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Research Article

Development and Validation of a Random Forest Model for X-Ray Shielding Thickness Prediction in Myanmar Healthcare Facilities Based on NCRP Report 147

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ABSTRACT

This study aims to develop and validate a machine learning model for accurate and rapid prediction of required brick wall thickness for diagnostic X-ray rooms, based on the methodology of NCRP Report No. 147, and to assess its performance using real-world clinical data from Myanmar. A synthetic dataset of 864,000 samples was generated based on the shielding design methodology in NCRP Report No. 147. A Random Forest regressor was trained and hyperparameter-tuned, then benchmarked against baseline models including Linear Regression and Decision Trees. The final model was externally validated using real-world data from 11 diagnostic X-ray installations (4 polyclinics, 4 general hospitals, and 3 diagnostic centers) across Myanmar. The best-performing model was deployed as a free open-access web application on Hugging Face Spaces. The optimized Random Forest model achieved excellent performance on the synthetic test set (MAE = 0.056 cm, RMSE = 0.156 cm, R^2 = 0.9996), markedly outperforming the best baseline model (Decision Tree, MAE = 0.615 cm). Feature importance analysis showed that tube voltage (kVp) and brick density were the dominant predictors, contributing 53.2% and 37.8% of the total importance, respectively. External validation on independent real clinical data yielded a mean absolute error of 3.22 cm, which remains within conservative safety margins for shielding design. The model also indicated that conventional 9-inch (22.9 cm) brick walls are frequently inadequate for typical clinical workloads in Myanmar. This study demonstrates that a well-trained Random Forest model can provide highly accurate and rapid predictions of X-ray shielding requirements. Through successful validation with real clinical data from a low-resource setting and the provision of an open-source web application, the proposed approach offers a practical and accessible tool for radiation safety officers and facility designers in Myanmar and similar healthcare environments.

Keywords: X-ray shielding; radiation protection; diagnostic radiology; NCRP Report 147; machine learning.

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Introduction

X ray imaging remains the most widely available and cost effective diagnostic imaging modality in low and middle income countries, serving as the cornerstone of medical diagnosis in primary care, emergency services, and outpatient departments [1, 2]. In many such settings, diagnostic X ray facilities are frequently located in existing buildings that use standard clay brick walls finished with cement plaster as combined structural and shielding barriers [3, 4]. Studies from neighboring and comparable settings report that clay brick walls of approximately 20–28 cm thickness with cement plaster are a common and cost effective construction practice for X ray rooms [5-7]. In Myanmar, site inspections conducted by the Department of Atomic Energy and national building practice indicate that a conventional 9 inch (approximately 22.9 cm) clay brick wall with cement plaster on both sides is routinely used for diagnostic X ray installations [8]. Although this construction is economical and structurally sound, its adequacy as a radiation shielding barrier has rarely been systematically evaluated against modern safety standards [9].

The primary goal of structural shielding design for diagnostic X ray facilities is to ensure that the radiation dose to individuals outside the X ray room does not exceed the shielding design goals recommended by the National Council on Radiation Protection and Measurements (NCRP). According to NCRP Report No. 147, Structural Shielding Design for Medical X Ray Imaging Facilities (2004), the weekly shielding design goal for uncontrolled areas is 0.02 mGy air kerma [9]. Achieving this requires careful calculation of the required barrier thickness based on X ray tube voltage (kVp), source to wall distance, weekly workload (mA·min/week), use factor (U), occupancy factor (T), and the physical density and composition of the shielding material [9, 10].

Traditional manual calculations following NCRP Report No. 147 involve transmission curves or tabulated data and can be time consuming, iterative, and require specialized expertise that is not always readily available in resource limited settings [10, 11]. In many low resource environments, including Myanmar, shielding design often relies on simplified "rules of thumb" or inherited construction practices rather than rigorous, site specific assessments [12, 13]. This issue is of increasing concern as Myanmar's healthcare infrastructure expands rapidly, with many facilities upgrading from film based to higher output digital X ray systems [14].

