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Predictive Modeling of Computed Tomography Facility Radiation Shielding Requirements Using Machine Learning Regression and Barrier Risk Classification

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ABSTRACT

Ionizing radiation from computed tomography (CT) examinations poses potential health risks to patients, radiation workers, and the general public if facilities are not adequately shielded. The study evaluated the performance of eight machine learning models for predicting lead-equivalent shielding thickness (mmPb). Machine learning analysis revealed Decision Tree achieved the highest test R^2 (0.731) with Unshielded Kerma contributing 97-99% of predictive importance, while Logistic Regression achieved perfect classification (Accuracy = 1.0) in distinguishing safe from at-risk barriers. With a test R^2 of 0.731 and the lowest RMSE of 0.159 mmPb, the Decision Tree model is the best performer. There are non-linear relationships in the data since all tree-based models perform better than linear models. Gradient Boosting shows the best cross-validation performance (CV $R^2 = 0.948 \pm 0.040$), indicating better generalization. The performance of linear models is moderate (R^2 = 0.61-0.65), however KNN and SVR perform badly, suggesting that they are not appropriate for this application. With an accuracy that is clinically acceptable and forecasts that are usually within 0.16 mmPb of actual values, the Decision Tree's R^2 of 0.731 indicates that it accounts for 73.1% of the variance in necessary shielding. Machine learning models effectively predict shielding requirements and identify at-risk barriers.

Keywords:
Radiation shielding,
Dose Optimization,
Patient Safety,
Occupational Exposure,
CT Scan.

