RESEARCH PAPER

# Relevance Of Automatic Techniques Including Artificial Intelligence On Radiation Dose Optimization In Computed Tomography

**Mr. Satnam Singh[1] , Dr. Manish Shaw[2] , Dr. Harmeet Kaur[3] , Dr. Bhavay Sonik[4] , Dr. Paramdeep Singh[5] , Dr. Jayant Jagtap[6]**

[1]Research Scholar, Department of Radiation and Imaging Technology, Nims College of Allied and Healthcare Sciences, Nims University Rajasthan, Jaipur, India (Satnamsinghaiims@gmail.com)
[*2]Professor, Department of Radiology and Interventional Radiology, NIMS&R, Nims University Rajasthan, Jaipur, India
[3]Additional Professor, Department of Radiodiagnosis, AIIMS Bathinda, Punjab, India
[4]Associate Professor, Department of Nuclear Medicine, AIIMS Bathinda, Punjab, India
[5]Additional Professor, Department of Radiodiagnosis, AIIMS Bathinda, Punjab, India
[6]Associate Professor, Nims Institute of Engineering & Technology, Nims University Rajasthan, Jaipur, India

***Corresponding Author:** Dr. Manish Shaw
(Professor, Department of Radiology and Interventional Radiology, NIMS&R, Nims University Rajasthan, Jaipur, India)

**Abstract-:**
AI (Artificial Intelligence) is revolutionizing every aspect of the modern world, including medical imaging. Artificial intelligence is increasingly being employed through machine learning (ML) and deep learning (DL) to address the issue of radiation dose. This study worked on the fundamental facets of computed tomography that have primary control over radiation exposure to determine the relevance of physics-based automatic algorithms and artificial intelligence algorithms used in computed tomography for optimizing radiation dose. For this study, patients were stratified based on BMI, considering basic CT parameters such as kVp selection, tube current modulation (mAs), scan length, pitch, and CT FOV (field of view), which directly affect radiation dose optimization and Radiation dose indices such as CTDIvol, dose length product and effective dose were calculated to know the effectiveness of the techniques. Considering the importance of mAs and kVp, work was mainly done on real time modulation of X-ray tube current and real time automatic kVp selection and fixed value of scan length, pitch, and FOV (field of view) to determine the effectiveness and limitations of current automatic techniques. Finally, the current role and future scope of artificial intelligence for radiation dose optimization in computed tomography were diagnosed.

**Result:** The Mean effective dose ranged from 1.42 mSv (head) to 4.71 (abdomen) and 5.22 mSv (chest). In the case of head CT scans, the effective dose varies across automatic exposures, with real time modulation of kV ranging from 1.210 mSv at a BMI of 16.8 (kg/m$^2$) - 2.062 mSv at BMI of 27.7 (kg/m$^2$) in an obese patient and 1.5 mSv at BMI of 24 (kg/m$^2$) in a patient scanned with a fixed 120 kVp to 2.041 mSv at BMI of 25.7 (kg/m$^2$) and 1.810 mSv at BMI of 32.5 (kg/m$^2$). While in the abdomen and pelvis it ranged from 2.595 mSv at a BMI of 19 (kg/m$^2$) - to 5.655 mSv at a BMI of 29.4 (kg/m$^2$). The low dose chest effective dose varies across the automatic exposures with real time modulation of kVp (80 kVp to 140 kVp), from 3.150 mSv for a thin patient with a BMI of 15.6 (kg/m$^2$) - to 6.45 mSv for an obese patient with a BMI of 30.4 (kg/m$^2$) and with a fixed 100 kVp, the effective dose ranged from 1.120 mSv at a BMI of 14.8 (kg/m$^2$) to 4.242 mSv at a BMI of 38.6 (kg/m$^2$), while with a fixed 120 kVp, the effective dose ranged from 2.450 mSv at a BMI of 18.7 (kg/m$^2$) to 4.242 mSv at a BMI of 38.6 (kg/m$^2$) but up to 6.006 mSv at a BMI of 29.5 (kg/m$^2$). In the case of cardiac CT scans, the effective dose ranged from 1.17 mSv at a BMI of 23.5 (kg/m$^2$), including 1.246 mSv at a BMI of 20.2 (kg/m$^2$) - 3.766 mSv at a BMI of 28 (kg/m$^2$).

Conclusions - AI holds significant promise for reducing radiation exposure in CT scans. AI-based technologies enhance positioning and scan range accuracy through automatic patient centering and delineation, thereby lowering radiation doses and minimizing over-scanning, but the selection of fundamental CT scan parameters is still performed by traditional physics-based automatic techniques which are performing better near the reference tube current/ control Tube current and modify the radiation exposure using scan scout images but more variation in exposure found in obese patients as well as underweight patients. The involvement of AI in AEC may consider fully automating the AEC system or removing AEC limitations but the current absence of FDA-approved AI algorithms to modulate mAs and kVp on AEC by any vendor defines that the scope of AI on automatic MA and KVP modulation is broad but under development
Keywords: Artificial Intelligence, Radiation Dose Optimization, Computed Tomography, Automatic Exposure Control, mA modulation, kVp selection.
**How to cite this article:** Singh S, Shaw M, Kaur H, Sonik B, Singh P, Jagtap J. Relevance Of Automatic Techniques Including Artificial Intelligence On Radiation Dose Optimization In Computed Tomography. Int J Drug Deliv Technol. 2026;16(53s): 636-647. DOI: 10.25258/ijddt.16.53s.114
**Source of support:** Nil.

*Author for Correspondence: Dr. Manish Shaw

**Conflict of interest**: None..

**Introduction- 1-** Computed tomography has revolutionized medical imaging and has become an integral part of medical imaging. Using X-ray technology with advanced computer processing, CT scans can generate detailed cross-sectional images of the body's internal structures. Various advancements in computed tomography have marked this modality as fast, detailed, and accurate imaging modality for imaging of internal body structures and has become a versatile modality in many specialties—including emergency medicine, oncology, cardiology, neurology, and surgery—demonstrates its vital role in patient care. Although, imaging benefits are undeniable, but CT scanning involves the use of ionizing radiation—a factor that raises concerns about risk of radiation dose, particularly with repeated or high-dose exposures.