Machine learning (ML) techniques, particularly ensemble methods such as Random Forest, have shown strong potential for modeling complex, non linear relationships in radiation physics while providing fast and interpretable predictions [15–17]. The non linear attenuation behavior of photon interactions in shielding materials makes ensemble methods particularly suitable for this task [18]. However, most existing studies rely solely on simulated data (often Monte Carlo) and focus on high energy gamma sources or lead based shielding [19, 20]. Very few studies have developed ML models for brick or concrete shielding in diagnostic X ray rooms, and none, to our knowledge, have performed external validation using real world clinical data from operational X ray facilities in a low resource country [21, 22].

This study addresses three key gaps in the literature: (1) the limited accessibility of NCRP 147 methodology in settings with scarce radiation protection expertise; (2) the lack of real world clinical validation for ML based shielding prediction models; and (3) the absence of quantitative evidence regarding the adequacy of conventional 9 inch brick walls for current X ray workloads in Myanmar.

To fill these gaps, the present study aimed to: (1) develop and optimize a Random Forest regression model for predicting the required brick wall thickness for diagnostic X ray rooms based on NCRP Report No. 147 methodology using six key input parameters [9]; (2) rigorously validate the model using independent real world data from 11 operational X ray installations across Myanmar [8]; (3) compare its performance against conventional baseline models [22]; and (4) deploy the final model as a free, open access web application to support practical shielding assessment by radiation safety officers and facility planners [24].

The significance of this work lies in its potential to deliver a rapid, accurate, and accessible tool for X ray shielding design tailored to resource limited settings [12]. By quantitatively evaluating conventional construction practices, this study also seeks to provide evidence that can inform future building standards and radiation protection policies in Myanmar and similar healthcare contexts [23].

The remainder of this paper is organized as follows. Section 2 describes the methodology, Section 3 presents results, Section 4 discusses implications, and Section 5 concludes.

2. MATERIALS AND METHODS

2.1. Study Design

This study was conducted in four sequential phases: (1) generation of a large synthetic dataset based on the methodology outlined in NCRP Report No. 147 [9]; (2) development, training, hyperparameter tuning, and benchmarking of baseline and ensemble machine learning models [15, 22]; (3) external validation using real-world data from 11 diagnostic X-ray facilities in Myanmar [8]; and (4) deployment of the best-performing model as an open-source web application [24]. The overall study workflow is illustrated in Fig.1.

