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Analyzing Computed Tomography Image Quality in Abdomen, Chest, and Skull Scans through Machine Learning

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ABSTRACT

The significance of medical imaging in disease diagnosis and treatment is undeniable, with Computed Tomography (CT) imaging leading the forefront. ML reveals organ abnormalities, lung conditions, and skull changes clinically. This investigation focuses on the application of machine learning techniques within medical imaging, specifically targeting the assessment of CT image quality in vital anatomical regions such as the abdomen, chest, and skull. The primary goal is to forge a robust and precise technique that can thoroughly evaluate CT image quality, offering an early identification mechanism for potential diagnostic discrepancies and elevating the standards of patient care. This study harnesses state-of-the-art machine learning approaches to comprehensively explore the efficacy and dependability of CT imaging modalities. Utilizing Machine Learning to discern effects of CT scan parameters on DLP and $CTDI_{vol}$, uncovering hidden patterns in images. There are promising prospects for refining diagnostic precision, streamlining patient care protocols, and ultimately augmenting clinical outcomes. This investigation into ML-driven CT image quality analysis yielded promising outcomes. ML reveals how CT scan parameters influence DLP and CTDIvol, guiding adjustments for optimal image quality and patient safety. This research not only substantiates the remarkable capabilities of machine learning but also underscores its pivotal role in reshaping the landscape of medical imaging. The result underscores the need for refined ML-based CT image quality analysis techniques, aiming to bridge existing gaps and deliver more precise diagnoses while advancing healthcare delivery. The implications of the findings (The highest mean scan length are 64.36cm, 62cm, and 169.01cm for abdomen, chest, and skull respectively while the highest mean pitch are 1.60,1.63 and 0.65 for abdomen, chest and skull respectively) transcend conventional radiology domains, signaling the advent of a novel era where artificial intelligence collaborates synergistically with human expertise to attain unprecedented excellence in healthcare delivery.

Keywords: Computed Tomography (CT) image quality, machine learning, medical imaging, Abdomen CT, Chest CT, Skull CT.

Introduction

The realm of medical imaging is profoundly influenced by Computed Tomography (CT), an indispensable modality providing detailed cross-sectional anatomical images for diagnosing various medical conditions (Shahbazian and Jacobs, 2012; Nagarajan *et al.,* 2014). Despite its efficacy, challenges surrounding CT image quality such as noise, artifacts, and exposure parameter inconsistencies persist (Van Timmeren.*et al*., 2020). Conventionally, quality assessment entails subjective, time-consuming manual inspection by radiologists.

Embracing machine learning (ML) which is a subfield of artificial intelligence that centers on using Algorithms to draw inference and find patterns in data, as a viable alternative promises automated, precise quality assessment and heightened diagnostic accuracy (De Groof *et al*., 2020; Edenbradt *et al*., 2022; Sahiner *et al*., 2019). The significance of medical imaging in disease diagnosis and treatment is undeniable, with CT imaging leading the forefront. ML models demonstrate immense promise in refining imaging parameters for enhanced anatomical visualization via noise reduction and artifact detection (You *et al.,* 2019; Kidoh *et al.,* 2020). Precise organ segmentation in abdominal CT scans holds pivotal significance in understanding disease progression and devising tailored treatment strategies (Sanchez and Gores, 2009).

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ML-driven deep learning models, when applied to chest imaging analysis, excel in identifying pulmonary abnormalities with remarkable sensitivity and specificity. Similarly, the application of ML algorithms in skull CT imaging accurately identifies cranial anomalies, vital for detecting conditions like brain tumors or traumatic injuries (Wang and Bovik, 2006; Bouxsein *et al*., 2010; Hoy *et al*., 2012). ML-based approaches have extended to optimizing treatment plans, accounting for individual patient characteristics and anatomical features derived from CT imaging (Takam et al., 2020; O'malley et al., 2005; Litjens et al, 2017). Such advancements promise heightened treatment efficacy and minimized radiation exposure and side effects. Prior studies emphasized the importance of meticulously verifying clinical trial data. While previous studies have made strides in CT image quality assessment using ML, achieving consistent results across diverse scans and anatomical regions remains an ongoing challenge (Wang and Bovik, 2006; Bouxsein et al., 2010; Hoy et al., 2012 and Rajpurkar *et al*., 2022).

Despite technological strides, CT image quality analysis remains a critical domain fraught with challenges (McCollough et al., 2009; Scarfe and Farman, 2008; Abbara *et al.*, 2016). The potential impact of enhanced CT image quality on patient outcomes and diagnostic accuracy fuels the significance of ML-based image analysis (Tatsugami *et al*., 2019; Rompianesi *et al*., 2022; Choe et al., 2022). Thus, meticulous evaluation of CT image quality becomes paramount to ensure reliability and enhance diagnostic precision. Machine learning (ML) algorithms have emerged as formidable tools in medical imaging research, offering substantial potential in revolutionizing CT image analysis (Luo *et al.,* 2016 ; Greenspan *et al.,* 2016; Kulkari *et al*., 2020 and Geras *et al*., 2019).

This study intends to offer new insights into how ML approaches can amplify existing CT image analysis practices. Analyzing multiple anatomical regions—abdomen, chest, and skull—aims to decipher ML's role from image formation to scanning parameter influence. A comprehensive understanding of ML's advantages and limitations will refine decision support systems for radiological evaluations, ultimately enhancing care quality while curbing healthcare costs.

This research aims to delve deeper into understanding the unique challenges of each anatomical region, consequently improving overall image quality assessment. This research endeavors to employ ML techniques for analyzing CT image quality in the abdomen, chest, and skull regions. By leveraging these computational methods on extensive datasets from diverse patients, we aim not only to assess their effectiveness but also to ascertain their potential in augmenting diagnostic accuracy while prioritizing patient safety.

In addressing the challenge of precisely evaluating CT image quality in abdominal, chest, and skull scans, this study aims to establish a methodology surpassing existing solutions. The objective is to construct a framework employing machine learning (ML) techniques, leveraging Scikit-learn, a Python-based library. This framework aims to comprehensively dissect various CT scanning parameters and their influence on essential image quality metrics. This study will also explore how these advanced computational techniques contribute to improving overall image quality by reducing noise levels, enhancing contrast resolution, and addressing artifacts commonly encountered in abdominal scans as well as those acquired from the chest and skull areas. The aim is to optimize image interpretation while minimizing any potential risks associated with misdiagnosis or unnecessary additional examinations.

Materials and Methods

Ethical Approval

In this study, ethical approval was secured from the relevant institutions, Federal Medical Centre, Yenagoa, Intercontinental Diagnostic Centre, Port Harcourt, Image Diagnostic, Port Harcourt and Uyo, Georges Diagnostic Centre Limited, Port Harcourt, University of Port Harcourt Teaching Hospitals, Port Harcourt, Orange Medical Diagnostic, Port Harcourt, University of Calabar Teaching Hospital, Calabar, Benin Medical care, Benin, and Westend Hospital, Warri, Delta State ensuring adherence to ethical standards and participant welfare. The approval process involved a comprehensive review, affirming the commitment to ethical conduct in medical physics research.