INTRODUCTION

The usage of suitable shielding materials and radiation protection have become essential in recent years due to the increase of cancer patients worldwide (Omojola *et al*., 2021). The National Council on Radiation Protection and Measurements (NCPR) guidelines, which form the basis for radiographic CT room design and shielding in most countries, provide standards for radiography facility shielding. The main objective of any CT facility's planning is to prevent nearby residents from being exposed to radiation levels that are higher than the current regulatory limitations, which are 5 mSv/yr for those with occupational exposure and 1 mSv/yr for the general public. Both primary and secondary radiation sources, such as scatter and leakage radiation, must be shielded in a diagnostic CT room (Dance *et al.*, 2014). Variations in workload and the replacement of CT machines necessitate periodic re-evaluation of the primary and secondary shielding thickness. Although there are dose limitations, it is essential to use the ALARA (as low as reasonably achievable) concept to keep radiation exposure well below these limits. Every activity involving the use of radiation must incorporate the ALARA concept, including the planning, construction, and operation of both existing and future facilities (Abuzaid *et al.*, 2020). A few studies have evaluated main and secondary barriers with differing suggestions in order to provide parameters that will help determine the thickness of materials necessary for a particular CT room depending on its location, radiography workload, use factor, and occupancy factor. By offering details on the level of radiation shielding provided at different CT facilities in Delta State, Nigeria, this study improves the safety of workers, patients, and the general public. Additionally, it improves the department's standing and makes recommendations for how to make shielding in these facilities better. However, the ability of radiation to ionise matter divides it into two primary categories: ionising and non-ionising. The energy carried by ionizing radiation is sufficient to take an electron from an atom or molecule either directly or indirectly, but non-ionising radiation lacks the same capacity (Podgorsak *et al.*, 2005, Dance *et* *al*., 2014). Electrons, protons, alpha particles, and heavy ions are examples of directly ionising radiation. Basic radiation shielding entails being aware of the fundamentals of ionizing radiation protection. Health concerns can arise from ionizing radiation, which includes beta, gamma, x-ray, neutron, and alpha particles (UNSCEAR. 2008). Effective shielding uses methods and materials to lower radiation exposure rate and intensity. High density and atomic number shielding materials, such as steel, concrete, and lead, are frequently utilized because of their capacity to reduce radiation. A shield's density, thickness, and composition all affect how effective it is. In a variety of fields, such as nuclear power, medical applications, industrial radiography, and research using radioactive materials, it is essential to comprehend these fundamentals in order to build and implement radiation safety measures (Salim, *et al.*, 2024). However, it is crucial to adhere to radiation safety regulations, standards, and recommendations in order to protect patients, staff, and the general public from ionizing radiation. Three fundamental ideas of radiation protection have been identified by the International Commission for Radiological Protection (ICRP, 1996). These are justification, optimization, and dose limit. The dose optimization principle states that imaging operations should be performed at doses as low as reasonably practicable (ALARA) while maintaining diagnostic information. Because ionizing radiation administered at the proper dosage for the particular medical purpose is a required instrument where the benefit justifies the risk, dose limitations do not apply to medical exposures (Arao *et al.*, 2024). Ionizing radiation has both therapeutic and diagnostic applications in medicine. Radiation protection and the usage of appropriate shielding materials have become essential due to the recent increase in the number of neoplasm patients worldwide. Radiation workers, patients, and the general public, even at modest doses, the general population may encounter both stochastic and deterministic effects (Hadiza *et al.*, 2023). The radio-diagnostic room where different types of radiographic investigations are carried out needs to be adequately protected to avoid radiation exposure to the general public owing to radiation leakage. This implies that the radio-diagnostic room must have wall shielding made of concrete, lead, and copper in order to contain the X-ray radiation. When designing any radio diagnostic facility, preventing radiation leakage is of utmost importance. The current recommended exposure limits are 1.0 mSv/year for the general population and 5.0 mSv/year for those exposed at work (Olurin., 2024). When safety is incorporated into a system rather than presented to users as an option, the best outcomes are achieved. The actions that manufacturers may take to give CT scanners new features that will help with patient dose management were highlighted in recognition of this tactic. The clearest example of this tactic is the "collision avoidance system," which was first utilized in the automotive industry and is now used in medical imaging equipment (Nkansah *et al*, 2013). The gantry of the imaging machine will immediately stop moving if it ever makes touch with a person. The outcomes cannot be the same when collisions must be prevented by instruction, training, and education. It should be automatic to identify the issue and prevent its effects. Similar safety measures have been put into place over the past ten years by CT manufacturers who use tube current modulation and automatic exposure control to lower radiation doses to patients. The device automatically detects attenuation and modifies exposure during each revolution of the x-ray tube around the subject in order to optimize dose and image quality. Technology is the key to future improvements in protection and safety (Rehani, 2015). The need for radiation protection and the usage of suitable shielding materials has increased in recent years due to the global increase in carcinoma cases. Research has indicated that workers exposed to radiation at work have a chance of developing malignant tumor because of the radiation's stochastic influence. Radiation protection now largely entails the overt weighing of the advantages of nuclear and radiation practices against radiation risk as well as measures to lower residual risk (Gemanam *et al*., 2017). Although there are many different kinds of radiation that can be harmful to health, X-rays, gamma rays, and neutron particles are the main ones to be concerned about. According to common consensus, the effects of the other radiation types can be deemed insignificant if sufficient shielding is offered for these types of radiation. All materials might theoretically be used to reduce radiation to safe levels; however, due to specific properties, lead, copper, and concrete are among the materials that are most frequently utilized

MATERIALS AND METHODS

Description of the Study Area

Study Area

The study was carried out in Delta State, which is part of the Niger Delta in the South-South area of Nigeria. It is located between latitudes 5˚00' N and 6˚30' N and longitudes 5˚00' N and 6˚45° E. Edo State, Anambra State, Bayelsa State, and Rivers State form its borders. Warri, Sapele, and Ughelli are important urban and medical hubs, while Asaba, the state capital, is situated on the western bank of the Niger River. The region is low-lying and flooded due to its location within the Niger Delta, which may have an impact on environmental radiation levels and CT facility building design. The population of Delta State is estimated to be about 4.6 million, with Warri, Asaba, Sapele, and Ughelli being the main cities. In Delta State, CT facilities are usually found in private diagnostic clinics, federal and state medical centers, and teaching hospitals. These facilities are mostly located in

urban areas with better access to healthcare, such as Asaba and Warri.
The main equipment used are.
CT scanner, digital Laser tape and radiation survey meter