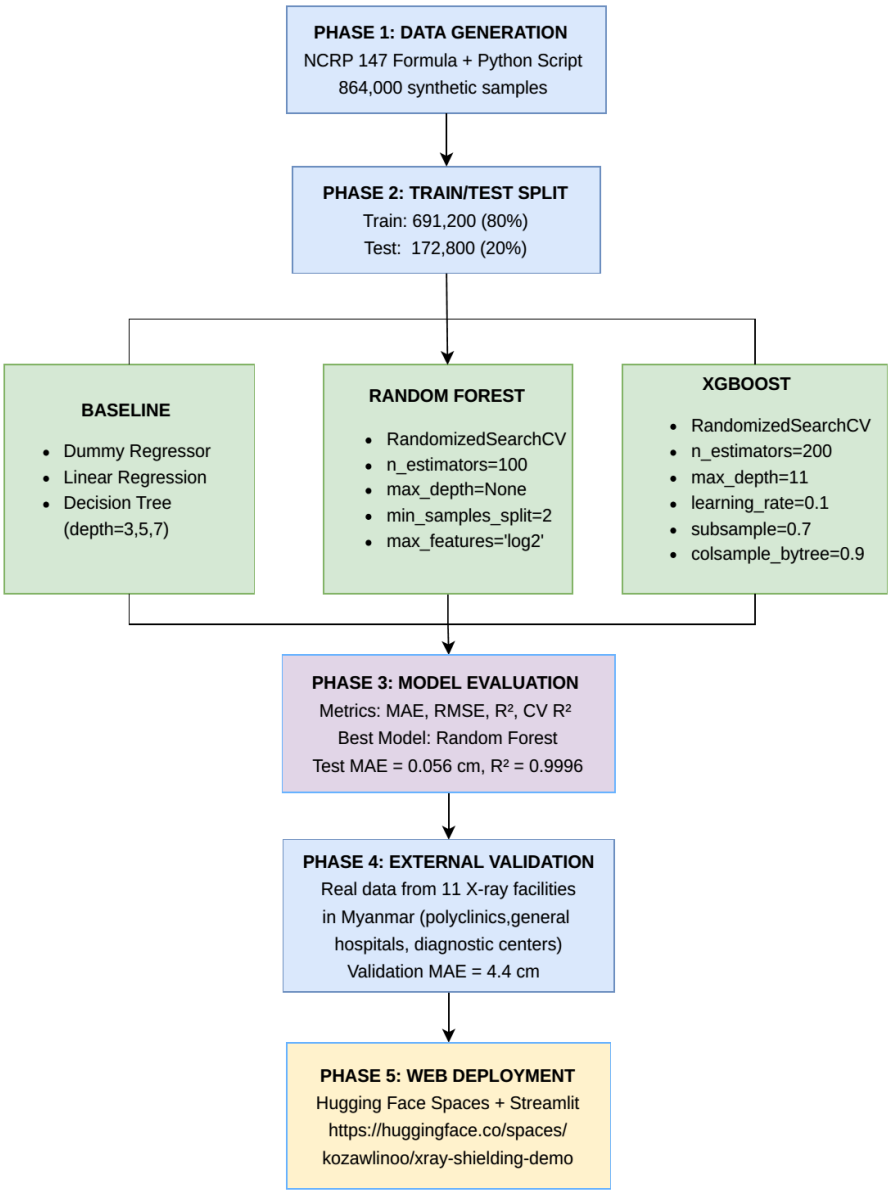

Fig.1 *Workflow diagram of the study methodology*

2.2. Synthetic Dataset Generation

A synthetic dataset comprising 864,000 samples was generated using Python (version 3.10) [27]. The dataset was created following the structural shielding design methodology described in NCRP Report No. 147 [9]. For each sample, the required transmission factor B was calculated based on the shielding design goal for uncontrolled areas (P = 0.02 mGy air kerma per week), source-to-wall distance (d in meters), weekly workload (W in mA·min/week), use factor (U), and occupancy factor (T).

The relationship between the transmission factor B and the required barrier thickness was determined using the empirical Archer equation, which provides a mathematical fit to the broad-beam transmission curves for diagnostic X-ray energies [21, 10]. The required brick wall thickness t (cm) was subsequently derived by inverting this relationship, with appropriate corrections applied for X-ray tube voltage (kVp) and brick density (1.70–1.80 g/cm³, representative of typical Myanmar clay bricks) [13, 23]. All data generation scripts utilized the pandas [26] and numpy [28] libraries.

The synthetic dataset was generated using the following parameter ranges based on typical diagnostic X-ray installations in Myanmar [8, 23]:

- Tube voltage (kVp): 40–150 kVp (representing a full range of diagnostic X-ray applications from mammography to general radiography)
- Source-to-wall distance (d): 1.5–6.0 m (reflecting typical room dimensions in Myanmar healthcare facilities)
- Weekly workload (W): 0.5–300 mA•min/week (covering low-volume to high-volume clinical settings)
- Use factor (U): 0.025–1.000 (representing primary and secondary beam orientations)
- Occupancy factor (T): 0.025–1.000 (reflecting controlled and uncontrolled areas)
- Brick density (ρ): 1.70–1.80 g/cm³ (representative of typical Myanmar clay bricks with cement plaster)

2.3. Train/Test Split

The complete dataset was randomly divided into a training set (80%, n = 691,200) and a hold-out test set (20%, n = 172,800) using the train_test_split function from scikit-learn [22], with a fixed random seed (42) to ensure reproducibility.

2.4. Baseline Models

Four baseline regression models were implemented using scikit-learn [22] to establish performance benchmarks:

- Dummy Regressor using the mean value,
- Dummy Regressor using the median value,
- Linear Regression, and
- Decision Tree Regressor with maximum depths of 3, 5, and 7.