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Collection of Computed Tomography (CT) Scans and Image Quality Standards

A dataset comprising of two thousand, eight hundred and twenty-eight (2828) CT scans sourced from ten medical institutions forms the study's foundation from Federal Medical Centre, Yenagoa, Intercontinental Diagnostic Centre, Port Harcourt, Image Diagnostic, Port Harcourt and Uyo, Georges Diagnostic Centre Limited, Port Harcourt, University of Port Harcourt Teaching Hospitals, Port Harcourt. Orange Medical Diagnostic, Port Harcourt, University of Calabar Teaching Hospital, Calabar, Benin Medical care, Benin, and Westend Hospital, Warri, Delta State. These scans underwent stringent radiologist assessment to adhere to stringent image quality standards. The dataset captures a diverse array of CT parameters and metrics, including kV, mAs, slice thickness, pitch, image uniformity, CT number variation, and low contrast resolution. Utilizing the functionalities of Scikit-learn, renowned for its prowess in regression and classification tasks in machine learning, an exhaustive analysis was conducted. The focus was on unraveling the intricate relationships between CT scan parameters and critical image quality metrics such as Dose Length Product (DLP) and CTDI vol.

Regression models

Robust regression models were applied to unravel the intricate relationships between CT scan parameters and critical image quality metrics such as Dose Length Product (DLP) and CTDI vol. This is to enable the discernment of nuanced correlations.

Preliminary Planning and Objective Setting

Defined the overarching goal: Precisely evaluated and comprehend the relationships between CT scanning parameters and image quality metrics. Established specific research objectives: Investigated how various CT parameters affect image quality metrics using machine learning techniques.

Data Collection and Curation

Source of comprehensive dataset: Collected CT scans encompassing abdominal, chest, and skull regions, from diverse sources ensuring a broad representation of imaging parameters and image quality metrics. To ensure rigorous quality control, the radiologists of the various institutions, assessed and validated the collected CT scans to meet predefined image quality standards.

Dataset Preparation and Feature Extraction

Preprocessed the collected dataset: Standardized and preprocessed CT scan data, ensuring consistency in format and structure. Extracted relevant features were isolated and categorized CT parameters such as kV, mAs, slice thickness, pitch, image uniformity, CT number variation, and low contrast resolution.

Machine Learning Model Development

Appropriate ML models of regression models within Scikit-learn suitable for correlating CT scanning parameters with image quality metrics (e.g., DLP, CTDI vol) were selected for the study. The models were trained and optimized using the prepared dataset, and adjusting hyper-parameters for optimal performance in discerning correlations.

Data Analysis and Correlation Investigation

Applied trained models: Use the trained ML models to analyze the dataset, uncovering intricate relationships between CT scan parameters and image quality metrics. Evaluated correlations: Assessed the strength and significance of correlations between CT parameters and image quality metrics, utilizing regression analysis.

Result Interpretation and Insights Generation

The findings from the investigation were interpreted. Derived insights from identified correlations, highlighting significant relationships between specific CT parameters and image quality metrics. Analyzed the impact: Discuss implications for healthcare settings, potential optimization of CT imaging protocols, and ways to mitigate radiation exposure without compromising diagnostic quality.

Results

In the realm of image quality assessment, our investigation delved into the intricate dynamics of Computed Tomography Dose Index (CTDI) and Dose Length Product (DLP), primarily concerning their association with pitch and scan length. The comprehensive outcomes of this analysis are vividly illustrated through Figures 1 to 12, while Table 1 meticulously elucidates the specific scanning configurations adopted in this study.

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Table 1: The Scanning Parameters for Image Quality Analysis of Multiple Anatomical Regions of the Abdomen, Chest, and Skull

Facilities Institutions	Abdomen				Chest				Skull			
	Mean Scan Length	Mean Pitch	Mean kV	Mean mAs	Mean Scan Length	Mean Pitch	Mean kV	Mean mAs	Mean Scan Length	Mean Pitch	Mean kV	Mean mAs
1	17.12	0.65	120	170.94	43.59	1.30	120	233.02	189.3	0.52	120	234.45
2	40.08	1.40	120	147.25	18.08	1.40	120	186.32	169.01	0.53	120	256.45
3	62.16	1.60	120	94.4	62	1.60	120	91.77	65.85	0.55	120	90.02
4	39.88	0.55	130	90.43	38.8	1.30	130	88.5	22.08	0.55	130	156.77
5	5.26	0.80	110	232.92	5.27	1.50	110	103.61	2.56	0.55	110	220
6	39.58	0.64	120	99.81	38.38	1.40	120	90.51	22.03	0.64	120	161.2
7	52.29	0.60	120	132.28	55.54	1.30	120	77.75	63.58	0.60	120	102.49
8	21.85	0.70	130	185.29	16.89	1.40	130	169.34	18.41	0.65	130	92.22
9	64.36	0.60	120	189.11	43.86	1.30	120	163.31	22.05	0.62	120	102.66
10	21.94	0.62	120	91.95	17.94	1.63	120	157.39	39	0.62	120	192.05

Key: kV =Kilovoltage ; mAs = Milliampere-Seconds

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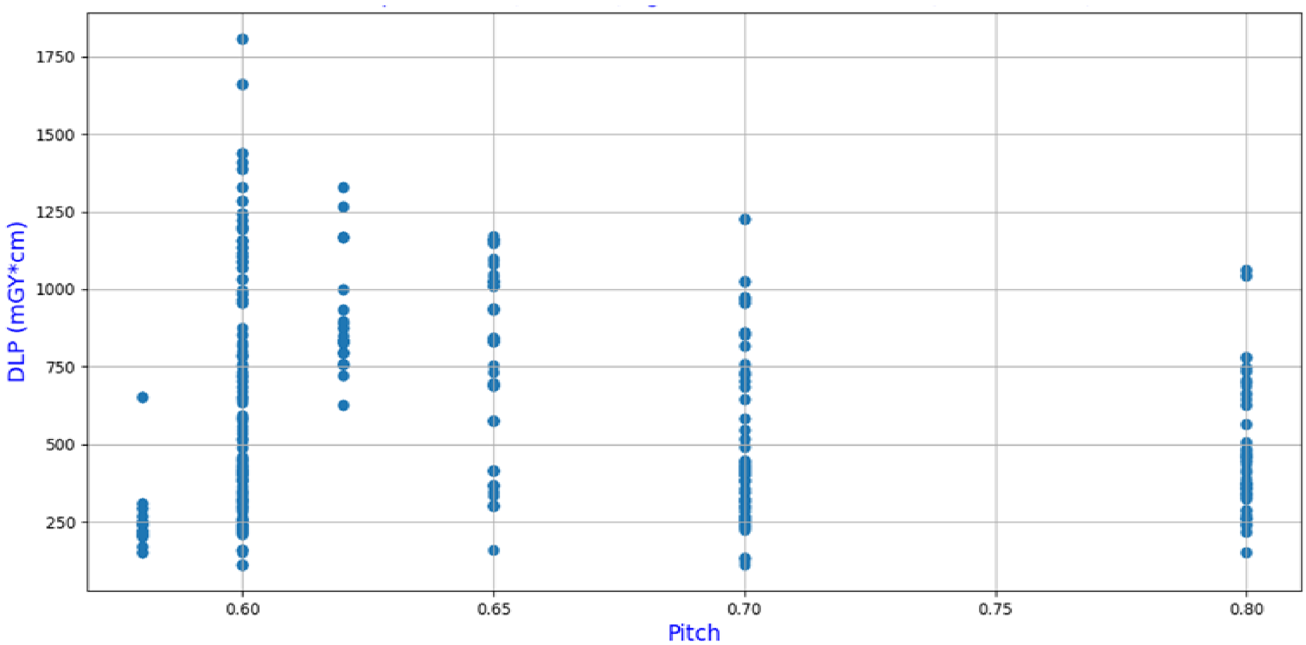

