP Graph.

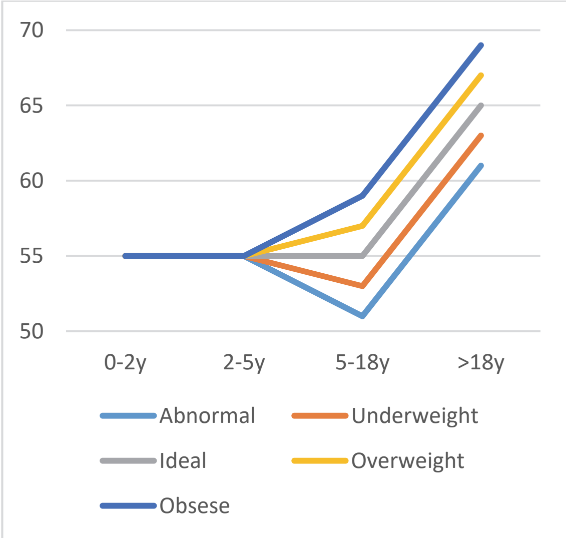

Figure 3: Thorax Lat Graph.

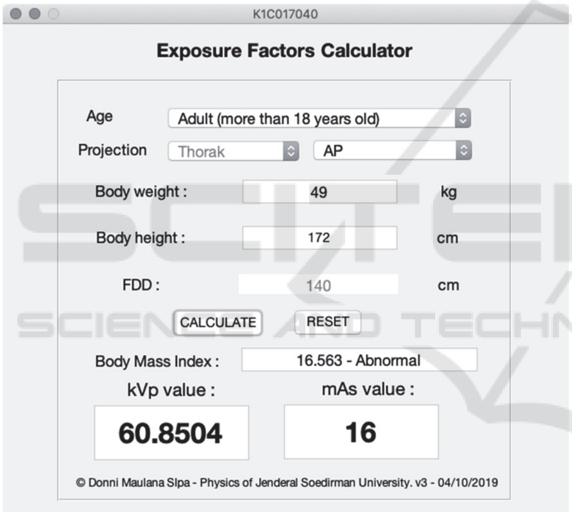

Figure 4: Thorax AP.

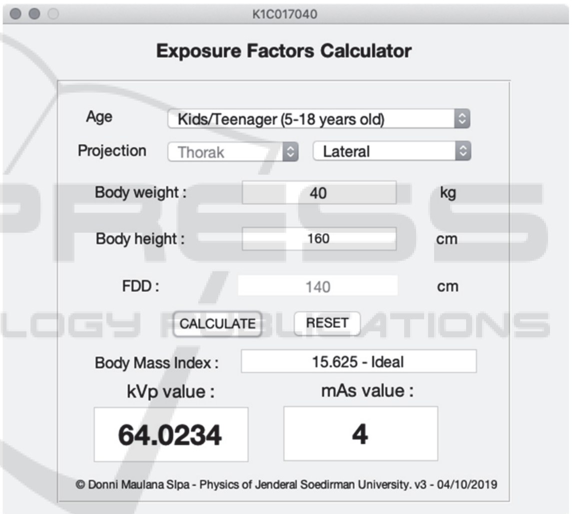

Figure 5: Thorax Lateral.

ACKNOWLEDGEMENT

The authors are thankful to the Dean of Faculty of Mathematics and Natural Sciences at Jenderal Soedirman University and his staff for providing the necessary facilities to complete this paper.

REFERENCES

Baş Mor, H., Altinsoy, N., & Söyler, İ. (2018). Estimation of Adult Patient Doses for Chest X-Ray Examinations and Comparison with Diagnostic Reference Levels (DRLs). *Radiation Protection Dosimetry*, *182*(3), 377–385. http://doi.org/10.1093/rpd/ncy076.

Bontrager, K. L., & Lampignano, J. P. (2014). *Bontrager's Handbook of Radiographic Positioning and Techniques* (8th ed.). St. Louis, MO: Elsevier.

Carlton, R. R., Adler, A. M., & Balac, V. (2019). *Principles of Radiographic Imaging: An Art and a Science* (6th ed.). Clifton Park, NY: Delmar, Cengage Learning.

Elster, A. D. (2010). Effective Doses in Radiology and Diagnostic Nuclear Medicine: A Catalog. *Yearbook of Diagnostic Radiology*, *2010*, 214–217.

Gois, M. L. C., Schelin, H. R., Denyak, V., Bunick, A. P., Ledesma, J. A., & Paschuk, S. A. (2019). Human factor in exposure from conventional radiographic examinations in very and extremely low birth weight patients. *Radiation Physics and Chemistry*, *155*, 31–37. http://doi.org/10.1016/j.radphyschem.2018.09.016.

Hiswara, E. (2002). *Pokok Dosimetri, Lokakarya Proteksi Radisasi, Pusat Standarisasi dan Penelitian (PSPKR)*. Jakarta: Badan Tenaga Nuklir Nasional.

Kementrian Kesehatan RI (2011). *Standar Azntropometri Penilaian Status Gizi Anak*.

Linear Neural Networks. (2019). Retrieved October 7, 2019, from https://www.mathworks.com/help/deeplearning/ug/linear-neural-networks.html

Munish, K. S. (2014). Accuracy of Conventional X-Rays in Diagnosing Airway Foreign Bodies among Children. *Indian Journal of Public Health Research and Development*, *6*(2), 4–6. http://doi.org/10.5958/0976-5506.2015.00061.3.

Omura, Y. (2018). Impact of X-ray Radiation on SOI MOSFET: Insulator Film Degradation and Hot-Carrier Reliability. *ECS Transactions*, *85*(8), 59–64. http://doi.org/10.1149/08508.0059ecst.

Santoso, S., Haddin, M., Nuryanto, E., & Utomo, A. S. (2016). Penentuan Faktor Ekposi Pada Pembangkit Sinar-X Konvensional Dengan Menggunakan Logika Fuzzy. *Prosiding SNST Fakultas Teknik*, *1*(1), 56–61.

Sari, A. W., & Fransiska, E. (2018). Pengaruh Faktor Eksposi dengan Ketebalan Objek pada Pemeriksaan Foto Thorax Terhadap Gambaran Radiografi. *Journal of Health*, *5*(1), 17–21. http://doi.org/10.30590/vol5-no1-p17-21.

van der Plaats, G. J. (1965). *Medical X-Ray Technique: Principles and Applications* (2nd ed.). Springfield, IL: C. C. Thomas.