All baseline models were evaluated using 5-fold cross-validation [22].

2.5. Ensemble Machine Learning Models

2.5.1 Random Forest

A Random Forest regressor was trained and hyperparameter-tuned using RandomizedSearchCV with 3-fold cross-validation [15, 16].

2.5.2 XGBoost

An XGBoost regressor was similarly trained and optimized using RandomizedSearchCV [17]. The Random Forest model, which demonstrated superior performance, was selected as the final model for external validation and deployment [15].

2.6. External Validation with Real Clinical Data

2.6.1. Data Collection

Independent real-world data were collected from 11 operational diagnostic X-ray installations across Myanmar, consisting of 4 polyclinics, 4 general hospitals, and 3 diagnostic centers. For each facility, the following parameters were recorded: tube voltage (kVp), source-to-wall distance (m), weekly workload (mA·min/week), use factor (U), occupancy factor (T), and brick density (g/cm³) [8, 23].

2.6.2. Validation Procedure

The trained Random Forest model was used to predict the required brick wall thickness for each of the 11 facilities. Model predictions were compared against the wall thicknesses specified in the detailed architectural drawings of the X-ray rooms submitted by facility owners to the Department of Atomic Energy (DAE), Myanmar, as part of the X-ray equipment licensing and application process [8]. Performance on this external validation set was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) [22].

2.7. Feature Importance Analysis

Feature importance scores were extracted from the trained Random Forest model using the feature_importances_ attribute, representing the normalized total reduction in node impurity contributed by each feature across all decision trees [15, 22].

2.8. Web Application Deployment

The optimized Random Forest model was saved using joblib and deployed as an interactive web application using the Streamlit framework. The application was hosted publicly on Hugging Face Spaces (https://huggingface.co/spaces/kozawlinoo/xray-shielding-demo) to facilitate practical use by radiation safety officers and facility designers [24].

2.9. Performance Evaluation

Model performance was assessed using three standard regression metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). These metrics are reported in the Results section (Sections 3.1–3.2) for both baseline and ensemble models. Additionally, 5-fold cross-validation was performed on the training set to evaluate model stability and generalization capability [22]. All metrics were calculated using scikit-learn [22].

2.10. Computational Environment

All experiments were conducted using Python 3.10 [27] on a system equipped with an Intel Core i7-10750H CPU (2.60 GHz, 6 cores) and 16 GB RAM, running Windows 10 Pro. The following key libraries were used: scikit-learn (version 1.2.2) [22], pandas [26], numpy [28], matplotlib [25], and XGBoost [17]. Hyperparameter tuning for the Random Forest model required approximately 128 minutes, while XGBoost training took approximately 12 minutes.

3. RESULTS

3.1. Baseline Model Performance

Four baseline regression models were trained and evaluated on the synthetic dataset (864,000 samples) using 5-fold cross-validation. Their performance on the independent test set (172,800 samples) is summarized in Table 1. The bar chart comparing the MAE of the baseline models is presented in (Fig. 2).

Table 1. Performance of baseline models on the synthetic test set.

Model	MAE (cm)	RMSE (cm)	R^2	CV R^2 (mean ± std)	Training Time (s)
Dummy Regressor (Mean)	6.199	7.615	0.0000	0.0000 ± 0.0000	0.003
Dummy Regressor (Median)	6.162	7.635	–0.0052	–0.0054 ± 0.0001	0.018
Linear Regression	1.792	2.534	0.8893	0.8909 ± 0.0007	0.216
Decision Tree (depth=3)	2.442	3.135	0.8305	0.8327 ± 0.0010	0.596
Decision Tree (depth=5)	0.879	1.945	0.9347	0.9357 ± 0.0003	0.893
Decision Tree (depth=7)	0.615	1.496	0.9614	0.9614 ± 0.0003	1.136