Fig.1: Scatter Plot of Dose Length Product (DLP) against Pitch for Abdomen

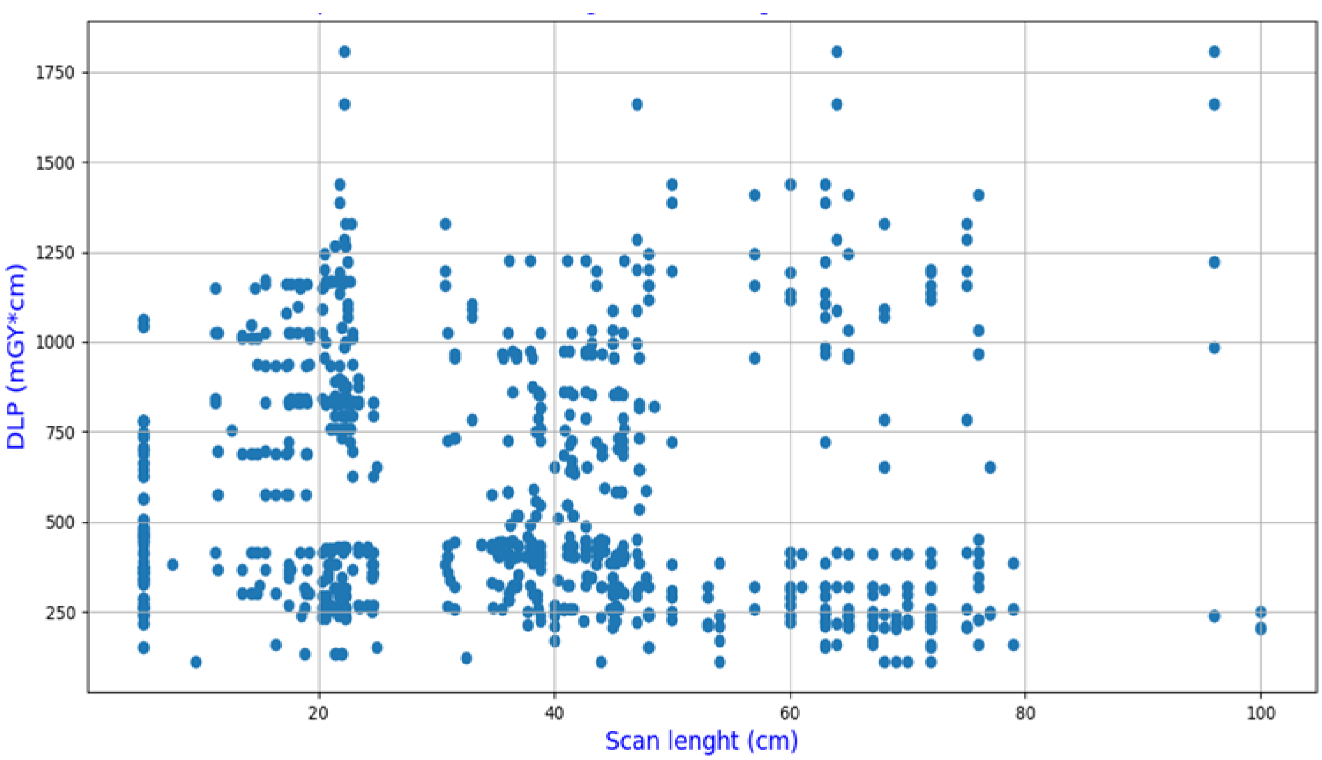

Fig. 2: Scatter Plot of Dose Length Product (DLP) against Scan Length for Abdomen

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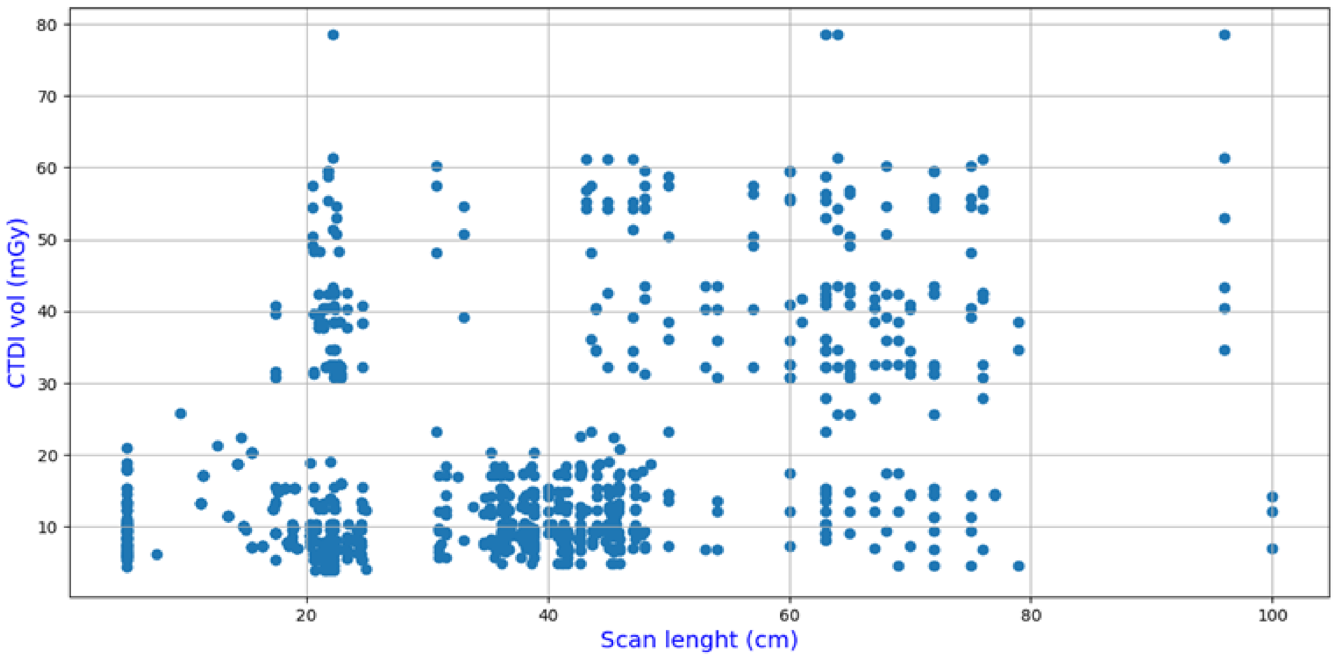