**1.2- Automatic Exposure Control Strategies-:** The most common technology used to reduce dose in CT is AEC. AEC is used for real time modulation of the X-Ray tube current in CT scanning which automatically adjusts the radiation exposure [1] and the introduction of AI Algorithms can further refine automatic tube current modulation which ensures optimal image quality with minimum radiation dose.

**1.3- Artificial intelligence (AI) –:** AI is a wide area of study that includes different strategies, each of which uses its own methods to accomplish a core goal. The core goal is
to create both hardware and software so that machines can perform smart, thinking tasks like decisions-making [2]. In machine learning, algorithms are taught to perform certain jobs by learning patterns from large data sets. Deep learning is a type of machine learning that uses artificial neural networks, which are like human brain, to solve very difficult problems with very large amount of data [3].

**1.4- Artificial Intelligence in computed tomography-** The introduction of AI in medical imaging has transformed every aspect of medical imaging and diagnosis.AI, in the form of traditional machine learning, or the more recent deep learning, other types of learning, has been successfully demonstrated to optimize radiation dose in Computed tomography. AI could revolutionize every involved aspect of computed tomography, from positioning the patient on the scanner to reconstruct final output image.

**1.5- Dose optimization** – Radiation-Dose optimization is a Basic rule of radiation protection of public as portion of healthcare. It is defined as maintaining doses "as low as reasonably achievable (ALARA principle). Dose optimization actually works with various Dose-saving measures to achieve greatest advantages while maintaining minimal radiation risk because the basic goal of diagnostic imaging is to get an accurate informative diagnostic image with very low radiation dose that is reasonable to achieve. Automatic control of some of the basic parameters of computed tomography which involves X-Ray tube current modulation(mAs), kVp selection, pitch, range and slice thickness directly impact the radiation exposure. AI-based algorithms such as machine learning and deep learning can optimize various CT parameters, including patient positioning, scan range, and technical factors like tube current and voltage, and claim to minimize radiation exposure compared to fixed tube current settings [4][5]. AI Algorithms may also refine traditional Physics and mathematics-based algorithms that are used to control Several basic parameters of a CT scans to optimize image quality and reduce patient's radiation dose. These parameters include tube current modulation, kVp selection, and slice thickness [6][7][8].

## 2. Material and Methods

In order to find out the relevance of current automatic techniques and AI based algorithms in radiation dose optimization, there is a need to understand the role of AI in every facet of CT scan imaging, from patient positioning to the final reconstruction of an image. Specifically, on the basic parameters of CT scans that manage radiation dose such as X-ray tube current, KVP selection, scan length, pitch, slice thickness and FOV (field of view) CT scans were performed with Biograpgh m CT (Siemens Healthcare, Forchheim, Germany) 128 slices with low-dose technology. The manufacturer introduced AIDAN (An application of Artificial Intelligent Scanner platform) with the various AI based algorithms in these Scanners and a dedicated CT scanner SOMATOM Drive Dual Source technology (Siemens Healthcare, Germany).

The study population consisted of 50 consecutive patients (25 women; 25 men). The mean age was 42 years and the study utilized patient data that was acquired with the following scan settings.

The data was collected for head, cardiac, chest, and abdominal scans.

Two different scanning setting were used in these patients.

A. Real time modulation of X-ray tube current (automated mAs selection) with automatically machine-defined fixed kVp of 120 kVp Head, 120 kVp cardiac, 120 kVp chest, 100 kVp chest, and 100 kVp abdomen.

B. Real time modulation of X-ray tube current and real time automatic kVp selection.

Radiation doses were measured using the CT Dose index CTDI (measured in units of mGy) which is actually radiation output of a CT Scanning machine and

$CTDI_W$ (mGy) (weighted average dose across single slice). $CTDI_W$ is divided by the pitch factor (the table movement during one rotation of the X-ray tube divided by the slice thickness) to obtain $CTDI_{voL}$.

**$CTDI_{voL}$= $CTDI_W$ / pitch**

Finally, the CT DLP was measured as follows to find the overall dose output or total radiation output.

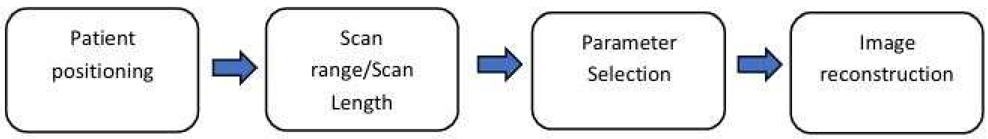
**DLP (mGy cm) = $CTDI_{voL}$(mGy) X Scan Length (cm).**

Finally, the effective dose is calculated using $W_T$= tissue weighing factor and $W_R$ radiation weighing factor according to the dose recommendation ICRP report 103 (2007).

$W_R$ radiation Weighing factor =1

**BMI Body Mass Index:** Measured using patients' weight and height.

**BMI** = Weight/ $(Height)^2$




Perspective of the interpretation of a computed tomography (CT) examination.

**Patient positioning** – The CT X-ray tube rotates around the patient isocentre. Accurate patient positioning at this centre is fundamental factor to maintain image quality [9] and radiation dose optimization. Positioning error >20 mm is clinical unacceptable and trained AI algorithms detects patients' anatomic landmarks to reduces positioning errors to 0 [10].

| Anatomic region and centring method | Average absolute error ± standard deviation (mm) | Maximum absolute error (mm) | Percentage of patients with error >20 mm |
|---|---|---|---|
| Chest | | | |
| Manual | 19 ± 9 | 39 | 50% |
| Automatic | 7 ± 4 | 15 | 0% |
| Abdomen | | | |
| Manual | 18 ± 11 | 43 | 40% |
| Automatic | 4 ± 2 | 9 | 0% |

Source: Saltybaeva et al. (2018).

**Scan Range and protocol Selection**- Automated scan range detection to minimise anatomical area subject to radiation exposure is an important facet under radiation dose optimization. Many manufacturers across the world are working to develop AI-Based algorithms for standardized clinical protocol strategy. FlowMotion AI, under AIDAN by Siemens-Healthineers, integrating continuous bed motion technology and AI algorithms for anatomical landmarks detection to automatically plan scan ranges using CT Scout image [20] and similar approaches are under development to optimize automated scan ranges and protocol selection by AI algorithms [19]. Fixed Scan range and Manual Protocol selection were considered for this study to find out scope of AI on fundamental CT Scan parameters for radiation dose optimization.