Methods

A total of six CT centers were used, out of which two are government owned and four private owned hospitals. Physical assessment was conducted to the background radiation with the help of the survey meter. Measurement of the supervised area and unsupervised area with the survey meter. Evaluation of the facilities shielding thickness and shielding integrity was also measured and recorded. Adjustment was made by varying both tube current and tube potential to 140 kVp alone with the slice thickness and pitch. Digital tape was used to measure the distance from the CT tube to the shielding room. Exposure setting was made to the patient, to ascertain the level of radiation dose absorb by the patient. Data was retrieved from the CT consoles of the display screen. Then calculation on the shielding barrier thickness and absorbed dose rate was determined. A systematic application of machine learning to predict radiation shielding requirements and identify safety risks in CT facility starts with defining the predictive objective, either regression to estimate the continuous shielding thickness in mmPb or classification to categorize barriers as safe or at-risk (a barrier will be classified as 'safe' when the estimated exposure is within the prescribed design or protection limit, while a barrier will be classified as 'At-risk' when the estimated exposure exceeds the applicable limit). Relevant input features such as distance from the CT source, unshielded kerma, occupancy factor, design goal and patient's workload were all measured from each barrier, cleaned and split into training and testing datasets. Based on the task, an appropriate model (python with the scikit-learn machine-learning library) is then selected, Decision Tree for regression and logistic regression for classification are recommended, both of which performed well in this study. The model is trained on the training data set to learn the patterns that connect the inputs to the outputs, and the accuracy of the model is evaluated by R^2 and RMSE for regression. The features importance analysis is then performed to identify the dominant predictors, where unshielded kerma is responsible for 97-99% of the shielding thickness prediction and the occupancy factor and design goal are more critical for the safety classification and to help guide design decisions to avoid unnecessary overshielding. This would provide a reliable and cost-effective method for routine radiation safety evaluation without the need for time-consuming manual calculations.

The dataset was split into training (80%) and testing (20%) groups at random. Ten-fold cross-validation, in which the data were divided into ten equal folds, was used to further assess the training subset. Nine folds were utilized for model training and one-fold for validation in each iteration. To ensure that every fold served as the validation set once, this procedure was carried out ten times. The independent 20% test set was kept aside for the final assessment of the machine learning models' predictive performance, and the average cross-validation performance was utilized for model selection and hyperparameter (maximum depth 5 and minimum samples per split 2) tuning. Below is the flowchart of the machine learning pipeline as shown in Figure 1;

Data collection →Preprocessing → Model training → Evaluation.

Figure 1: the flowchart of the machine learning pipeline

RESULTS AND DISCUSSION

Results

From Table 2. The Decision Tree model emerges as the top performer, with a test R^2 of 0.731 and the lowest RMSE of 0.159 mmPb. All tree-based models outperform the linear models, indicating the presence of non-linear relationships in the data. Gradient Boosting exhibits the highest and most stable cross-validation performance (CV $R^2 = 0.948 \pm 0.040$), suggesting superior generalization. Linear models show moderate performance ($R^2 = 0.61$-0.65), while KNN and SVR perform poorly, indicating they are unsuitable for this application. The Decision Tree's R^2 of 0.731 means it explains 73.1% of the variance in required shielding, with predictions typically within 0.16 mmPb of actual values and accuracy that is clinically acceptable. From Table 3. Feature importance analysis reveals that Unshielded Kerma dominates across all models, contributing 97-99% of importance, while Distance contributes only 0.2-1.2%, and all other features combined account for less than 1%. This highlights a critical insight: shielding designers should prioritize accurate calculation of unshielded kerma, as it drives nearly all variation in required barrier thickness. Optimizing protocols to reduce unshielded kerma is therefore the most effective way to minimize shielding requirements, rather than altering facility layout. Table 4. Linear model coefficients confirm expected directional effects: Distance (m) has a negative coefficient (-0.1357), indicating that increasing distance reduces required shielding, while Unshielded Kerma has a positive coefficient (0.0850), indicating that higher unshielded kerma increases requirements. Effect sizes suggest that a 1 m increase in distance reduces required shielding by approximately 0.14 mmPb, whereas a 1 mGy/wk increase in unshielded kerma raises requirements by about 0.09 mmPb. From Table 5. The Logistic Regression model achieved perfect classification, with Accuracy, Precision, Recall, F1-Score, and ROC-AUC all equal to 1.0. All other classification models performed well but less perfectly, with an accuracy of 0.8889. The confusion matrix confirms that the logistic model correctly identified all eight at-risk barriers and the one safe barrier in the test set. This perfect separation indicates that the distinction between "Safe" and "At-Risk" barriers is linearly separable, suggesting that relatively simple decision rules could reliably identify at-risk barriers without complex modeling. From Table 5. Feature importance differs between classification and regression tasks. Logistic Regression coefficients show Occupancy Factor and Design Goal (0.667 each) as the most influential features, followed by Distance (m) (-0.460). In contrast, tree-based classification models highlight Distance (m) and Unshielded Kerma as dominant, together accounting for 60-70% of importance. This shift indicates that the factors driving the magnitude of required shielding differ from those determining safety classification like occupancy and distance become more critical when predicting the risk of dose-limit exceedance.