Fig. 3: Scatter Plot of CT Dose Index (CTDI) Vol against Scan Length for Abdomen

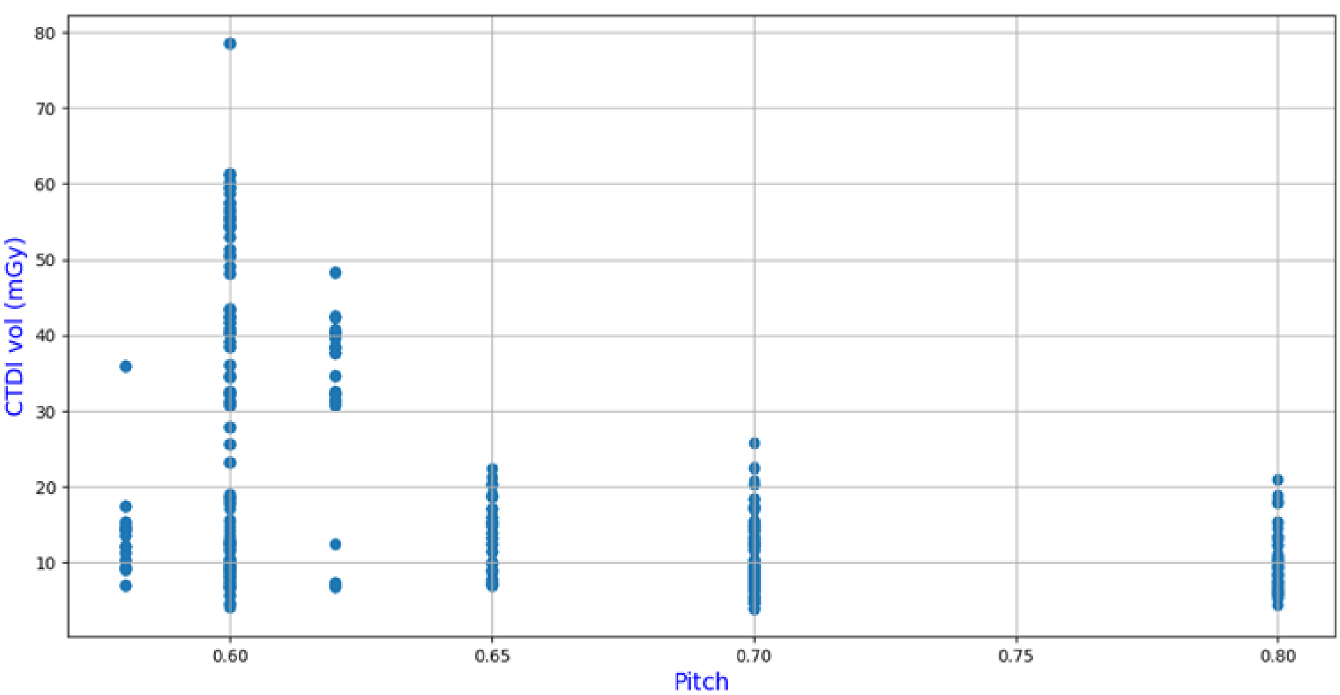

Fig. 4: Scatter Plot of CT Dose Index (CTDI) Vol against Pitch for Abdomen

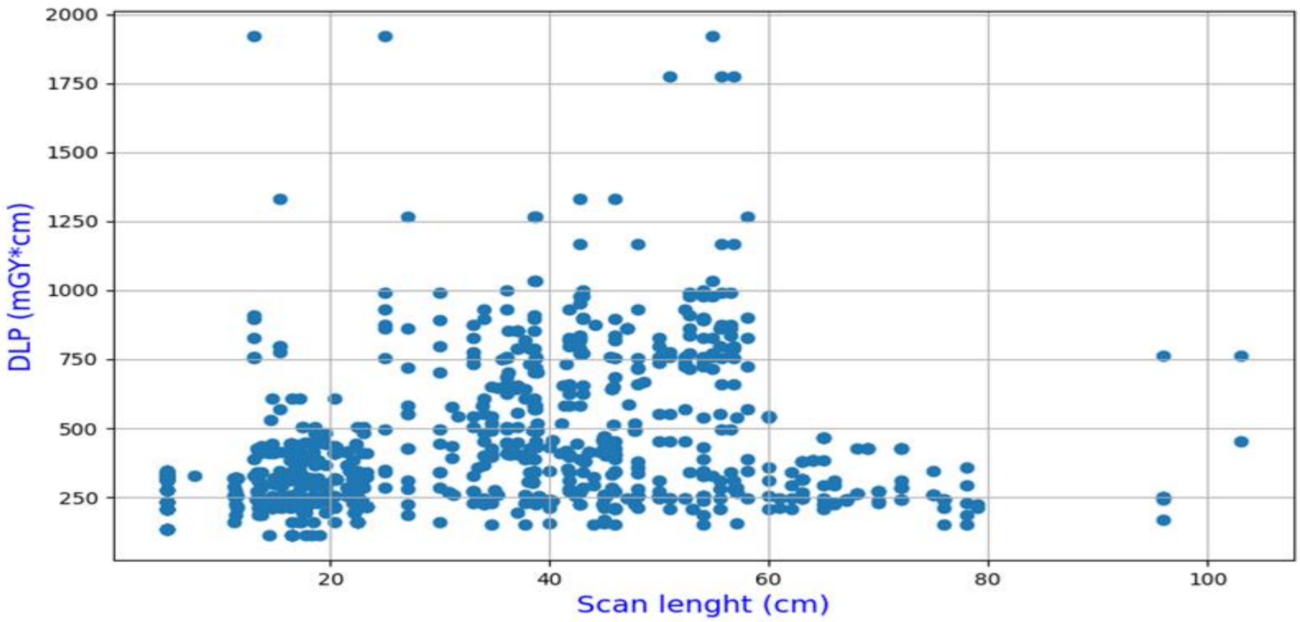