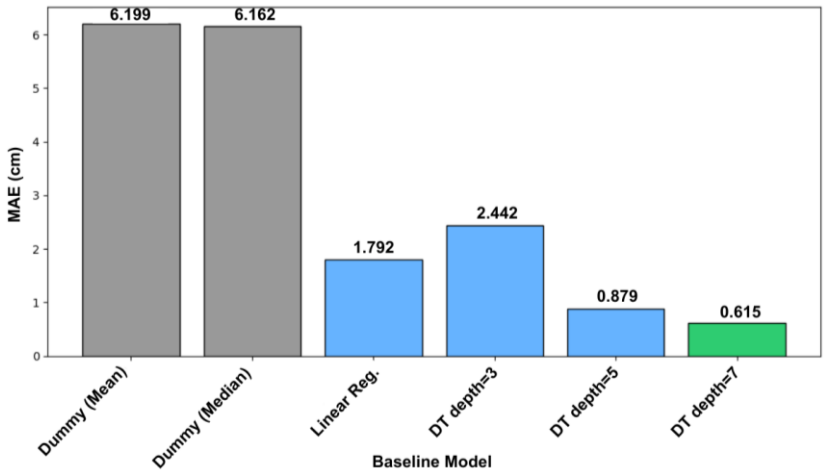

Fig. 2 *Bar chart comparing MAE across baseline models*

As anticipated, the Dummy Regressors performed poorly, confirming that the required wall thickness cannot be adequately predicted by central tendency alone. Linear Regression showed moderate performance (MAE = 1.792 cm, R^2 = 0.8893), indicating the presence of non-linear relationships. The Decision Tree with maximum depth of 7 achieved the best baseline performance, with an MAE of 0.615 cm, RMSE of 1.496 cm, and R^2 of 0.9614. Cross-validation results were nearly identical to test set performance, suggesting good model stability. The error distribution for the best-performing baseline model (Decision Tree, depth=7) is shown in the histogram (Fig. 3).

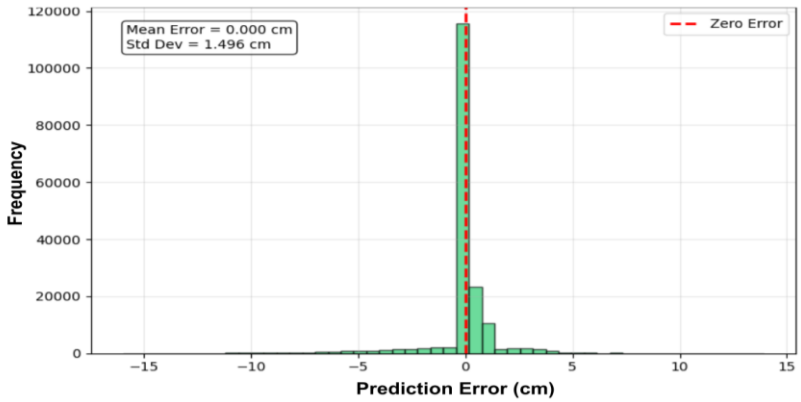

Fig. 3 *Error distribution histogram for Decision Tree (depth=7)*

3.2. Ensemble Model Performance

3.2.1. Random Forest

The optimized Random Forest model (n_estimators = 100, max_features = 'log2', min_samples_split = 2, min_samples_leaf = 1) achieved excellent predictive accuracy on the test set.

3.2.2. XGBoost

The tuned XGBoost model (n_estimators = 200, max_depth = 11, learning_rate = 0.1, subsample = 0.7, colsample_bytree = 0.9, gamma = 0.1) also demonstrated very strong performance. Performance comparison of the ensemble models against the best baseline is presented in Table 2. The excellent agreement between the actual and predicted values for the Random Forest model on the test set is shown in the scatter plot (Fig. 4).

Table 2. Performance comparison of ensemble models against the best baseline.