**Scout image parameters-** Cardiac and head scout images were acquired at 120 kVp with a maximum tube current of 35mAs while chest and abdomen Scout images were acquired at 100 kVp with a maximum tube current of 35 mAs. Average CTDI volume range during scout image = 0.05 - 0.09 mGy.

AEC determines the tube current based on scout images [24] which is further used for real time modulation of the X-ray tube current in CT. Currently, some AEC systems use simple machine learning techniques to select optimal tube potential and tube current [4]. In obese patients, AEC raises the tube current and consequently X-ray exposure compensates for attenuation by the thick tissues and preserves the number of detected photons [19].

The images shown in Figure -1 define the use of attenuation-based AEC tube current setting to reduce radiation exposure comparison to the fixed mAs (Figure -1a) setting which exposes the body to high radiation and Figure -1c defines the need for additional algorithm to reduce the attenuation-based raised mAs.


(a) (b) (c)

Figure -1: AEC based real time modulation of X-ray tube current compared to fixed tube current Low-dose technology Biograph m CT where a long scan (from head to thigh) is performed to guide other modalities like PET. The figure (a) shows constant mA with constant radiation exposure throughout the body (b) shows real-time modulation of the X-ray tube current in a normal patient (c) shows real-time modulation of the X-ray tube current in an obese patient where the minimum and maximum mA settings on the AEC define the mA at which the X-ray tube current is increased beyond certain limits.

**Parameters selection**– Many parameters determine how the radiation is delivered to the patient but radiation exposure is primarily bent upon mAs and kVp. The relationship between mAs and patient dose is direct, exhibiting a 1:1 linear relationship when all other exposure factors remain constant and increasing the kVp value raises both the average energy of the photons in an X-ray beam and the total number of photons [12].

The main focus in this study is on mAs and kVp and the fixed value of scan length, pitch and FOV (field of view) has been considered to explore the scope of machine learning on the basic parameters of radiation dose in CT.

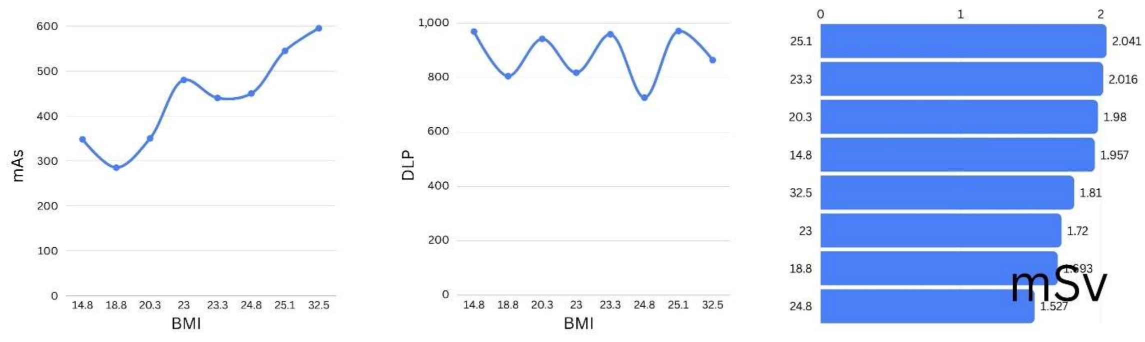
During automatic exposure Control a reference mAs is customized for a standard size patient and the AEC modulates real time tube current around this value based on patient attenuation.

AEC adjusts mAs upwards for larger patients and downwards for smaller patients to maintain image quality [13]. Predefined, minimum and maximum mAs setting maintain mAs within certain limits to reduce radiation exposure [14,15]. AEC systems vary between manufacturers in terms of parameters to be set and resulting radiation dose modulation [11, 16, 17]. Currently, some AEC systems use simple machine learning techniques to select optimal tube potential and tube current [4].

Before the CT scan, each patient's weight and height were measured, and their BMI was calculated. The groups of patients were then divide d based on their BMI: underweight (UW) if their BMI was below 19.5 $kg/m^2$ (underweight less than 16 $kg/m^2$ is severe thinness ), normal weight (NW) if their BMI was between 20-24.9 $kg/m^2$, overweight (OW) if their BMI was between 25 and 29.9 $kg/m^2$, and obese (OB) if their BMI was 30 $kg/m^2$ or higher [22].

**A. Scan data acquired with real time modulation of X-ray tube current and automatic exposure with fixed auto selected kVp.**

**1. Head Scan** CTDIvol (mGy), and DLP (mGy.cm) and effective dose (mSv) of procedures performed using automatic exposure with real time modulation of X-ray tube current under reference tube current/control Tube current of 340mAs and with fixed auto selected 120 kVp, 0.55Pitch, 164mm scan length, and 300 mm FOV. Predefined automatically selected minimum mAs of 37mAs and maximum mAs of 1200 mAs.

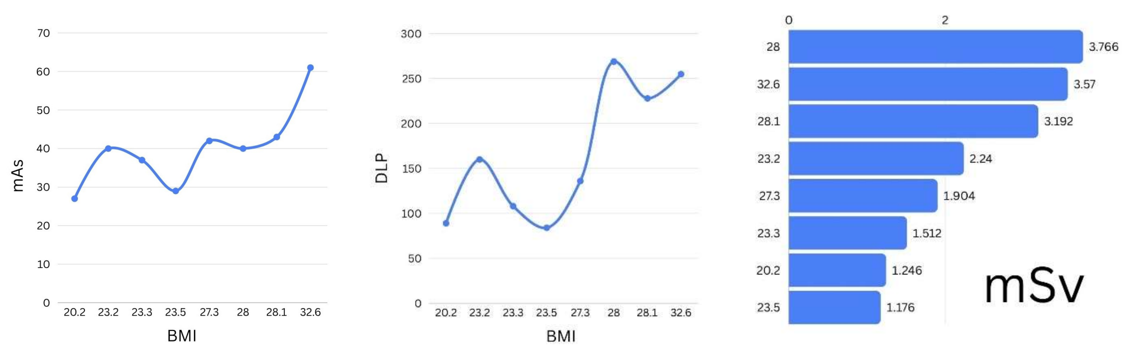



(a) (b) (c)

**Figure -2: Graphical representation of head scans data (a) mAs vs BMI (b) DLP vs BMI (c) Comparison of effective dose with respect to BMI.**

In CT scans, the AEC modulates mAs according to the scout image used to determine radiation dose modulation. Additional predefined settings of maximum mAs and minimum mAs act as a check on the doses modulated by the AEC which are clearly visible as the difference between the mAs and DLP curves. The mAs defined by AEC in obese with a BMI of 32.5 (kg/m$^{2)}$ is higher but dose length product is diminished. Furthermore, the AEC response in the underweight thin patient listed on serial number 1, whose BMI is 14.8 (kg/m2), approaching the reference tube current/control tube current of 340 mAs results in radiation exposure similar to that of a patient with a BMI of approximately 23 (kg/m$^2$).