Fig. 5: Scatter Plot of Dose Length Product (DLP) against Scan Length for Chest

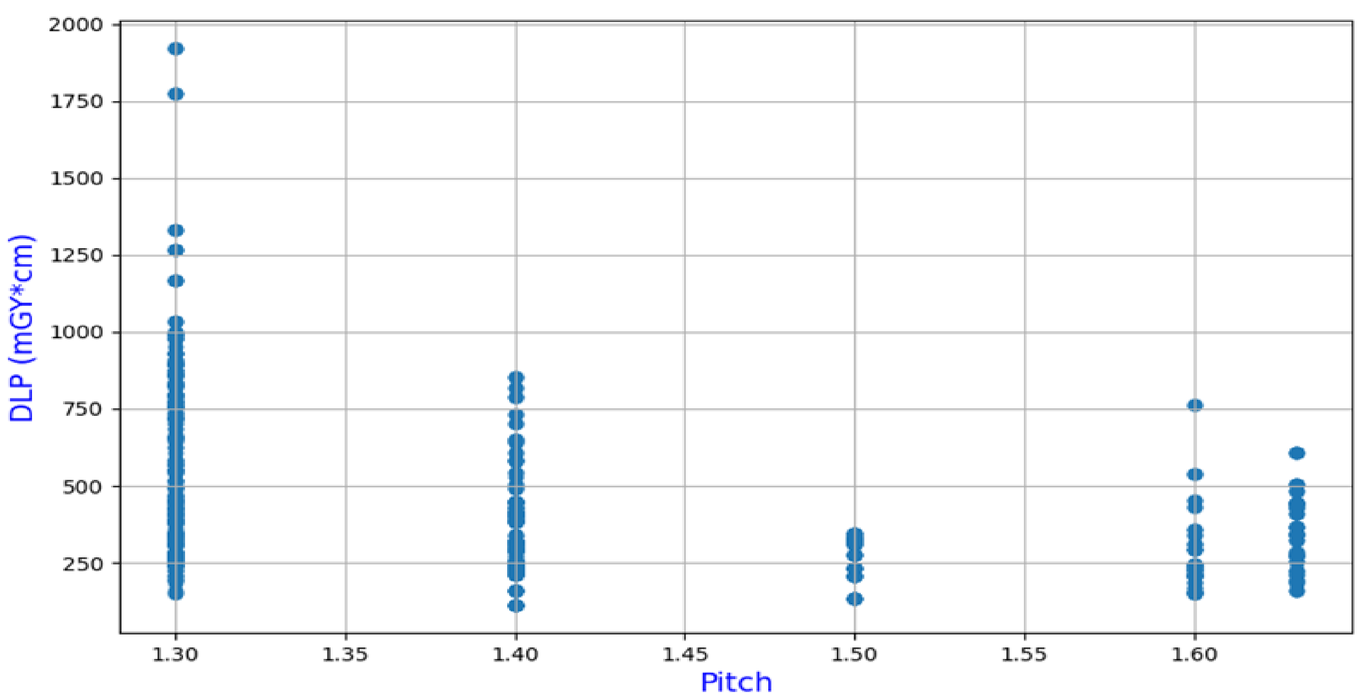

Fig. 6: Scatter Plot of Dose Length Product (DLP) against Pitch for Chest

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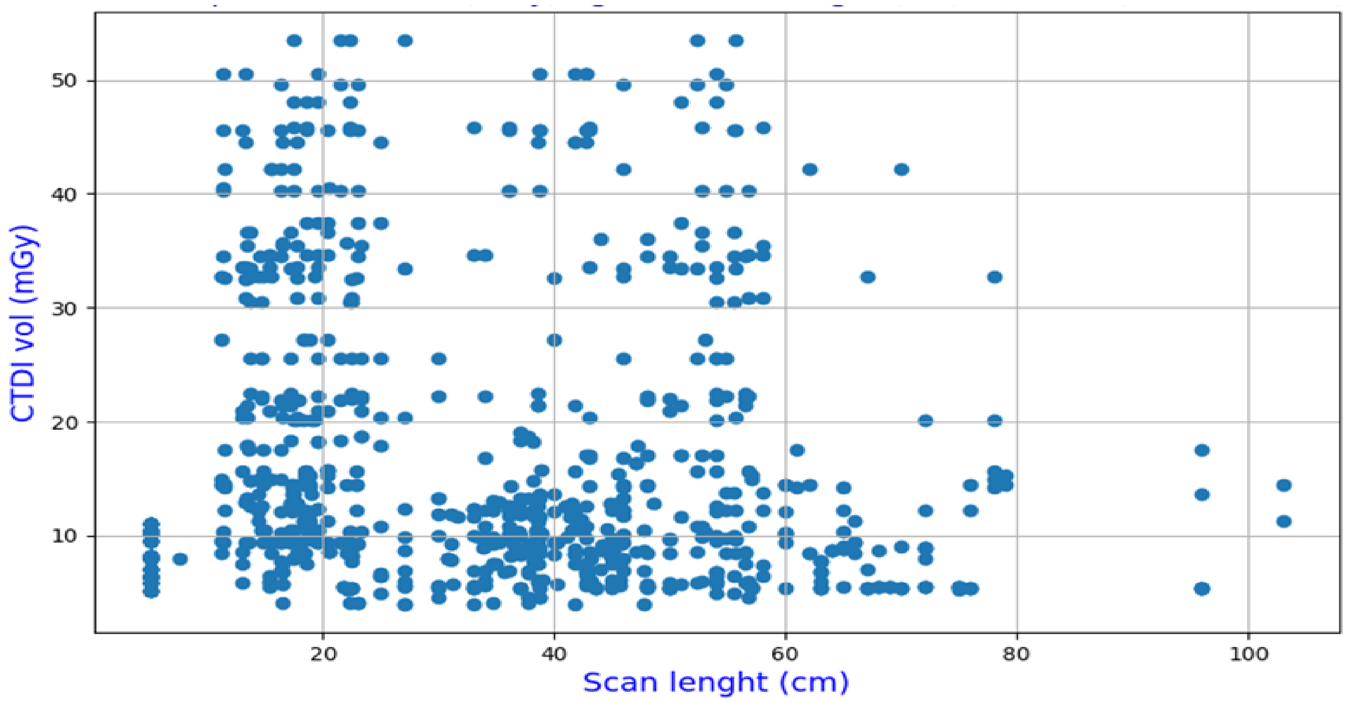

