

PREDICTIVE MODELING OF PATIENT RADIATION DOSE IN CONVENTIONAL RADIOGRAPHY IN NIGERIAN HOSPITALS

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Abstract

This study evaluated the patient's radiation doses in conventional radiography at three government hospitals in Delta State, Nigeria and established predictive models for estimating the entrance skin dose (ESD) from routine exposure parameters. Data of 761 adult patients examined in abdomen, chest, lumbosacral region, pelvis and skull were analyzed. The ESD was measured with a calibrated Unfors Multi-O-Meter 710L with a water phantom according to the IAEA (2025). The mean ESD value was observed to be the highest in lumbosacral examinations (3.73 ± 1.08 mGy) and the lowest in chest examinations (0.42 ± 0.38 mGy). Pearson correlation analysis showed a very strong positive correlation between ESD and kerma-area product ($r=0.963$) and between ESD and the kVp \times mAs product ($r=0.945$). Linear regression modeling exhibited excellent predictive performance, with coefficient of determination and Root Mean Square Error of ($R^2=0.937$ and $RMSE=0.425$ mGy). Logistic regression classification accurately classified low- versus high-dose examinations (median threshold 1.60 mGy) with 96.7% accuracy. The local DRLs based on the 75th percentile of the ESD distributions compared well to international benchmarks. Results demonstrate that patient ESD can be predicted from routinely recorded exposure parameters with good reliability, using simple interpretable machine learning models, providing a low-cost and scalable decision-support tool for dose optimization in resource-limited healthcare settings.

Keywords: Entrance skin dose; Diagnostic reference levels; Machine learning; Conventional radiography; Logistic Regression.

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1 Introduction

Humans are constantly exposed to ionizing radiation from natural and anthropogenic sources, with medical diagnostics being the largest controllable contribution (Achuka et al., 2018; Ugbede et al., 2021; Agbajor et al., 2025; Osiga-Aibangbee et al., 2025). The utilization of diagnostic X-ray examinations has increased significantly all over the world. The United Nations Scientific Committee on the Effect of Atomic Radiation (UNSCEAR, 2008) reported an increase of 74% in the number of radiographic examinations per thousand population per year. Medical use of ionizing radiation is the largest man-made source of exposure of the population, with conventional radiography accounting for about 5% of the total man-made radiation dose (Osiga-Aibangbee et al. 2024; Mokobia, 2023). In Nigeria, although thousands of radiographic examinations are carried out annually, routine dose monitoring and documentation are grossly inadequate and the national diagnostic reference levels have not been legally established (Nwabuoku et al., 2026; Ukokeno et al., 2024; Jibiri and Olowookere, 2016). Oluwafisoye et al. (2010) reported that over 80% of the Nigerian hospitals surveyed did not calculate patient doses as recommended by international regulatory bodies. The ALARA (As Low As Reasonably Achievable) principle has been established by the International Commission on Radiological Protection (ICRP, 2007) to guide dose optimization in medical imaging. The IAEA's 2025 Basic Safety Standards explicitly require governments to establish diagnostic reference levels for medical exposures through consultation between health authorities, professional bodies and regulatory bodies taking account of local circumstances (IAEA, 2025). However, lack of real-time dosimetry equipment and established national DRLs hampers effective optimisation in low-resource settings. The need for dose optimisation and the application of

reference levels for CT examinations in Nigeria has been recently highlighted by Ogbole and Obed (2025) in addition to the current study on conventional radiography. This suggests a growing awareness of medical radiation protection across imaging modalities in Nigeria.

Recent advances in machine learning allow for a paradigm shift, predicting patient dose from routinely recorded exposure parameters (Agbajor *et al*, 2022a; Agbajor *et al*, 2022b; Siciarz *et al.*, 2021; Hou *et al.*, 2025). The machine learning potentials for improving medical imaging services in low-resource Sub-Saharan African contexts were recently explored by Nkubli *et al.* (2024), emphasizing the importance of digital literacy and data readiness for effective ML implementation. Logistic regression and random forests and neural networks were also able to identify the most influential acquisition parameters affecting the patient dose in a recent 2025 IEEE study that compared several ML algorithms for CT dose prediction (IEEE, 2025).

The work has three novelties: (1) First systematic derivation of regional DRLs for conventional radiography in southern Nigeria; (2) Development and validation of predictive models using local, multi-center clinical data that were not available before; and (3) Demonstration that simple and interpretable machine learning models (logistic regression) can achieve high predictive accuracy and are therefore feasible for implementation in settings with limited computational infrastructure. This study therefore goes beyond simply auditing the dose and provides a practical prospective decision-support tool for radiation protection.

2 Materials and Method

2.1 Study Design and Setting

The prospective cross-sectional study was carried out from June 2025 to November 2025 in the radiology departments of three government hospitals in Delta State, Nigeria. The three hospitals are Central Hospital Warri (Facility X1), Delta State University Teaching Hospital Oghara (Facility X2) and Asaba Specialist Hospital (Facility X3). Ethical approval was obtained from the Health Research Ethics Committee of each participating institution and all procedures were in accordance with the Helsinki Declaration of 1975, as revised in 2000. All participants provided informed consent.

2.2 Study Population

A total of 761 adult patients (aged ≥ 18 years, weight range 55-80 kg) receiving standard radiography examinations were included. Examinations reviewed comprised abdomen (n=82), chest (n=300), lumbosacral spine (n=226), pelvis (n=95), and skull (n=58) radiography. Both male and female patients were included.