Table 1: Predictive Model Performance Comparison for mmPb Estimation

Model	Test R^2	RMSE (mmPb)	MAE (mmPb)	CV R^2 (Mean ± SD)	Rank
Decision Tree	0.7312	0.1589	0.0744	0.907 ± 0.072	1
Random Forest	0.7033	0.1669	0.0731	0.921 ± 0.049	2
Gradient Boosting	0.6861	0.1717	0.0769	0.948 ± 0.040	3
Linear Regression	0.6467	0.1821	0.1058	0.811 ± 0.110	4
Ridge Regression	0.6445	0.1827	0.1040	0.826 ± 0.104	5
Lasso Regression	0.6083	0.1918	0.1054	0.825 ± 0.085	6
KNN	0.5420	0.2074	0.1822	0.211 ± 0.263	7
SVR	0.5054	0.2155	0.1585	0.599 ± 0.165	8

Table 2: Feature Importance Rankings from Tree-Based Models

Rank	Feature	Random Forest	Gradient Boosting	Decision Tree
1	Unshielded_Kerma_(mGy/wk)	0.9757	0.9900	0.9923
2	Distance(m)	0.0119	0.0049	0.0021
3	Facility_A	0.0025	0.0015	0.0011
4	Avg_DLP	0.0019	0.0001	0.0017
5	Avg_CTDI	0.0017	0.0003	0.0013
6	Total_Patients_Per_Week	0.0011	0.0017	0.0000
7	Occupancy_Factor	0.0010	0.0005	0.0008
8	Avg_mAs	0.0007	<0.0001	0.0000

Table 3: Linear Model Coefficients

Feature	Linear Regression	Ridge Regression	Lasso Regression
Distance(m)	-0.1357	-0.1302	-0.1167
Unshielded_Kerma (mGy/wk)	0.0850	0.0876	0.1043
Total_Patients_Per_Week	0.0383	0.0374	0.0867
Occupancy_Factor	-0.0160	-0.0160	-0.0211
Design_Goal_(mSv/yr)	-0.0160	-0.0160	~0

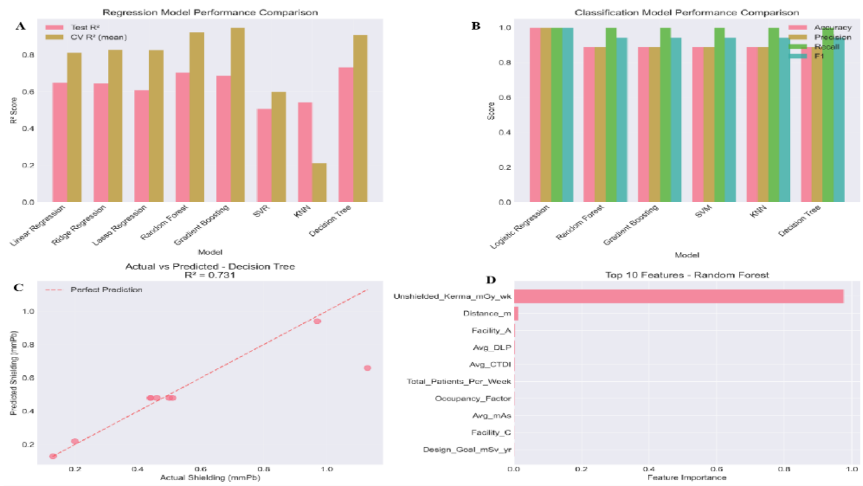

Figure 2: Machine learning model performance. (A) Regression model comparison (Test R^2 vs. CV R^2); (B) Classification model performance metrics; (C) Actual vs. predicted scatter plot for Decision Tree ($R^2 = 0.731$); (D) Top 10 feature importance from Random Forest