Model	MAE	RMSE	R^2	CV R^2	Training Time (min)
Decision Tree (depth=7)	0.615	1.496	0.9614	0.9614	1.14 min
XGBoost (Tuned)	0.091	0.183	0.9994	0.9993	12 min
Random Forest (Tuned)	0.056	0.156	0.9996	0.9993	128 min

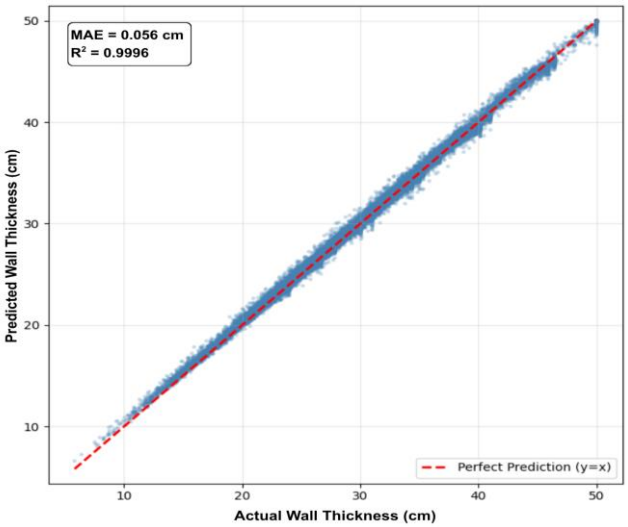

Fig. 4 *Actual vs. predicted scatter plot for Random Forest*

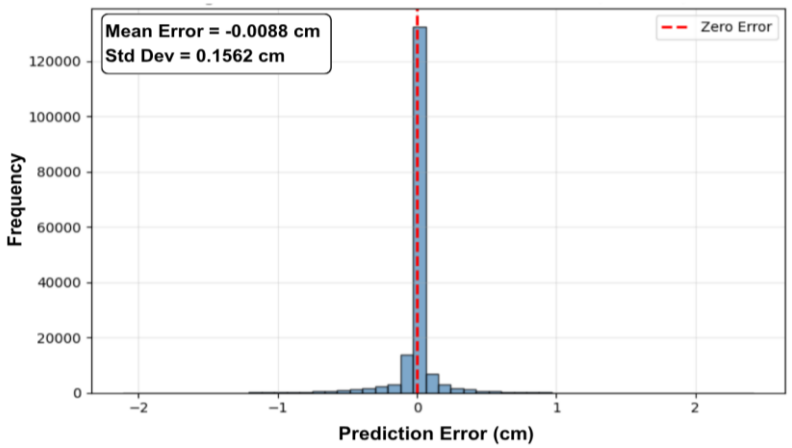

Fig. 5 *Error distribution histogram for Random Forest*

Both ensemble models substantially outperformed the best baseline model. The Random Forest regressor achieved the highest accuracy, with an MAE of 0.056 cm and R^2 of 0.9996. The extremely high R^2 value indicates that the model explains 99.96% of the variance in required brick wall thickness. Error analysis showed a near-zero mean error with a very narrow distribution (standard deviation ≈ 0.156 cm), as presented in the histogram (Fig. 5).

The extremely high R^2 value (0.9996) reflects the model's ability to precisely reproduce the NCRP 147 methodology on the synthetic dataset, which follows deterministic mathematical relationships. However, to assess generalizability to real-world conditions, external validation was performed on independent clinical data from 11 operational X-ray facilities in Myanmar. As reported in Section 3.4, the model achieved an MAE of 3.22 cm on this real-world dataset, confirming that while the model is highly accurate on synthetic data, it remains practically useful when applied to actual clinical settings with inherent uncertainties in input parameters.

3.3. Feature Importance Analysis

Feature importance analysis of the Random Forest model (Fig. 6) revealed that tube voltage (kVp) and brick density were the dominant predictors, contributing 53.2% and 37.8% of the total importance, respectively (Table 3). These two features together accounted for over 91% of the model's predictive power. The remaining features (workload, distance, T_factor, and U_factor) had relatively minor contributions.