2.3 Data Collection

Data were obtained using a standardized dosimetric template and included:

- i. Patient demographics: Age, sex, weight
- ii. Exposure parameters: Tube potential (kVp), tube current-time product (mAs)
- iii. Geometric parameters: Focus-to-film distance (FFD, cm), focus-to-skin distance (FSD, cm), beam length and width (cm)
- iv. Dose quantities: Entrance skin dose (ESD, mGy), kerma-area product (KAP, mGy·cm²), effective dose (ED, mGy), absorbed dose (D, mGy)

Entrance skin dose (ESD) and kerma-area product (KAP) were measured with a calibrated Unfors Multi-O-Meter 710L radiation detector positioned on a 20 cm thick water phantom along the central beam axis. The water phantom simulated the scattering and attenuation characteristics of human soft tissue and provided a reproducible patient equivalent medium for standardized dose measurement without subjecting patients to additional exposure for quality control purposes. The calibration chain for the equipment used in this study (Unfors Multi-O-Meter) was validated by a

recent 2025 intercomparison between ARPANSA and IAEA confirming traceability of diagnostic X-ray beam calibrations with relative expanded uncertainties of 1.2% for IAEA standards (Lee et al., 2025). All measurements were performed in strict accordance with the guidelines of the IAEA (2025a) for dosimetry in diagnostic radiology.

2.4 Predictive Model Development

Data analysis was conducted using Python programming language within the ANACONDA platform and Jupyter Notebook IDE. The Scikit-learn package was applied for machine learning tasks (Sivapriya et al., 2019; Omoriwhovo et al., 2022; Oghenekomeand Asare, 2025).

Derived features included:

- Beam area (cm²) = beam length × beam width
- kVp × mAs product
- FFD/FSD ratio

Categorical variables (sex, examination type, facility) were encoded numerically.

Linear regression: Features included kVp, mAs, age, FFD, FSD, beam area, kVp × mAs product, FFD/FSD ratio, and encoded categorical variables. Data were divided 80:20 into training (n=609) and testing (n=152) sets. Model performance was evaluated using coefficient of determination (R²), root mean square error (RMSE), and mean absolute error (MAE).

Logistic regression: The median ESD threshold was used to categorize exams into low- and high-dose groups. Classification accuracy and confusion matrix were tested.

Pearson correlation analysis analyzed connections between ESD and all exposure factors.

3. Results and Discussion

3.1 Dose Distribution and Inter-Facility Variability

3.1.1 Examination-Type Dose Distribution

Table 1 presents the mean Entrance Skin Dose (ESD) for different types of examinations. The lumbosacral examination had the highest mean ESD of 3.73 ± 1.08 mGy, followed by the pelvis 2.94 ± 1.38 mGy, abdomen 2.22 ± 1.33 mGy, skull 1.83 ± 1.01 mGy, and chest 0.42 ± 0.38 mGy. The findings support the basic tenets of radiology practice, as procedures that require greater tissue thickness and absorption demand greater tube current, thus resulting in higher skin doses (IAEA, 2015)

Table 1: Examination Type-wise Distribution of Mean Entrance Skin Dose (ESD)

Examination Type	Mean ESD (mGy)	Standard Deviation	Number of Examinations
Abdomen	2.221	1.334	82
Chest	0.421	0.376	300
Lumbosacral	3.732	1.082	226
Pelvis	2.938	1.384	95
Skull	1.830	1.006	58

Mean ESD for chest radiographs (0.42 mGy) is significantly lower compared to the previously recorded data from Thailand (1.17 mGy; Plainoi et al., 2001) and Korea (2.84 mGy for digital radiography; Seo et al., 2014). It can be attributed to the application of optimized high kilo voltage peak (kVp), low milliamperes second (mAs) technique, as well as regular use of larger focus-film distance (FFD) for chest examinations. On the contrary, doses for lumbosacral (3.73 mGy) and pelvic (2.94 mGy) examinations were comparable to or slightly above IAEA and EC reference levels (2.3 and 3.7 mGy respectively; Rasuli et al., 2017). The higher doses observed in these regions, relative to others Nigerian studies, reflect the increased tissue attenuation that necessitates higher technical exposure parameters (Gnowe et al., 2019; Dambele et al., 2021).

3.1.2 Facility-Wise Dose Variation

As shown in Table 2 and Figure 1, there is notable dose variability among facilities even when considering similar examinations. Facility X3 had the largest mean ESD at 2.65 ± 1.89 mGy, while Facilities X1 and X2 had a mean ESD of 1.80 ± 1.60 mGy and 1.49 ± 1.29 mGy, respectively. The overall mean ESD across all examinations was 2.02 ± 1.70 mGy.