2. **Cardiac Scans** CTDIvol (mGy), and DLP (mGy.cm) and effective dose (mSv) of procedures performed using Automatic exposure with real time modulation of X-ray tube current under reference tube current/ control Tube current of 40 mAs with fixed auto selected 120kVp, 0.3 Pitch, 164mm scan length, and 780mm FOV. Predefined automatically selected minimum mAs of 7mAs and maximum mAs of 219 mAs.



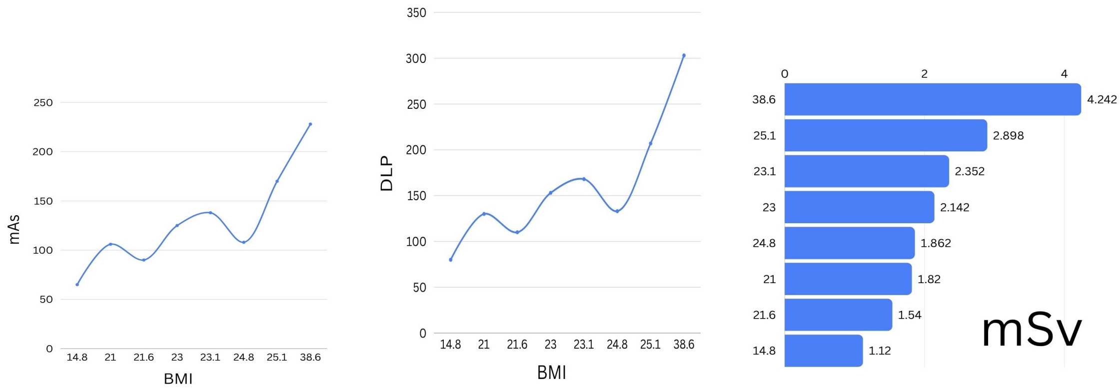

(a) (b) (c)

**Figure -3: Graphical representation of cardiac scans data (a) mAs vs BMI (b) DLP vs BMI (c) Comparison of effective dose with respect to BMI.**

In cardiac CT scans, the AEC modulated mAs shown in Figure 3 show the response of mAs vs. BMI and DLP vs. mAs except for the BMI of the obese patient where the effective dose is slightly reduced at higher AEC defined mAs with a higher effective dose of 3.7 mSv at a BMI of 28 (kg/m$^{2)}$ which is slightly higher than the effective dose of 3.6 (3.57) mSv at a BMI of 32.6 (kg/m$^2$).

**3. Chest Scan**

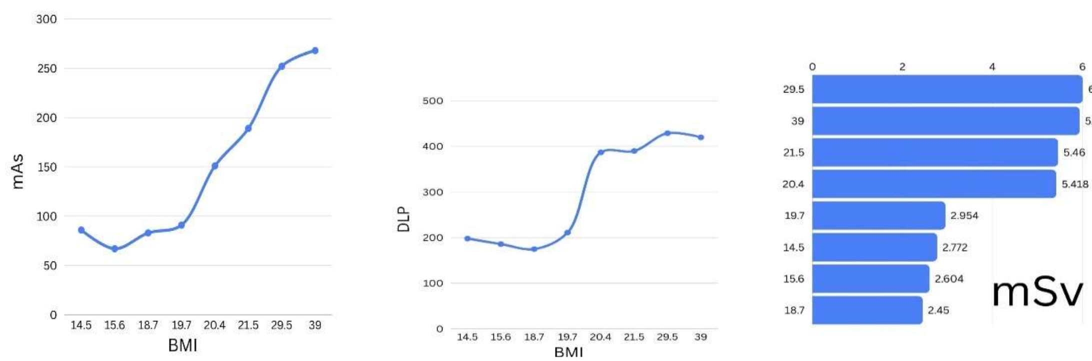
(a) procedures performed using Automatic exposure with real time modulation of X-ray tube current with fixed 100 kVp under reference tube current/control Tube current of 110mAs, 1.3 Pitch, 253.5mm scan length, and 780 mm FOV. Predefined automatically selected minimum mAs of 8mAs and maximum mAs of 256 mAs.




(a) (b) (c)

**Figure -4.1: Graphical representation of chest scan (100 kVp) data (a) mAs vs. BMI (b) DLP vs. BMI (c) Comparison of effective dose with respect to BMI.**

In a chest CT scan performed at 100 KVp, the AEC modulated mAs shown in Figure 4.1 shows a response of mAs curve similar to the DLP curve with a higher effective dose of 4.242 mSv at a BMI of 38.6 (kg/m$^{2)}$.
(b) Chest Scan - procedures performed using Automatic exposure with real time modulation of X-ray tube current with fixed 120 kVp under reference tube current/ control Tube current of 110mAs, 1.3 Pitch, 253.5mm scan length, and 780 mm FOV. Predefined automatically selected minimum mAs of 8mAs and maximum mAs of 256 mAs.