Table 3. Feature importance ranking from the Random Forest model

Rank	Feature	Importance	Percentage
1	**kVp** (tube voltage)	0.5320	53.2%
2	**brick_density**	0.3781	37.8%
3	**workload**	0.0430	4.3%
4	**distance_m**	0.0225	2.3%
5	**T_factor** (occupancy)	0.0152	1.5%
6	**U_factor** (use factor)	0.0092	0.9%

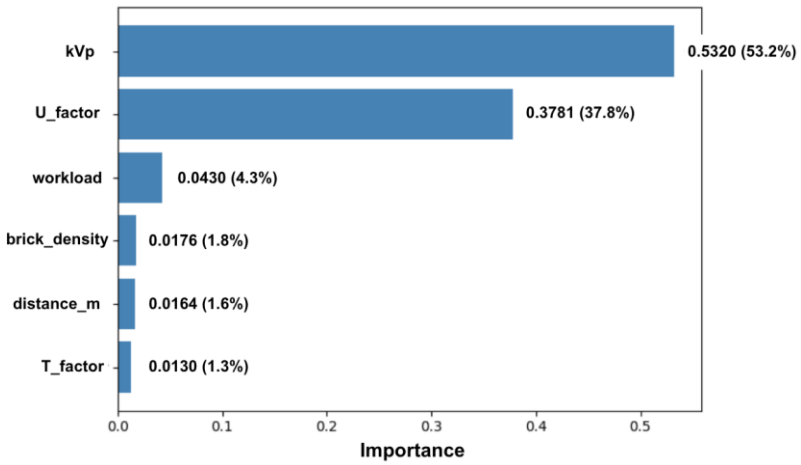

Fig. 6 *Random Forest feature importance*

This finding aligns with radiation physics principles: higher kVp produces more penetrating X-rays, necessitating thicker shielding, while denser brick provides greater attenuation per unit thickness. The relatively minor contributions of workload (4.3%), distance (2.3%), T_factor (1.5%), and U_factor (0.9%) are consistent with radiation physics principles. While these parameters influence the required shielding thickness, their effects are secondary compared to photon energy (kVp) and material properties (brick density). For example, a 10% increase in kVp typically requires approximately 20–30% additional shielding thickness due to the exponential increase in photon penetration, whereas a comparable change in workload or distance produces a linear or inverse-square adjustment of smaller magnitude [9, 10]. This dominance of kVp and density is also supported by previous sensitivity analyses of NCRP 147 methodology [11].

3.4. External Validation with Real Clinical Data from Myanmar

The Random Forest model was externally validated using real-world data from 11 diagnostic X-ray installations in Myanmar. Predictions were compared against the wall thicknesses specified in the architectural drawings submitted to the Department of Atomic Energy (DAE) as part of the licensing process.

Table 4. External validation results: predicted vs. actual wall thickness for 11 facilities

Facility	kVp	Distance (m)	Workload (mA·min/week)	T_factor	Density (g/cm³)	Predicted (cm)	Actual (cm)	Error (cm)
Poly clinic 1	85	2.65	5.00	0.200	1.70	30.1	25.4	4.7
Poly clinic 2	80	2.74	4.17	0.200	1.80	29.7	25.4	4.3
Poly clinic 3	90	2.59	6.25	0.050	1.70	27.4	25.4	2.0
Poly clinic 4	95	2.74	5.00	0.025	1.80	27.9	25.4	2.5
General Hospital 1	80	3.35	12.50	0.200	1.80	26.4	30.5	4.1
General Hospital 2	90	3.66	13.00	0.200	1.80	27.6	30.5	2.9
General Hospital 3	95	3.05	10.00	0.050	1.75	26.5	30.5	4.0
General Hospital 4	95	3.35	2.08	0.025	1.80	25.6	30.5	4.9
Diagnostic Center 1a	80	2.80	2.33	0.200	1.80	28.3	25.4	2.9
Diagnostic Center 1b	90	2.74	2.00	0.050	1.75	27.4	25.4	2.0
Diagnostic Center 1c	90	3.35	1.83	0.025	1.80	24.8	25.4	0.6