Fig. 7: Scatter Plot of CT Dose Index (CTDI) Vol against Scan Length for Chest

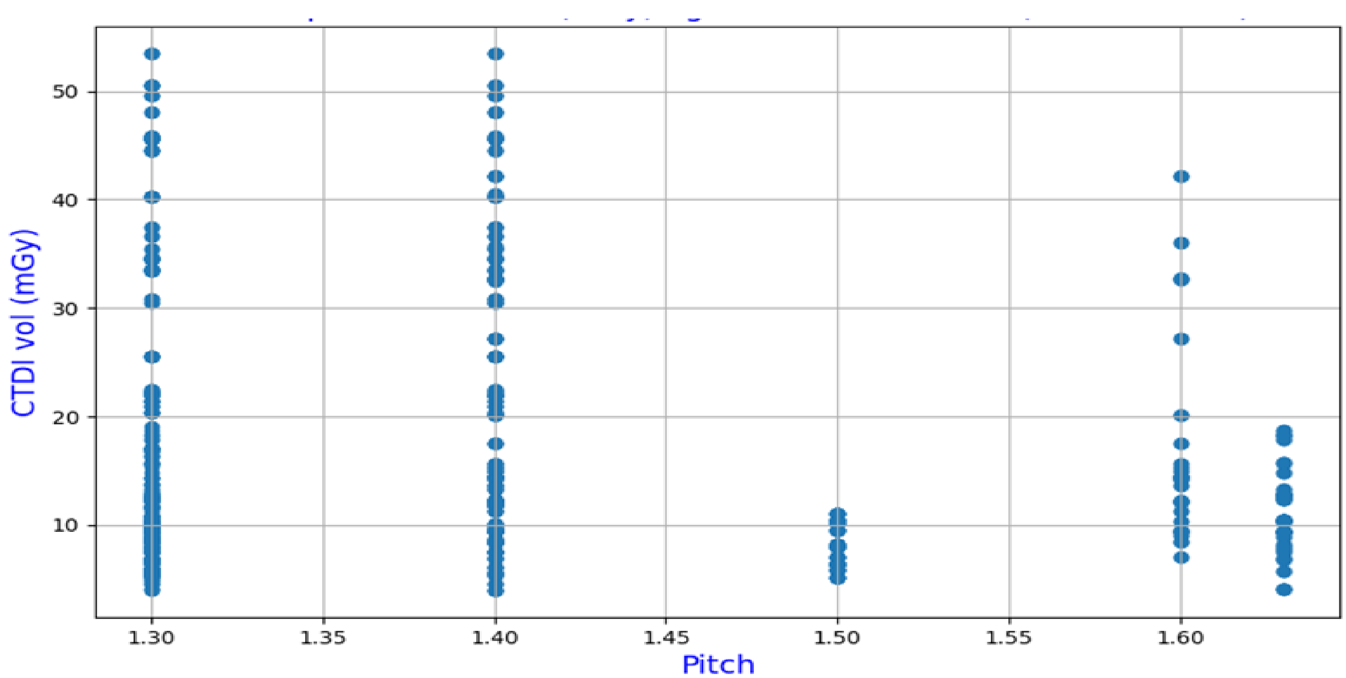

Fig. 8: Scatter Plot of the CT Dose Index (CTDI) Vol at against Pitch for Chest

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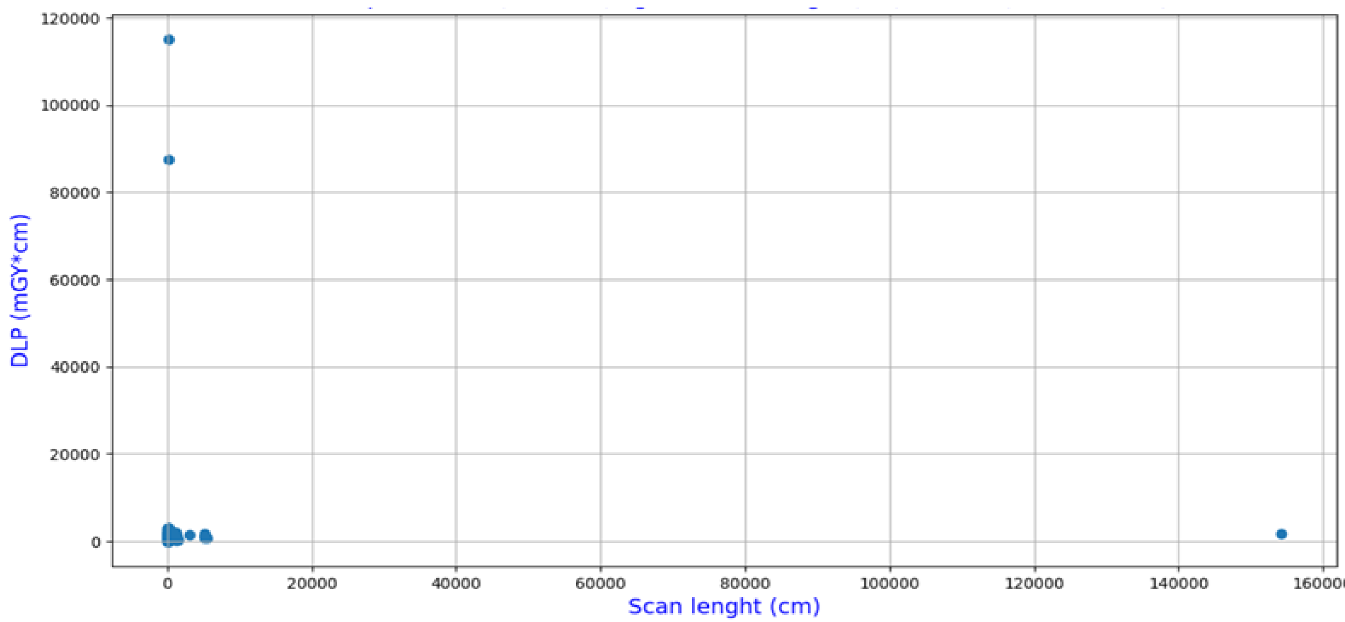