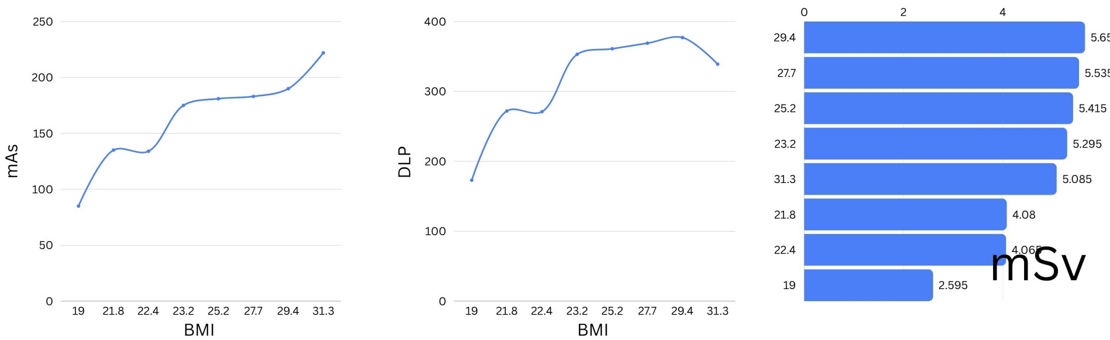



(a) (b) (c)

**Figure -4.2: Graphical representation of chest scans (120 kVp) data (a) mAs vs BMI (b) DLP vs BMI (c) Comparison of effective dose with respect to BMI.**

In a chest CT scan performed at 120 KVp, the AEC modulated mAs shown in Figure 4.2 shows that the response of the mAs curve is different from the DLP and there are some situations with diminished radiation dose length product curve (DLP) compared to mAs curve. Whereas, the high effective dose of 6.006 mSv at a BMI of 29.5 (kg/m$^2$) which is higher than the effective dose of 5.94 mSv at a BMI of 39 (kg/m$^2$).

**4. Abdomen with pelvis**- The abdominal scan was performed with real time automatically modulated X-ray tube current mAs and automatically modulated kVp with a reference tube current/ control Tube current of 210mAs, 0.8Pitch, 431.5mm scan length, and 780 mm FOV. Predefined automatically selected minimum mAs of 17mAs and maximum mAs of 555 mAs.



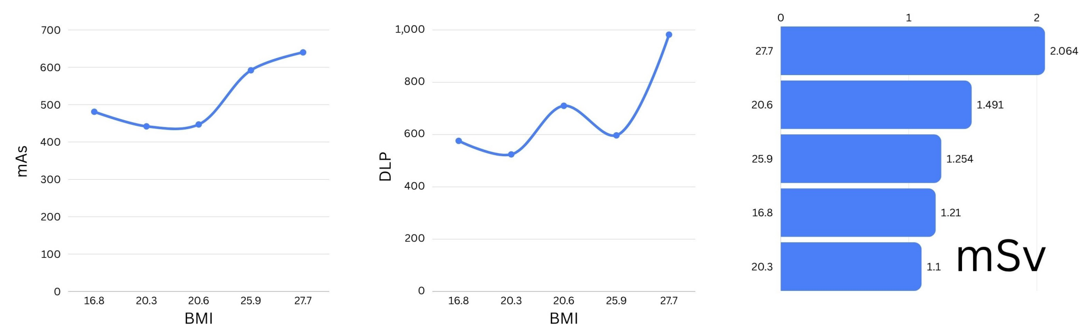

(a) (b) (c)

**Figure -5: Graphical representation of abdomen scans (120 kVp) data (a) mAs vs. BMI (b) DLP vs. BMI (c) Comparison of effective dose with respect to BMI.**

In abdominal CT scans, the AEC modulated mAs shown in Figure 5 shows a response of the mAs curve similar to the DLP curve with a lower radiation dose length product curve (DLP) in obese patients. The highest effective dose of 5.655 mSv at a BMI of 29.4 (kg/m$^{2)}$ is higher than the effective dose of 5.085 mSv found at a BMI of 31.3 (kg/m2).

**B. Scan data acquired with automatic exposure with real time modulation of X-ray tube current and automatic exposure with real time modulation of kVp.**

(a) **Head Scan** – Real time automatically modulated X-ray tube current mAs and automatically modulated kVp with reference tube current/control at 340mAs, 0.55Pitch, 164mm scan length, and 300 mm FOV. Predefined auto selected minimum mAs of 37mAs and maximum mAs of 1200 mAs.

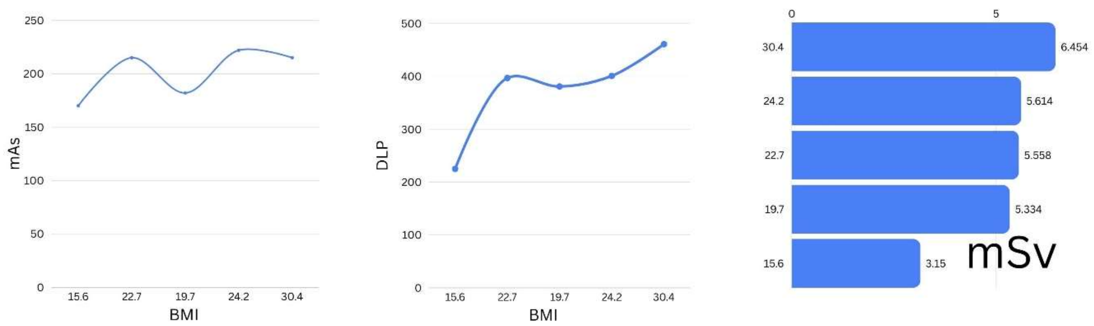



(a) (b) (c)

**Figure -6: Graphical representation of head scans (real time automatically modulated X-ray tube current mAs and real time automatically modulated kVp) data (a) mAs vs. BMI (b) DLP vs. BMI (c) Comparison of effective dose with respect to BMI.**

In a head CT scans performed with real time automatically modulated X-ray tube current (mAs) and real time automatically modulated Energy (kVp), the AEC response in a lean underweight patient with a BMI 16.8 (kg/m$^{2)}$ reached higher than reference tube current/ Control tube current of 340 mAs resulting in a radiation exposure greater than that of a patient with a BMI of 20.3 (kg/m$^2$) but less than that of a patient with a BMI of 20.6 (kg/m$^2$). A high effective dose of 2.064 mSv was found at a BMI of 27.7 (kg/m$^2$).
A comparison of real-time modulation of energy (kVp) versus fixed kVp shows that real-time modulation of energy (kVp) increases mAs while reducing kVp to compensate for the loss in the number of low-energy X-ray photons at the reduced kVp to maintain image quality.
.