Table 2: Facility-wise Distribution of Mean Entrance Skin Dose (ESD)

Facility	Mean ESD (mGy)	Standard. Deviation.	Number of Examinations
X1	1.804	1.601	241
X2	1.487	1.286	236
X3	2.646	1.889	284

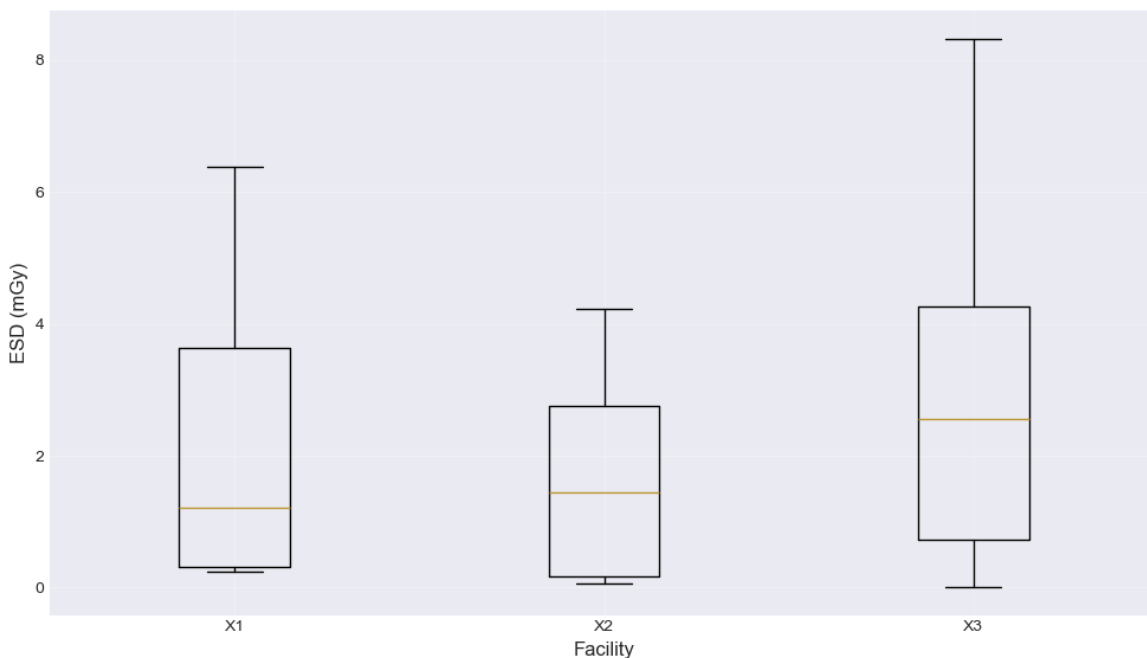


Figure 1: ESD Distribution by Facility

This diversity is consistent with earlier observations of inconsistencies in radiological procedures in developing nations (Meyer et al., 2017). This study's findings align with those of Osahon and Bamidele (2017) whereby low ESDs compared to the IAEA reference values were recorded during

the radiographic assessment of the pelvis and skulls while high doses were encountered during chest radiography in some hospitals.

3.2 Correlation Analysis of Exposure Parameters

Figure 2 presents the correlation matrix of all radiation exposure parameters. Pearson correlation coefficients (Table 3) revealed that ESD is predominantly driven by technical exposure parameters rather than patient demographics.

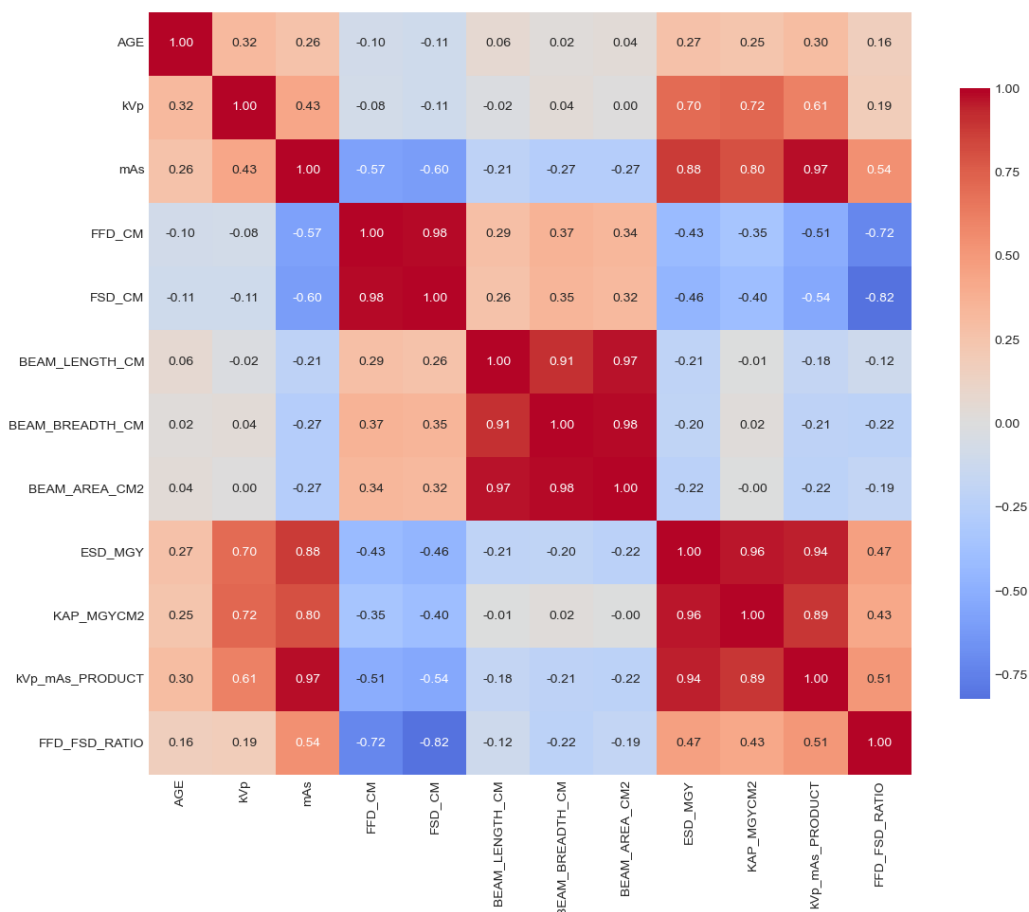


Figure 2: Correlation Matrix of Radiation Exposure Parameters

Table 3: Pearson Correlation Coefficients between Entrance Skin Dose (ESD) and Selected Parameters