Fig. 9: Scatter Plot of Dose Length Product (DLP) against Scan Length for Skull

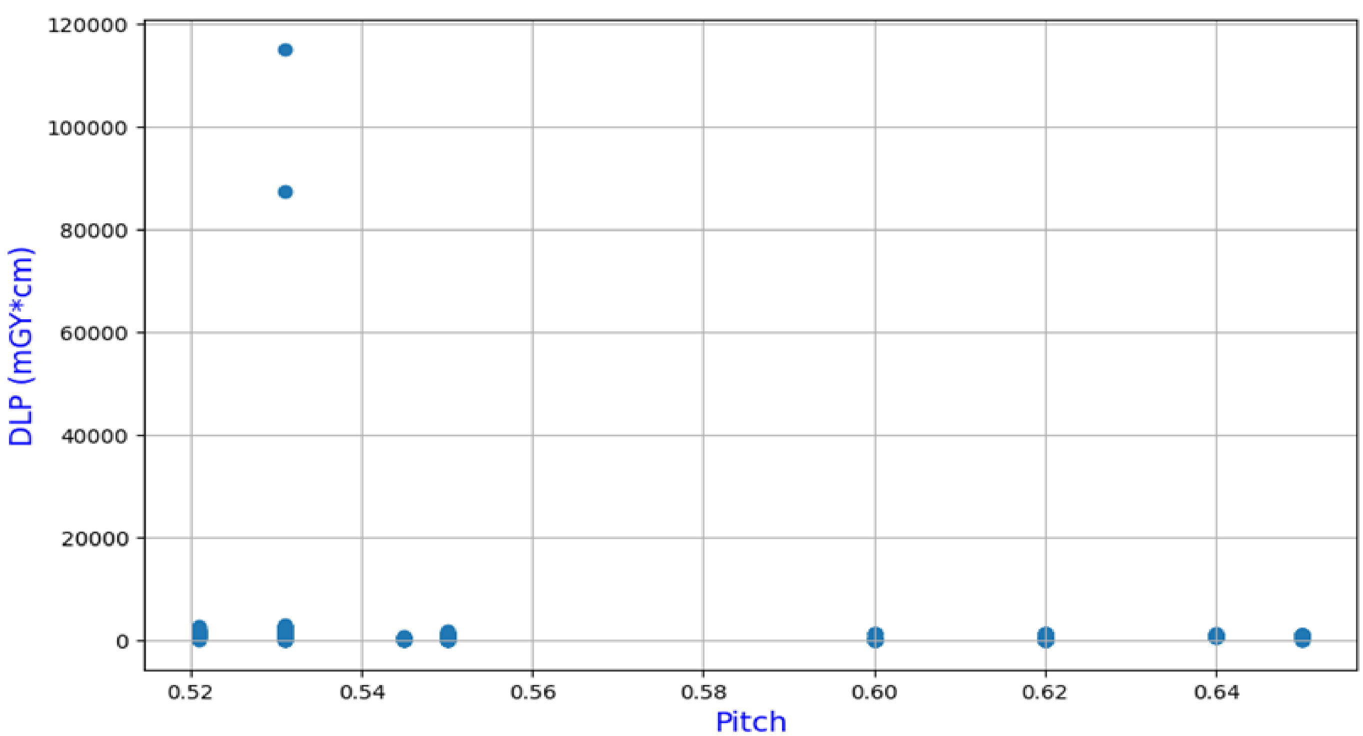

Fig. 10: Scatter Plot of Dose Length Product (DLP) against Scan Length for Skull

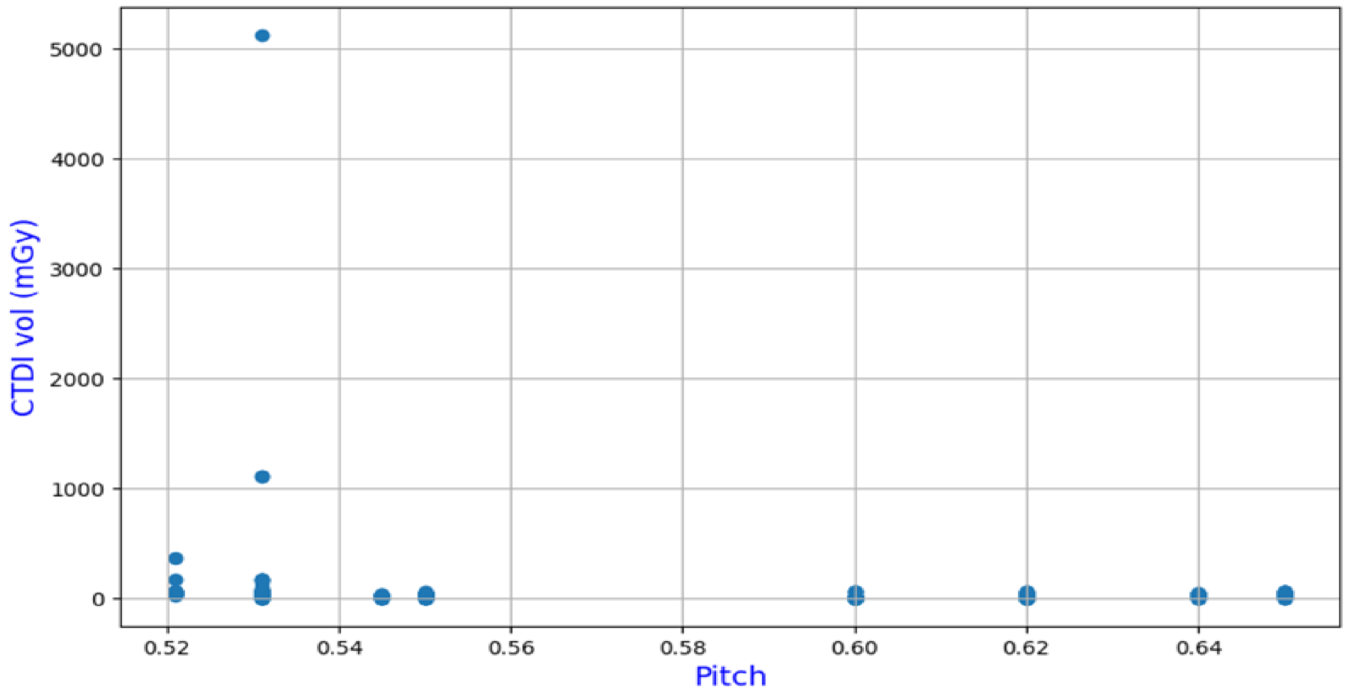

Fig. 11: Scatter Plot of CT Dose Index (CTDI) Vol against Pitch for Skull

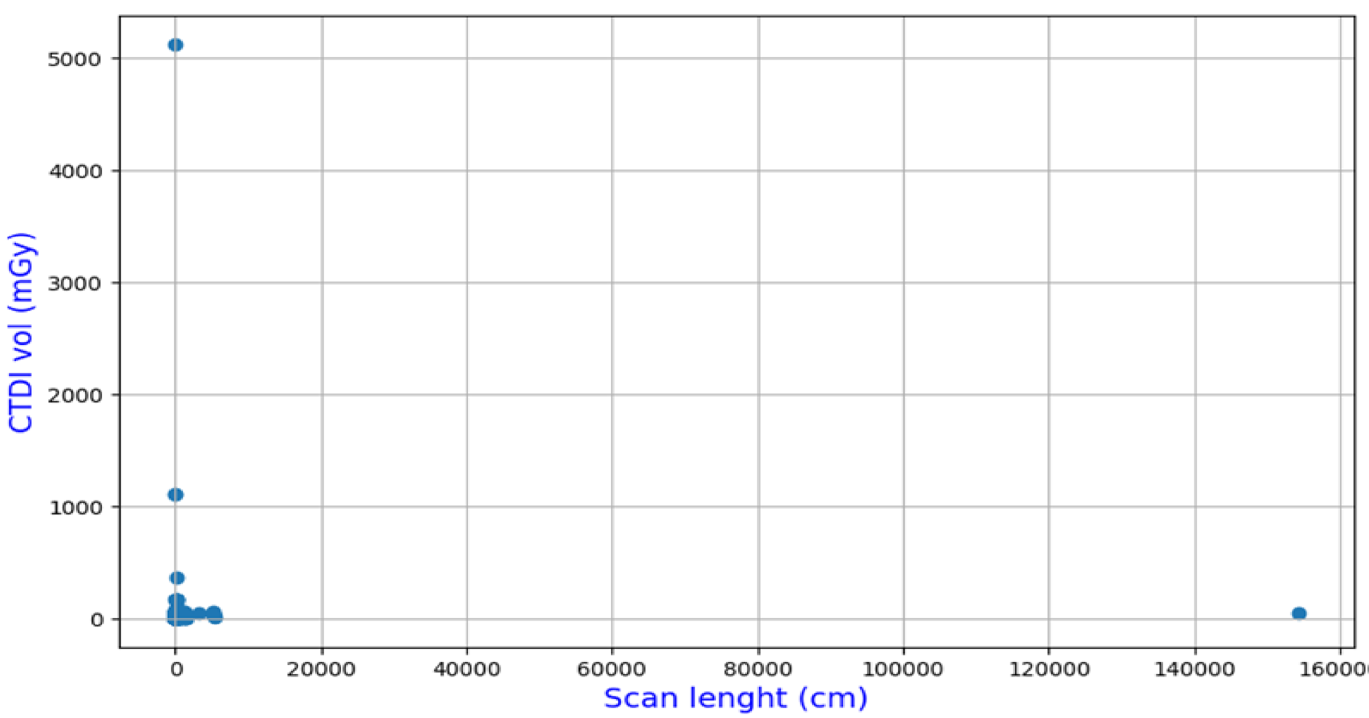

Fig. 12: Scatter Plot of CT Dose Index (CTDI) Vol against Scan Length for the Skull