(b) **Chest Scan** - Performed with real time automatically modulated X-ray tube current mAs and automatically modulated kVp under reference tube current/ control tube current of 210mAs, 0.55Pitch, 164mm scan length, and 300 mm FOV. Predefined automatically selected minimum mAs of 8 mAs and maximum mAs of 256 mAs.




(a) (b) (c)

**Figure -7: Graphical representation of chest scans (real time automatically modulated X-ray tube current mAs and automatically modulated kVp) data (a) mAs vs. BMI (b) DLP vs. BMI (c) Comparison of effective dose with respect to BMI.**

In chest CT scan performed with real-time automatically modulated X-ray tube current (mAs) and real-time automatically modulated Energy (kVp), the AEC response in an underweight, thin patient with a BMI of 15.6 (kg/m$^{2)}$ decreased kVp to 100 but increased mA compared to the mA defined in the same BMI of 15.6 (kg/m2) scan performed with fixed 120 kVp setting. A high effective dose of 6.454 mSv was found at a BMI of 30.4 (kg/m$^{2)}$.

The effect of the diminished DLP curve in comparison to mAs curve is reduced in scans that were performed with automatic exposure with real time modulation of the X-ray tube current and automatic exposure with real time modulation of kVp compared to the mAs curve found in scans performed with fixed kVp.

**AI in Reconstruction and Lesson Detection-** exciting application of AI in CT is the use of a convolution neural network (CNN)-based deep learning approach to reduce image noise (also referred to as 'denoising') [25] [26] [27]. The promising DLR algorithms for dose reduction technique has been approved by the FDA USA and is now being developed for commercial use.

**Stastistical Analysis** – Continuous variables were presented as mean plus standard deviation (range) and categorical variables as frequencies or percentages.

| Group | Scan Type and kVp Defined | BMI (kg/m²) Mean ± SD | Tube Current (mAs) Mean ± SD | CTDIvol (mGy) Mean ± SD | DLP (mGy·cm) Mean ± SD | Effective Dose (mSv) Mean ± SD |
|---|---|---|---|---|---|---|
| Group 1 | Head CT (Mixed 120 & 100 kVp) | 22.83 ± 5.49 | 398.25 ± 85.64 | 50.33 ± 7.68 | 865.83 ± 133.59 | 1.82 ± 0.30 |
| Group 2 | Cardiac CT (120 kVp AutoFixed) | 25.78 ± 4.20 | 39.88 ± 9.47 | 8.92 ± 3.67 | 157.41 ± 62.77 | 2.20 ± 0.88 |
| Group 3 | Head CT (Auto 100 kVp) | 22.26 ± 4.30 | 440.40 ± 115.20 | 40.55 ± 14.36 | 708.40 ± 235.20 | 1.97 ± 0.31 |
| Group 4 | Chest CT (100 & 120 kVpFixed) | 22.75 ± 6.12 | 130.87 ± 52.31 | 7.53 ± 2.88 | 200.27 ± 99.52 | 2.88 ± 1.39 |
| Group 5 | Chest CT Auto kVp | 20.87 ± 1.51 | 168.33 ± 41.26 | 12.06 ± 3.86 | 447.00 ± 130.15 | 6.26 ± 1.74 |
| Group 6 | Abdomen CT Auto 100 kVp | 24.97 ± 4.26 | 152.86 ± 36.92 | 6.82 ± 1.76 | 307.71 ± 72.94 | 4.61 ± 1.09 |

**TABLE1.defining Mean and Standard deviation of parameters.**

| Parameter | 120 kVp (n=6) | 100 kVp (n=2) | p-value |
|---|---|---|---|
| CTDIvol (mGy) | 53.74 ± 6.98 | 40.30 ± 9.89 | 0.048 |
| DLP (mGy·cm) | 921.10 ± 121.80 | 697.50 ± 171.00 | 0.041 |
| Effective Dose (mSv) | 2.10 ± 0.24 | 1.46 ± 0.36 | 0.039 |

TABLE 2: Comparison of 100 vs 120 kVp (Head CT)

| Parameter | 120 kVp (n=5) | 100 kVp (n=10) | p-value |
|---|---|---|---|
| CTDIvol (mGy) | 9.80 ± 2.75 | 5.69 ± 2.33 | 0.012 |
| DLP (mGy·cm) | 298.40 ± 107.20 | 141.30 ± 66.10 | 0.008 |
| Effective Dose (mSv) | 4.18 ± 1.50 | 1.98 ± 0.92 | 0.006 |

**TABLE 3: Comparison of Auto selected 100 vs 120 kVp (Chest CT)**

Head CTChest CT

| Parameter | % Reduction | Parameter | % Reduction |
|---|---|---|---|
| CTDIvol | 25.0% ↓ | CTDIvol | 41.9% ↓ |
| DLP | 24.3% ↓ | DLP | 52.6% ↓ |
| Effective Dose | 30.5% ↓ | Effective Dose | 52.6% ↓ |
| | | | |

**TABLE 4: Percentage Dose Reduction (100 vs 120 kVp)**

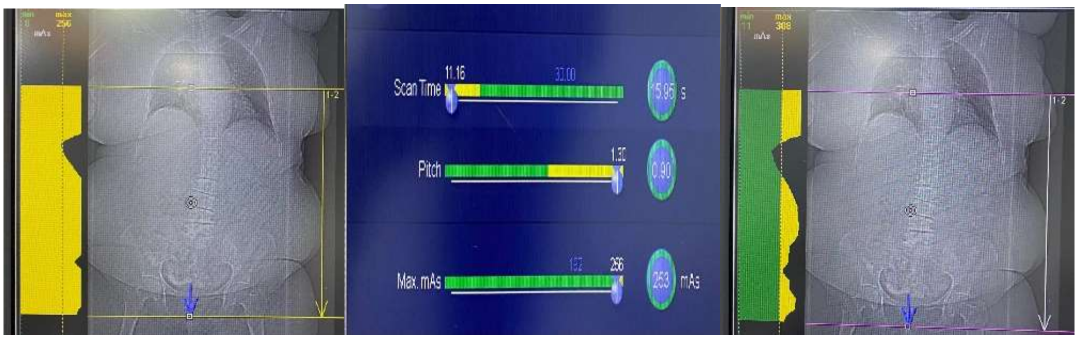
| Variable | CTDIvol | DLP | Effective Dose |
|---|---|---|---|
| BMI | r = 0.62 | r = 0.66 | r = 0.65 |

**TABLE 5: Correlation (BMI vs Radiation Dose)**

A significant reduction in radiation dose was observed with 100 kVp compared to 120 kVp protocols. In head CT, CTDIvol, DLP, and effective dose were reduced by 25.0%, 24.3%, and 30.5%, respectively ($p < 0.05$). In chest CT, a more pronounced reduction was noted, with CTDIvol, DLP, and effective dose decreased by 41.9%, 52.6%, and 52.6%, respectively ($p < 0.01$). Additionally, a moderate positive correlation was observed between BMI and radiation dose parameters ($r = 0.62$-$0.66$), indicating increased dose requirements with higher patient body mass.