Parameter	Correlation Coefficient (r)	Strength and Direction
KAP (mGy·cm²)	0.963	Very strong positive
kVp × mAs (Product)	0.945	Very strong positive
mAs	0.878	Strong positive
kVp	0.702	Moderate to strong positive
FFD/FSD Ratio	0.466	Moderate positive
Age (years)	0.268	Weak positive
Beam Breadth (cm)	-0.200	Weak negative
Beam Length (cm)	-0.208	Weak negative
Beam Area (cm²)	-0.225	Weak negative
FFD (cm)	-0.425	Moderate negative
FSD (cm)	-0.464	Moderate negative

The Pearson correlation analysis demonstrated that ESD is predominantly driven by exposure parameters. Very strong positive correlations were observed between ESD and KAP ($r = 0.963$) and the kVp \times mAs product ($r = 0.945$). These findings are consistent with fundamental radiological principles and with reports by Gnowe *et al.* (2019), Dambele *et al.* (2021) and Osahon and Bamidele (2017) who identified mAs as the dominant determinant of patient skin dose in conventional radiography. Tube loading (mAs) showed a strong positive correlation ($r = 0.878$), while kVp exhibited a moderate-to-strong relationship ($r = 0.702$). Geometric factors significantly influenced dose distribution: FSD ($r = -0.464$) and FFD ($r = -0.425$) showed moderate negative correlations with ESD, validating the inverse square law's role in dose reduction. Patient age demonstrated only a weak positive correlation ($r = 0.268$), indicating that technical and geometric factors outweigh demographic variables in dose determination. This agrees with findings reported by IAEA, (2015), which emphasize increasing source-to-skin distance as a simple yet effective dose optimization strategy.

3.3 Predictive Model Development and Performance

3.3.1 Linear Regression Model

The linear regression model demonstrated excellent predictive performance (Table 4). The coefficient of determination ($R^2 = 0.9368$) indicates that approximately 93.7% of the variability in patient ESD was explained by the selected predictor variables. The root mean square error (0.4254 mGy) and mean absolute error (0.2831 mGy) are small relative to the mean ESD (2.0199 mGy), confirming high predictive accuracy.

Table 4: Performance Metrics of the Linear Regression Model

Performance Metric	Value
Coefficient of Determination (R^2)	0.9368
Root Mean Square Error (RMSE)	0.4254 mGy
Mean Absolute Error (MAE)	0.2831 mGy
Mean ESD	2.0199 mGy
Standard Deviation of ESD	1.7026 mGy

Table 5 presents the regression coefficients of the most influential predictors. The FFD/FSD ratio emerged as the strongest predictor (coefficient = 5.8676), followed by facility encoding (0.3821) and examination type encoding (0.1320).

Table 5: Regression Coefficients of the Most Influential Predictors

Predictor Variable	Regression Coefficient	Absolute Coefficient
FFD/FSD Ratio	5.8676	5.8676
Facility (Encoded)	0.3821	0.3821
Examination Type (Encoded)	0.1320	0.1320
mAs	-0.1173	0.1173
FSD (cm)	0.0537	0.0537