Table 4: Classification Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	CV Accuracy
Logistic Regression	1.0000	1.0000	1.0000	1.0000	1.0000	0.8476
Random Forest	0.8889	0.8889	1.0000	0.9412	1.0000	0.8476
Gradient Boosting	0.8889	0.8889	1.0000	0.9412	0.7500	0.8476
SVM	0.8889	0.8889	1.0000	0.9412	-	0.8810
KNN	0.8889	0.8889	1.0000	0.9412	0.8125	0.8810
Decision Tree	0.8889	0.8889	1.0000	0.9412	0.5000	0.7905

Table 5: Feature Importance across Classification Models

Feature	Logistic Regression (Coefficient)	Random Forest	Gradient Boosting	Decision Tree
Occupancy Factor	0.667	0.0857	0.0627	0.0000
Design Goal (mSv/yr)	0.667	0.0598	0.0393	0.2276
Distance_m	-0.460	0.3435	0.5153	0.2266
Unshielded Kerma (mGy/wk)	0.232	0.2551	0.1772	0.4519
Facility C	-0.445	0.0498	0.0863	0.0939

Discussion

The analysis in Table 2 and Figure 2 shows that tree-based models outperform linear models in predicting required shielding thickness. The Decision Tree achieved an R^2 of 0.731 compared to 0.647 for Linear Regression, suggesting that non-linear relationships in the data are important and better captured by non-parametric approaches. This has methodological implications for radiation shielding research, indicating that machine learning methods may offer advantages over traditional regression when modeling complex shielding behaviors. Similar benefits of machine learning have been reported in other areas of medical physics, such as treatment planning optimization and image quality assessment (Lyon *et al.*, 2018). The Decision Tree's R^2 of 0.731 means it explains about 73% of the variance in required shielding, with predictions typically within 0.16 mmPb of actual values. Given that safety margins of 0.25-0.5 mmPb are commonly applied in shielding design (NCRP, 2004), this level of accuracy is practically sufficient. The model's ability to estimate required shielding from easily measurable parameters such as distance, unshielded kerma, and facility characteristics points to potential applications in rapid shielding assessments and preliminary design, which could be particularly valuable in resource-limited settings. Gradient Boosting showed excellent cross-validation performance (CV $R^2 = 0.948 \pm 0.040$), demonstrating strong generalization to new facilities and minimal risk of overfitting. This supports the potential for developing predictive tools for shielding assessment, in line with computational approaches used in medical data analysis (Lyon *et al.*, 2018). In contrast, K-Nearest Neighbors ($R^2 = 0.542$) and Support Vector Regression ($R^2 = 0.505$) performed poorly, likely due to the high-dimensional feature space and non-linear relationships that these methods struggle to capture with the available dataset. This highlights the importance of careful model selection in machine learning, as not all algorithms are equally suitable for all types of predictive tasks. The value of machine learning in shielding design has been confirmed by more recent international research (Chika., 2024), demonstrated that machine learning can significantly reduce computational time while retaining high accuracy by combining Random Forest regression with Monte Carlo simulations to identify the ideal radiation shielding thickness and his report outstanding predictive performance. This confirms the current study's finding that machine learning can produce quick and accurate predictions for CT shielding evaluation. (Bilmez *et al.*,2022). Evaluated a number of machine learning algorithms for simulating gamma-ray shielding behavior and found that artificial intelligence approaches performed better than conventional regression techniques due to their ability to capture intricate, non-linear interactions between shielding variables and his results are consistent with the current study, which found that the Decision Tree algorithm outperformed linear regression in terms of prediction.

CONCLUSION

Machine learning approaches effectively predict shielding requirements, with Decision Tree models achieving R^2 = 0.731 and RMSE = 0.159 mmPb. These models demonstrate the potential for rapid preliminary assessments and screening in facility design or renovation. Logistic Regression achieved perfect classification of "Safe" versus "At-Risk" barriers, correctly identifying all exceedances. This indicates that simple, data-driven screening tools can reliably identify barriers requiring targeted evaluation. The practical value of the proposed approach lies in its potential to potential to provide a rapid, data-driven screening tool for CT radiation-shielding assessment. For facility designers, it can assist in identifying potentially inadequate barriers early in the design process. Optimising shielding materials and supporting cost-effective radiation protection. Future research should concentrate on expanding datasets, validating models across different CT facilities, improving model interpretability.

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