**Result**- The Mean effective dose ranged from 1.42 mSv (head) to 4.71 (abdomen) and 5.22 mSv (chest). In the case of head CT scans, the effective dose varies across automatic exposures, with real time modulation of kV ranging from 1.210 mSv at a BMI of 16.8 (kg/m$^2$) - 2.062 mSv at BMI of 27.7 (kg/m$^2$) in an obese patient and 1.5 mSv at BMI of 24 (kg/m$^2$) in a patient scanned with a fixed 120 kVp to 2.041 mSv at BMI of 25.7 (kg/m$^2$) and 1.810 mSv at BMI of 32.5 (kg/m$^2$). While in the abdomen and pelvis it ranged from 2.595 mSv at a BMI of 19 (kg/m$^2$) - to 5.655 mSv at a BMI of 29.4 (kg/m$^2$). The low dose chest effective dose varies across the automatic exposures with real time modulation of kVp (80 kVp to 140 kVp), from 3.150 mSv for a thin patient with a BMI of 15.6 (kg/m$^2$) - to 6.45 mSv for an obese patient with a BMI of 30.4 (kg/m$^2$) and with a fixed 100 kVp, the effective dose ranged from 1.120 mSv at a BMI of 14.8 (kg/m$^2$) to 4.242 mSv at a BMI of 38.6 (kg/m$^2$), while with a fixed 120 kVp, the effective dose ranged from 2.450 mSv at a BMI of 18.7 (kg/m$^2$) to 4.242 mSv at a BMI of 38.6 (kg/m$^2$) but up to 6.006 mSv at a BMI of 29.5 (kg/m$^2$). In the case of cardiac CT scans, the effective dose ranged from 1.17 mSv at a BMI of 23.5 (kg/m$^2$), including 1.246 mSv at a BMI of 20.2 (kg/m$^2$) - 3.766 mSv at a BMI of 28 (kg/m$^2$).

**Discussion-**Dose optimization in CT includes numbers of CT scan parameters but this study primely focused on facets affecting the automatic modulation of fundamental parameters such as mAs and kVp using fixed Scan Length, Pitch and FOV. AEC (Automatic exposure control) an attenuation-based techniques showed limitation in both obese patients and underweight thin patients and defined a significant correlation between scout image attenuation and BMI. The use of predefined maximum and minimum mAs work to control radiation exposure (shown in figure 8) but in case of overweight obese patient the accuracy of these predefined mAs limits is affected and obese patients receive higher radiation exposure.




(a) (b) (c)

Figure -8: Scout image of an and overweight and obese patient showing AEC defined mAs exceeding the maximum mAs limit (a) Image Shows the automatically selected minimum of 8 mAs and maximum of 256 mAs while the AEC (Automatic exposure control) directs mAs exceeding this limit (b) Image shows adjustment of Scan time, Pitch, and increasing the maximum mAs limits. (c) image shows the increased minimum mAs and maximum mAs limits.

Procedure performed with a fixed 100 kVp compared to 120 kVp or higher affects image quality, but the similar scan performed with automatically modulated kVp and mAs increases mAs while reducing kVp to maintain the required number of X-ray photons required for the image and maintains image quality. In the case of an underweight patient, the mAs defined by the AEC approaches near to the reference tube current/ control tube current indicating dominance of the control tube current as shown in figure 2. The selection of tube potential based on a single and exclusive parameter such as BMI will not reflect the automated algorithm in a complete manner [21]. THE use of predefined maximum and minimum mAs as check on AEC defines mAs setting to remove this limitation raises further question on complete automation of AEC Algorithm and impacts both radiation dose as well as image quality in obese and overweight patients. This is also evidenced by Hatem Alkadhi et al 2011 [21] that the AEC Algorithm considers various factors beyond patient attenuation and BMI. For example, some AEC systems use simple machine learning techniques to select the optimal tube potential and tube current [19].

**Conclusion-** AI holds significant promise for reducing radiation exposure in CT scans. AI-based technologies enhance positioning and scan range accuracy through automatic patient centering and delineation, thereby lowering radiation doses and minimizing over-scanning, but the selection of fundamental CT scan parameters is still performed by traditional physics-based automatic techniques which are performing better near the reference tube current/ control Tube current and modify the radiation exposure using scan scout images but more variation in exposure found in obese patients as well as underweight patients. The involvement of AI in AEC may consider fully automating the AEC system or removing AEC limitations but the current absence of FDA-approved AI algorithms to modulate mAs and kVp on AEC by any vendor defines that the scope of AI on automatic MA and KVP modulation is broad but under development

**Limitations**-The limited number of patients considered for this study is a limitation of this study and the results can be improved considering the higher number of patient data and various FDA approved AI algorithms have been introduced to reduce noise in reconstructed images which significantly reduce the radiation dose of the patient but these algorithms have not been considered under this study. In the current era, various CT manufacturers have introduced iterative reconstruction (IR) in conjunction with artificial intelligence-based algorithms to overcome the limitations of the FBP strategy. Thus, there are limitations to define the effectiveness of deep learning algorithm-based trained reconstruction techniques which may raise concerns of image appearance change with reduced anatomical details to maintain the contrast resolution of diagnostic information. Various articles related to deep neural networks trained on very extensive training data to achieve advanced tomographic reconstruction reviewed by Reya V et al 2022 [23] concluded that advanced CT image reconstruction is moving towards AI reconstruction and improves issues related to resolution accuracy and reconstruction time at low radiation dose

**References**

[1] Kalra MK, Maher MM, Toth TL, et al. Strategies for CT radiation dose optimization. Radiology. 2004;230:619–628.
[2] Medicine AAoPi. The measurement, reporting, and management of radiation dose in CT: report of AAPM task group 23 of the diagnostic imaging council CT committee. 2008. AAPM report no. 96. Available at: http://www.aapm.org/

pubs/reports/rpt_96.pdf. Accessed January 05, 2011

[3] Yu L, Li H, Fletcher JG, et al. Automatic selection of tube potential for radiation dose reduction in CT: a general strategy. Med Phys. 2010; 37:234 243.