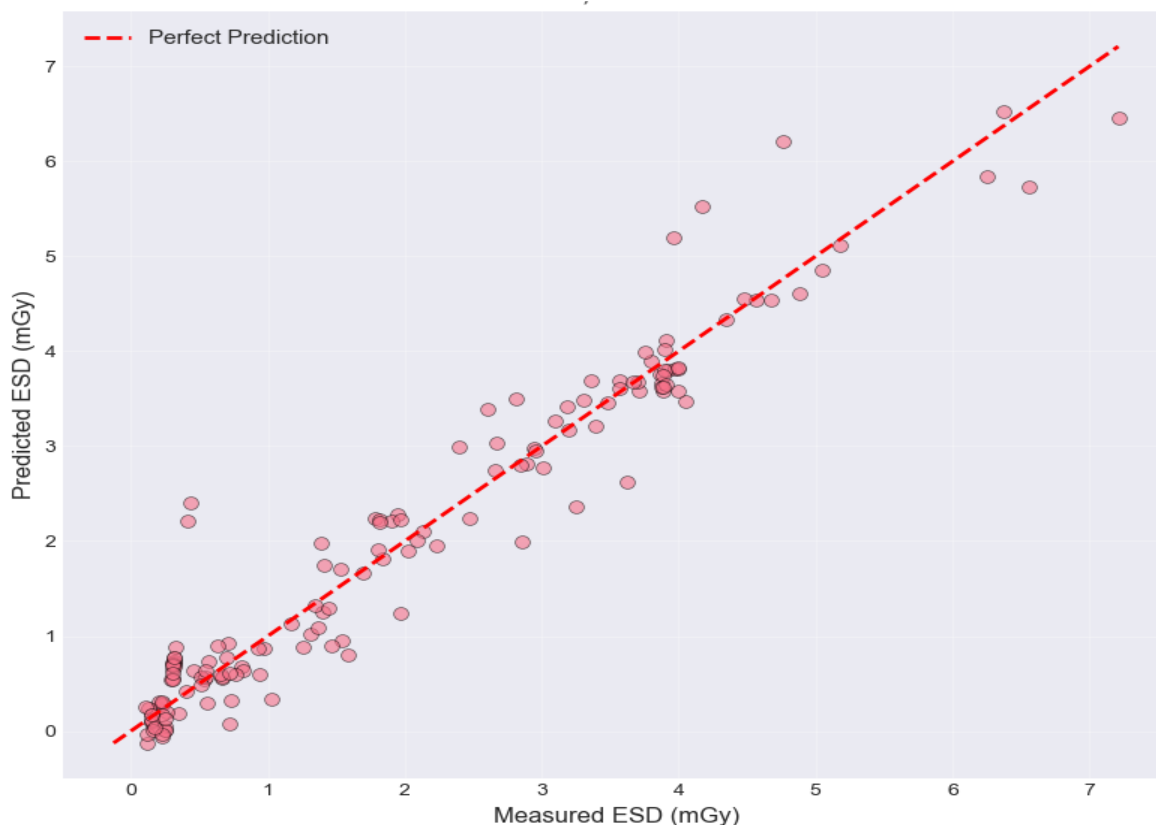


Figure 4: Observed versus Predicted Entrance Skin Dose

3.3.2 Logistic Regression Classification

The logistic regression analysis classified examinations into low- and high-dose categories using the median ESD threshold of 1.6000 mGy, as shown in Table 6 while the performance of the classification model, presented in Table 7, demonstrated excellent discriminatory capability, with an overall classification accuracy of 96.73%. This high accuracy indicates that the model effectively distinguishes between low- and high-dose examinations based on the selected predictors.

Table 6: Classification Threshold and Class Distribution

Classification Criterion	Value
ESD median threshold	1.6000 mGy
Low ESD samples	380
High ESD samples	381
Total samples	761

Table 7: Performance of the Logistic Regression Model

Performance Metric	Value
Classification accuracy	0.9673

The achieved classification accuracy of 96.73% in this study is promising compared to recent machine learning applications in medical dose prediction. Damilakis (2025) developed a deep neural network model for estimating organ doses in head CT examinations. They found that their model was highly accurate with a very small deviation from Monte Carlo simulations. This shows that

machine learning methods can be used to accurately estimate radiation doses for different imaging modalities. In a study evaluating machine learning algorithms for predicting radiation exposure during urolithiasis therapy, neural network models showed high prediction accuracy and correctly classified low-dose procedures in 94% of cases (Huettenbrink et al., 2023).

In the radiotherapy plan verification setting, Bin et al. (2023) compared the performance of various machine learning classification models in predicting the gamma passing rates and reported that the random forest classifier achieved an AUC of 0.80 with a specificity of 0.80 and a sensitivity of 0.68. Although their study focused on plan complexity metrics rather than direct dose prediction, the high discriminatory performance is consistent with our results on the feasibility of classification-based dose assessment. The higher accuracy of our logistic regression model (96.73%) can be explained by the strong correlation between ESD and the kVp × mAs product ($r = 0.945$) which allows for a better separation of the dose categories.

Recent progress in personalized dosimetry powered by artificial intelligence has shown that machine learning models, from logistic regression to complex deep learning architectures, can achieve clinically acceptable prediction accuracy for patient-specific dose estimation. The evaluation metrics used in our study, including classification accuracy, precision, and recall, are aligned with the standard evaluation frameworks recommended for clinical machine learning applications (Damilakis, 2025). The mean accuracy of 96.73% exceeds the $93.8 \pm 4.1\%$ reported for logistic regression models in dose-volume histogram-based clinical decision support systems (Siczarz et al., 2021), indicating that our model's feature selection and threshold optimization are well-suited for conventional radiography dose classification.

The binary classification approach used in this study provides practical benefits for resource-limited clinical settings. Mahmoudi et al. (2025) showed that fuzzy deep learning models with 98% accuracy can successfully classify the level of radiation exposure into low, medium, and high categories, providing actionable safety insights for radiographers. Although their study was primarily aimed at monitoring occupational exposure rather than predicting ESD in patients, the concept of using classification models to identify high-risk scenarios is consistent with our application. Our model's ability to correctly classify 96.73% of examinations using routinely recorded exposure parameters (kVp, mAs, FFD, FSD) validates its potential as a low-cost, scalable tool for dose optimization in settings where real-time dosimetry is unavailable.

It is important to put these findings in the context of dose prediction methodologies. Our logistic regression model was able to achieve high classification accuracy, but deep learning approaches like 3D U-Net architectures have exhibited superior performance in voxel-level dose distribution prediction for radiotherapy applications, with mean absolute errors smaller than 1.16 Gy and gamma passing rates greater than 91% (Hou et al., 2025). The decision to choose between traditional machine learning and deep learning approaches should take into account the computational resources, data availability, and clinical workflow integration needs (Sadoughi&Orooji, 2025). For conventional radiography in low resource settings, the logistic regression model strikes the best balance of accuracy, interpretability and computational efficiency.