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Discussion

This study highlighted how machine learning technique can effectively extract meaningful information from Computed Tomography (CT) images by automatically identifying relevant features and patterns. This capability has the potential to assist radiologists in making accurate diagnoses and facilitating timely interventions. In the abdomen, ML can reveal subtle patterns related to organ morphology, such as the liver, spleen, and kidneys, which can aid in the early detection of tumors or abnormalities. In the chest, ML can uncover patterns indicative of lung nodules, consolidations, or other pulmonary conditions that may not be immediately apparent. In the skull, ML can detect subtle changes in bone density or structure, which may indicate conditions such as fractures, tumors, or degenerative diseases.

The Dose Length Product (DLP) constitutes a cumulative measure of radiation exposure in CT scans, derived from the product of the dose per scan and the scan length. On the other hand, the pitch, also recognized as the table feed, represents the ratio of table speed to the X-ray collimation width. Higher pitch values expedite scan times but potentially compromise image quality. The variability observed in scan length, pitch, and DLP across distinct institutions is attributed to several factors. These include the CT scanner type, patient physiology, anatomical variations, and the clinical necessity for the scan. Generally, extended scans tend to elevate DLP, while lower pitch values correspond to reduced DLP due to prolonged X-ray emission and wider beam coverage, respectively. Nevertheless, the relationship between DLP, pitch, and scan length isn't consistently linear. Noteworthy research by Almujally *et al*. (2023) and Lestariningsih *et al*. (2019) revealed higher DLP for skull CTs compared to chest CTs, largely due to the former necessitating higher kV and mAs. Conversely, investigations by Quadah *et al*. (2017) and Duan *et al*. (2020) reported reduced DLP for scans conducted at lower pitches, attributed to slower scan rates that mitigate the dose per scan.

In the comprehensive analysis, significant variations in scanning parameters were apparent, especially in abdomen, chest, and skull scans. Higher pitch values demonstrated increased table feed rates and expanded slice intervals, impacting radiation dose and image contrast in accordance with Ehsan et al., (2020) and Lestariningsih et al. (2019).

The careful selection of kV and mAs is crucial in balancing image quality against radiation dose. The absence of a direct linear correlation between CT Dose Index (CTDI) and pitch suggests that factors beyond pitch values contribute to radiation exposure variations in CT scans in agreement with Emmanual et al., (2019).

Similarly, the lack of significant correlation between mean scan length and CTDI implies a multifaceted interplay among multiple determinants influencing CTDI values. The influential factors, apart from pitch and scan length that play crucial roles in determining radiation exposure in CT scans include;

Patient-specific Characteristics: Variances in patient size, body composition, and anatomical structures significantly impact radiation absorption rates in agreement with Xiyu et al, (2022). Patients with larger body sizes or different anatomies may absorb or scatter radiation differently, leading to fluctuations in radiation exposure.

Scanner-specific Factors: The characteristics and technical specifications of the CT scanner, such as tube voltage (kV), tube current (mA), collimation, and detector configuration, influence the intensity and distribution of X-ray beams, affecting radiation exposure in conformity with Kalra et al., (2004)

Scan Protocols and Techniques: Variations in scanning protocols, such as exposure parameters, scan modes (e.g., sequential or helical), and imaging settings, can substantially affect radiation doses. Differences in protocols among institutions or clinicians may contribute to variations in radiation exposure levels in conformity with Smith -Bindman et al., (2022).

Image Reconstruction Algorithms: Various image reconstruction algorithms employed in CT imaging affect the noise, resolution, and overall image quality. Optimizing these algorithms might involve trade-offs between image quality and radiation dose, thereby influencing radiation exposure which verify the claims of Lambert et al., (2014).

Radiation Dose Modulation Techniques: Advanced dose modulation techniques, like automatic exposure control or tube current modulation, dynamically adjust radiation doses based on the patient's anatomy during scanning (Ramirez – Giraldo et al., (2014). Variability in the application or effectiveness of these techniques impacts radiation exposure.

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Radiation Shielding and Positioning: Correct positioning of patients during scans and the use of shielding materials or techniques to protect sensitive organs affect the amount of radiation absorbed and scattered, thus influencing overall exposure levels (Martin et al., 2017). These factors interact in a complex manner, contributing to variations in CTDI values despite the absence of a direct linear relationship with pitch or scan length (Goldman, 2007). Understanding these multifaceted influences is crucial for optimizing CT imaging protocols and minimizing radiation exposure while maintaining diagnostic image quality.

The study underscores the importance of optimizing scanning parameters and radiation doses to uphold CT image quality standards. Machine learning algorithms enabled the discernment of subtle trends in image quality metrics, enhancing patient safety and diagnostic precision (Najj, 2023). Moving forward, further research and standardization efforts are necessary to formulate comprehensive guidelines for optimal scanning parameters and radiation dosage across medical institutions, highlighting the potential of machine learning in automating CT image quality assessment.

In conclusion, this study contributes to the field of medical physics by demonstrating the potential of machine learning in evaluating CT image quality in abdomen, chest, and skull regions. The findings of this study offer insights into the complex interplay between CT scanning parameters and resultant image quality metrics. These insights hold promise for healthcare decision-makers, empowering them to optimize CT imaging protocols to mitigate radiation exposure while maintaining diagnostic image quality. The findings underscore the significance of developing automated tools for image quality assessment, ultimately enhancing diagnostic accuracy and patient care. This research contributes to substantiating enhancements in CT imaging strategies. By elucidating relationships between scanning parameters and image quality metrics, the comprehensive analysis and visualization techniques lay a foundation for future advancements in imaging protocols, elevating standards of patient care and diagnostic precision in medical imaging. Analysis of CT image quality in the abdomen, chest, and skull using machine learning techniques is a groundbreaking approach that holds significant potential for advancing medical imaging. Through this research endeavor, valuable insights into the effectiveness of applying machine learning techniques to enhance diagnostic accuracy, their potential impact on clinical decision-making processes and improve patient care has been established.

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