[4] McCollough CH, Bruesewitz MR, Kofler JM Jr. CT dose reduction and dose management tools: overview of available options. Radiographics. 2006;26: 503–512.

[5] NagayamaY, Iwashita K, Maruyama N, Uetani H, Goto M, Sakabe D, et al. Deep learning-based reconstruction can improve the image quality of low radiation dose head CT. EurRadiol 2023;33(5). https://doi.org/10.1007/s00330-023 09559-3.

[6] Sun J, Li H, Wang B, Li J, Li M, Zhou Z, et al. Application of a deep learning image reconstruction (DLIR) algorithm in head CT imaging for children to improve image quality and lesion detection. BMC Med Imag 2021;21(1). https://doi.org/10.1186/s12880-021-00637-w.

[7] Greffier J, Durand Q, Frandon J, Si-Mohamed S, Loisy M, de Oliveira F, et al. Improved image quality and dose reduction in abdominal CT with deep learning reconstruction algorithm: a phantom study. EurRadiol 2022;33(1). https://doi.org/10.1007/s00330-022-09003-y.

[8] International Commission on Radiological Protection. The 2007 recon emendations of the international commission on radiological protection. ICRP publication 103. Ann ICRP. 2007;37:1–332.

[9] Erickson, B.J., Korfiatis, P., Akkus, Z., et al., 2017. Machine learning for medical imaging. Radiographics 37, 505–515.

[10] Saltybaeva, N., Schmidt, B., Wimmer, A., et al., 2018. Precise and automatic patient position ing in computed tomography: avatar modeling of the patient surface using a 3-dimensional camera. Invest. Radiol. 53, 641–646.

[11] Franck C and Bacher K. Influence of localizer and scan direction on the dose-reducing effect of automatic tube current modulation in com puted tomography. Radiat Prot Dosimetry 2016; 169: 136-142.

[12 ]Erickson, B.J., Korfiatis, P., Akkus, Z., et al., 2017. Machine learning for medical imaging. Radiographics 37, 505–515.

[13] Franck C and Bacher K. Influence of localizer and scan direction on the dose-reducing effect of automatic tube current modulation in com puted tomography. Radiat Prot Dosimetry 2016; 169: 136-142.

[14] Söderberg M. Overview, practical tips and po tential pitfalls of using automatic exposure control in ct: siemens CARE dose 4D. Radiat Prot Dosimetry 2016; 169: 84-91.

[15] Abuzaid MM, Elshami W, Tekin H, Issa B. Assessment of the willingness of radiologists and radiographers to accept the integration of artificial intelligence into radiology practice. Acad Radiol. (2020) 29:87–94. doi: 10.1016/j.acra.2020.09.014.

[16] Söderberg M and Gunnarsson M. Automatic exposure control in computed tomography--an evaluation of systems from different manufacturers. Acta Radio 2010; 51: 625-634.

[17] Iball GR and Tout D. Computed tomography au tomatic exposure control techniques in 18F FDG oncology PET-CT scanning. Nucl Med Commun 2014; 35: 372-381.

[18] The 2007 recommendations of the international commission on radiological protection. ICRP Publication 103. Ann ICRP 2007; 37: 1-332.

[19] C.H. McCollough, S. Leng.ICRP 2019 ProceedingsCT Clinical Innovation Center, Department of Radiology, Mayo Clinic, 200 First Street SW, Rochester, MN, USA; e-mail: mccollough.cynthia@mayo.edu

[20] White paper Automatic landmarking and parsing of human anatomy (ALPHA) for innovative and smart MI applications Siemens Healthineers.

[21] AnnaWinklehner,* Robert Goetti , Hatem Alkadhi, MD, MPH, Institute of Diagnostic and Interventional Radiology, University Hospital Zurich, Raemistrasse 100, CH-8091 Zurich, Switzerland. E-mail: hatem.alkadhi@usz.ch. Copyright © 2011 by Lippincott Williams & Wilkins ISSN: 0020-9996/11/4612-0767 Invest Radiol 2011;46: 767–773.

[22] Obesity, BMI, and Health: A Critical Review FrankQ.Nuttall,MD,PhD,MinneapolisVAMedical Center, One Veterans Dr 111G, Minneapolis, MN 55417 (Nutta001@umn.edu)

[23] Reya V. Gupta, Mannudeep K. Kalra, MD, Shadi Ebrahimian, MD, Parisa Kaviani, MD, Andrew Primak, PhD, Bernardo Bizzo, MD, PhD, Keith J. Dreyer, DO, PhDAcad Radiol 2022; 29:1709–1719

[24] Yusuke Inoue, Kazunori Nagahara, Hiroko Kudo, Hiroyasu Itoh Department of Diagnostic Radiology, Kitasato University School of Medicine, Sagamihara, Kanagawa 252-0374, Japan Am J Nucl Med Mol Imaging 2018;8(2):143-152 www.ajnmmi.us /ISSN:2160 8407/ajnmmi0076225

[25] Chen H, Zhang Y, Kalra MK, Lin F, Chen Y, Liao P, et al. Low-dose CT with a residual encoder-decoder convolutional neural network. IEEE Trans Med Imag 2017;36(12):2524e35. https://doi.org/10.1109/TMI.2017.2715284.

[26] Yi X, Babyn P. Sharpness-aware low-dose CT denoising using conditional generative adversarial network. J Digit Imag 2018;31(5):655e69. https://doi.org/10.1007/s10278-018-0056-0. PMID: 29464432; PMCID: PMC6148809.

[27] Kang E, Chang W, Yoo J, Ye JC. Deep convolutional framelet denosing for low dose CT via wavelet residual network. IEEE Trans Med Imag 2018;37(6): 1358e69. https://doi.org/10.1109/TMI.2018.2823756. PMID: 29870365.