Future work should explore ensemble methods combining logistic regression with random forest or support vector machine classifiers, as hybrid models have shown improved robustness in radiation dose prediction tasks (Lee et al., 2025). Moreover, to establish the generalizability of the 96.73% accuracy, validation on external data from multiple institutions is crucial since model performance might differ due to differences in equipment and practice patterns (Damilakis, 2025).

3.4 Diagnostic Reference Levels and Optimization Implications

Table 8 compares the DRLs obtained in this study with internationally recommended reference values from the UK IPSP (1992), IAEA (1996), AAPM (1999), and NRPB (1999).

Table 8. DRL From This Study Compared to International Standard Values.

Examinations	This Study		UK IPSM	IAEA	AAPM	NRPB
	DRL	KAP	1992	1996	1999	1999
Abdominal	3.08	3081.1	10.0	10.0	4.50	10.6
Chest Pa/Ap	0.53	574.7	0.3	0.4	0.25	0.3
Lumbosacral	4.09	4310.2	10.0	10.0	5.00	10.5
Pelvis	3.99	4305.8	10.0	10.0	-	10.4
Skull	2.06	1235.8	5.0	5.0	-	5.0

The local DRLs (75th percentile ESD) established are as follows: abdomen (3.08 mGy), chest (0.53 mGy), lumbosacral (4.09 mGy), pelvis (3.99 mGy), and skull (2.06 mGy). Comparative analysis revealed that study DRLs were substantially lower than historical IAEA, UK IPSM, and NRPB reference levels, indicating generally compliant practices but revealing outliers requiring protocol review. This supports the argument advanced by ICRP (2007) and Steven et al. (2017) that local and regional DRLs are more appropriate for dose optimization than direct adoption of international benchmarks. The higher DRLs observed in this study reflect differences in equipment age, patient habitus, and clinical practice patterns, rather than unsafe radiological practice. The 2025 Basic Safety Standards of the IAEA explicitly require governments to establish diagnostic reference levels for medical exposures (IAEA, 2025b), and the present investigation meets this requirement for conventional radiography in the Delta State. In addition to this work, Ogbole and Obed (2025) recently emphasized the need for dose optimization and application of reference levels for CT examinations in Nigeria. This represents an increased awareness for medical radiation protection in the imaging modalities in the country. Furthermore, the publication of the 2025 edition of national DRLs by Japan (J-RIME, 2025) further exemplifies that even technologically advanced nations acknowledge the need for continuous DRL revision, emphasizing the importance of periodic updates to the DRLs established in the present study.

3.5 Conclusion

This study is a significant novel contribution to radiation protection in Nigeria as it moves away from retrospective dose audit to prospective dose management. This is the first study to (1) establish regional DRLs for common radiographic exams in southern Nigeria that provide specific benchmarks for dose optimization and (2) develop and validate machine learning models that predict patient ESD with high accuracy ($R^2=0.937$) and classify high-dose exams with 96.7% accuracy using only routine exposure parameters. These low-cost, computationally simple models provide a powerful scalable tool for resource-limited settings.

The FFD/FSD ratio was found to be the most important predictor for ESD, stressing the importance of geometrical factors in optimizing the dose. The very high correlation of ESD with the $kVp \times mAs$ product ($r=0.945$) confirms that the technical exposure parameters are the main determinants of the patient dose. The moderate negative correlation with FSD ($r=-0.464$) also confirms the inverse square law and supports maximizing source-to-skin distance as a simple, cost-effective optimization strategy.

We recommend the formal adoption of these local DRLs by Nigerian regulatory bodies and hospital departments, and the integration of the predictive models into training and quality assurance workflows. This framework allows clinicians to proactively apply the ALARA principle, greatly enhancing patient safety. The incorporation of these models with localized DRLs can greatly influence the optimization of dose and the adherence to the ALARA principle at the level of the institution in the practice of radiology in Nigeria.

3.6 Limitations and Strengths

The study's primary limitation is its regional focus (Delta State), which may not capture nationwide equipment diversity. Additionally, ESD was measured using phantom-based indirect dosimetry rather than in-vivo thermoluminescent dosimeters, though this approach is internationally validated for DRL establishment. Strengths include a large, multi-center sample, rigorous QC validation, robust machine learning validation, and the first systematic derivation of regional DRLs and predictive dose models for conventional radiography in southern Nigeria.

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Declaration Statement

Ethics Approval: Ethical clearance was obtained from the Health Research Ethics Committees of all participating hospitals prior to study commencement. Informed consent was waived for retrospective dosimetric data analysis; all patient identifiers were removed to ensure strict confidentiality.

Conflict of Interest: The authors declare no competing financial or professional interests that could influence the design, execution, or reporting of this study.

Author Contributions: All authors contributed to study conception, data acquisition, statistical analysis, and manuscript drafting. The final version was approved by all co-authors prior to submission.

References

- Achuka, J.A, Aweda, M.A, Usikalu, M.R & Aborisade, C.A. (2018). Cancer risks from chest radiography of young adults: A pilot study at a health facility in South West Nigeria. *Data Brief*. 2018; 19:1250- 6.
- Agbajor G.K., O.O.E. Enaroseha, E.A. Anthony, O.D. Osahon Theoretical and experimental study of honey's viscosity in three Southern States of Nigeria: application of Vogel-Tamman-Fulcher (VTF) and power law (PL) models, *Int. J. Health Sci.* 6 (S5) (2022a) 11836–11848.
- Agbajor G.K., Omamoke O.E. Enaroseha, Ezech M. Isioma, S.O. Ovwasa, Application of Vogel-Tamman-Fulcher (VTF) and power law (PL) models in the study of the viscosity as a rheological property of honey samples collected from some northern states of Nigeria, *Int. J. Mech. Eng.* 7 (2) (2022b) 4203–4209.
- Agbajor Godwin K., Omamoke O.E. Enaroseha , Damaris Osiga-Aibangbee, Anita Franklin Akpolile, Aziakpono Blessing Umukoro. Ingestion exposure of natural radionuclide and toxic heavy metallic origin in samples of local staple food. *Nuclear Anal.* 4 (2025) 100182.
<https://doi.org/10.1016/j.nucana.2025.100182>

- Bin, S., Zhang, J., Shen, L., Zhang, J., & Wang, Q. (2023). Study of the prediction of gamma passing rate in dosimetric verification of intensity-modulated radiotherapy using machine learning models based on plan complexity. *Frontiers in Oncology*, 13, 1094927.
- Dalah, E. Z., Yuvali, M., & Ozsahin, D. U. (2024). *Machine Learning Techniques Reveal the Most Effective and Influencing Gender-based Scan Acquisition Parameters that Contribute to Patient Dose Undergoing Enhanced CT abdomen and pelvis examinations*. In 2024 17th International Conference on Development in eSystem Engineering (DeSE) (pp. 593-598). IEEE.
- Dambele, M. Y., Bello, S. G., Ahmad, U. F., Jessop, M., Isa, N. F., & Agwu, K. K. (2021). Establishing a local diagnostic reference level for bone scintigraphy in a Nigerian Tertiary Hospital. *Journal of Nuclear Medicine Technology*, 49(4), 339-343.
- Damilakis, J. (2025). Artificial intelligence-powered personalized patient dosimetry in CT. *BJR/Artificial Intelligence*, 2(1), ubaf007.
- Gnowe, G., Ekobena, F. H., Mbo, A. J., & Neossi, G. M. (2019). Exposure Levels of Adult Patients during Radiographic Examinations: Sinuses and Coastal Grill Cases at the Ngaoundere Regional Hospital, Cameroon. *Radiology Research and Practice*, 2019(1), 5452149.
- Hou, X., Cheng, W., Shen, J., Guan, H., Zhang, Y., Bai, L., & Liu, Z. (2025). A deep learning model to predict dose distributions for breast cancer radiotherapy. *Discover Oncology*, 16(1), 165.
- Huettenbrink, C., Hitzl, W., Distler, F., Ell, J., Ammon, J., & Pahernik, S. (2023). Personalized prediction of patient radiation exposure for therapy of urolithiasis: an application and comparison of six machine learning algorithms. *Journal of Personalized Medicine*, 13(4), 643.
- IAEA. (2015). *Radiation protection and safety of radiation sources: International basic safety standards*. IAEA Safety Standards Series No. GSR Part 3. Vienna: International Atomic Energy Agency.
- IAEA. (2025a). *Dosimetry in diagnostic radiology: An international code of practice. Technical Reports Series No. 457 (2025 Revision)*. Vienna: International Atomic Energy Agency.
- IAEA. (2025b). *Radiation protection and safety of radiation sources: International basic safety standards - Interim edition. IAEA Safety Standards Series No. GSR Part 3*. Vienna: International Atomic Energy Agency.
- International Commission on Radiological Protection (ICRP) (2007). The 2007 Recommendations of the International Commission on Radiological Protection. *Annals of the ICRP*, 37(2-4), 1-332
- Japan Network for Research and Information on Medical Exposures (J-RIME). (2025). *Japanese Diagnostic Reference Levels 2025 Edition*. Tokyo: Ministry of the Environment, Japan.
- Jibiri, N.N. & Olowookere, C.J. (2016). Patient dose audit of the most frequent radiographic examinations and the proposed local diagnostic reference levels in southwestern Nigeria:

- Imperative for dose optimization. *Journal of Radiation Research and Applied Sciences*, 9 (2016), 274e281
- Lee, T. F., Chang-Chien, L. C., Tsai, L., Chen, C. H., Tseng, P. S., Shiau, J. P., ... & Chao, P. J. (2025). Dose-Guided Hybrid AI Model with Deep and Handcrafted Radiomics for Explainable Radiation Dermatitis Prediction in Breast Cancer VMAT. *Cancers*, 17(23), 3767.
- Lee, K. L., Msimang, Z., Butler, D., Thomas, P., & Cardoso, J. (2025). Comparison of the air kerma standards of ARPANSA, Australia, and the IAEA in RQR, RQA, and RQT diagnostic X-ray beams. *Physical and Engineering Sciences in Medicine*, 48(3), 1137-1144.
- Mahmoudi, L., Bouiadjra, R. B., & Salem, M. (2025). Predicting and Monitoring Radiation Exposure of Radiographers Using Fuzzy Preprocessing and Deep Learning. *Journal of Control Engineering and Applied Informatics*, 27(3), 72-80.
- Meyer, S., Groenewald, W. A., & Pitcher, R. D. (2017). Diagnostic reference levels in low-and middle-income countries: early "Alaram" bells?. *Acta Radiologica*, 58(4), 442-448.
- Mokobia C.E. (2023): *My Three arrows: A victory over cyber phobia*. 100th inaugural lecture, Delta state University, Abraka.
- Nkubli, B. F., Jeremiah, M., Chigozie, N., Akpan, A. G., & Geofery, L. (2024). Exploring machine learning potentials to improve medical imaging services of children and adolescents in low-resource settings. *Journal of Radiography and Radiation Sciences*, 38(1), 14-16.
- Nwabuoku Augustine Onyema, Oluwadamilare Peter Olagbaju, Anita Franklin Akpolile, Omamoke O. E. Enaroseha and Ogheneovo Akpoyibo (2026) Radiological Impact Assessment of Radon Levels in Drinking Water and its Associated Health Risks in Aniocha North, Delta State, Nigeria. *Nigerian Journal of Applied Physics* 2(2): 1-20.
<https://doi.org/10.62292/njap-v2i2-2026-41>
- Ogbole, G. I., & Obed, R. (2025). Radiation doses in computed tomography: Need for optimization and application of dose reference levels in Nigeria. *West African Journal of Radiology*, 21(1), 1-6.
- Oghenekome, O. J., and Asare, G. K. (2025). Integrating the asymptotic iteration method with machine learning for predicting the vibrational energies of diatomic molecules. *Physical Science International Journal*, 29(2), 12-2.
- Oluwafisoye, P. A., Olowookere, C. J., Jibiri, N. N., Bello, T. O., Alausa, S. K., & Efunwole, H. O. (2010). Quality control and environmental assessment of equipment used in diagnostic radiology. *International Journal of Research and Reviews in Applied Sciences*, 3(2), 148-158.
- Omoriwhovo, J. O., Agbajor, G. K., Akpolilie, A. L., and Akpojotor, G. (2022). Python AIM solver to obtain vibrational energy spectra of diatomic molecules. *African Journal of Physics*, 15, 15-31.

- Osahon, O. D., & Bamidele, L. (2017). Radiation doses to patients undergoing selected radiographic examinations in three hospitals South-West, Nigeria. *International Journal of Chemical and Biomedical Science (IJCBS)*, 3(3), 26-31.
- Osiga-Aibangbee D, A.F. Akpolile, M.O. Ofomola, O.O.E. Enaroseha, G.K. Agbajor, C.E. Mokobia, Radionuclide evaluation in sediment samples in some communities in Edo state, Nigeria, J. Phys. Sci. Eng. 10 (2) (2024) 67–73.
- Osiga-Aibangbee D, Omamoke O.E. Enaroseha, Godwin K. Agbajor, Potential health risk assessment of sediment and water in some Niger Delta areas of Nigeria, Nuclear Anal. 4 (2025a) 100159, <https://doi.org/10.1016/j.nucana.2025.100159>.
- Plainoi, P., Diswath, W., & Manatrakul, N. (2001). *Quality control and Patient Doses from X-ray examinations in some Hospitals in Thailand* (No. IAEA-CSP--7/P, pp. 99-103)..
- Rasuli, B., Juybari, R. T., Forouzi, M., & Ghorbani, M. (2017). Patient dose measurement in common medical x-ray examinations and propose the first local dose reference levels to diagnostic radiology in Iran. *Polish Journal of Medical Physics and Engineering*, 23(3), 67-71.
- Sadoughi, H & Orooji, A. (2025). Leveraging Advanced AI Technologies for Radiotherapy Dose Calculation: A Narrative Review. *Trends in Advanced Technologies in Medicine*, 1(1), e167315
- Seo, D., Jang, S., Kim, J., Kim, J., Sung, D., Kim, H., & Yoon, Y. (2014). A comparative assessment of entrance surface doses in analogue and digital radiography during common radiographic examinations. *Radiation protection dosimetry*, 158(1), 22-27.
- Siciarz, P., Alfaifi, S., Van Uytven, E., Rathod, S., Koul, R., & McCurdy, B. (2021). Machine learning for dose-volume histogram based clinical decision-making support system in radiation therapy plans for brain tumors. *Clinical and Translational Radiation Oncology*, 31, 50-57.
- Sivapriya, J., Kumar, A., Sai, S. S., and Sriram, S. (2019). Breast cancer prediction using machine learning. *International Journal of Recent Technology and Engineering (IJRTE)*, 8(4), 4879-4881.
- Ugbede, F.O., Osahon, O.D, and Akpolile, A.F. (2021). Natural radioactivity levels of ²³⁸U, ²³²Th and ⁴⁰K and radiological risk assessment in paddy soil of Ezillo rice fields in Ebonyi State, Nigeria. *Environmental Forensics*, DOI: 10.1080/15275922.2021.1892881
- Ukokeno O.H., Omamoke O.E. Enaroseha, I.G. Omogbiya, C.E. Mokobia, Measurement of background gamma radiation in scrap sites, automobile mechanic and wood workshops in Delta Central area, Nigeria, Int. J. Sci. Technol. 1 (1) (2024) 29–35.
- United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR) (2008) *UNSCEAR 2008 Report*. Volume I. Annex A. Available at: www.unscear.org/docs/reports/2008/09-86753_Report_2008_Annex_A.pdf (accessed 22 November 2015).