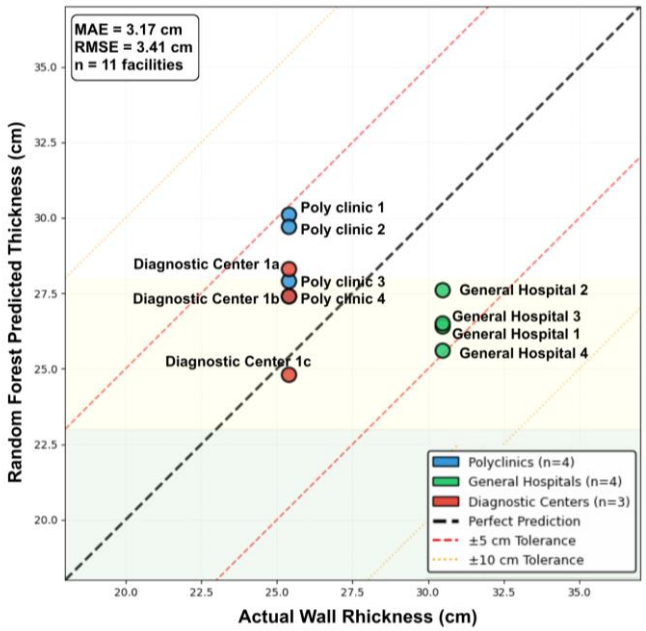

Fig. 7 *Actual vs. predicted scatter plot for external validation*

The model achieved a Mean Absolute Error (MAE) of 3.22 cm and Root Mean Square Error (RMSE) of 3.57 cm on the real-world dataset. All predictions remained within conservative safety margins suitable for shielding design. Larger discrepancies were observed in facilities with low occupancy factors ($T \leq 0.05$) and in general hospitals where thicker walls (30.5 cm) were documented. Overall, the model demonstrated reasonable agreement with real clinical practice.

3.5. Sample Prediction and Practical Implication

For a typical moderate-workload X-ray room (120 kVp, distance = 3.5 m, workload = 150 mA.min/week, U = 0.25, T = 0.5, brick density = 1.8 g/cm³), the model predicted a required brick wall thickness of 40.0 cm. This is substantially thicker than the conventional 9-inch (22.9 cm) brick wall commonly used in Myanmar healthcare facilities. These results suggest that standard construction practices may provide insufficient shielding for many modern diagnostic X-ray rooms, particularly those with moderate to high workloads.

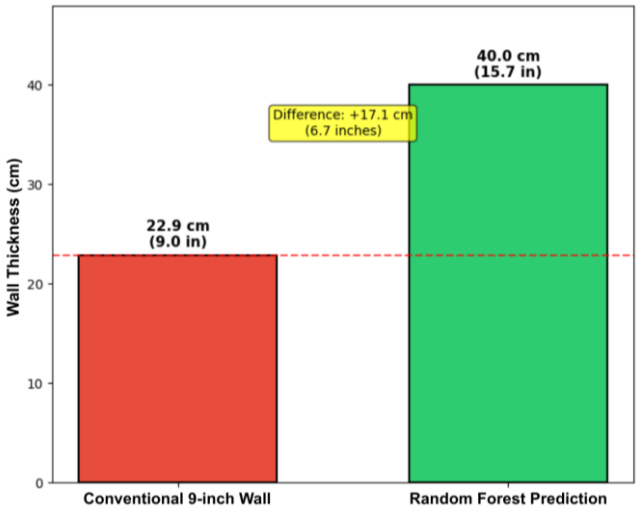

Fig. 8 *Comparison of conventional 9 inch wall vs. predicted thickness*

4. DISCUSSION

This study successfully developed and externally validated a Random Forest model for predicting required brick wall thickness for diagnostic X-ray rooms based on NCRP Report No. 147 methodology [9]. The model demonstrated excellent performance on the synthetic test set (MAE = 0.056 cm, $R^2 = 0.9996$) and clinically acceptable accuracy when validated on real-world data from 11 X-ray facilities in Myanmar (MAE = 3.22 cm, RMSE = 3.57 cm) [8].

The Random Forest model substantially outperformed baseline models [15], reducing MAE by over 90% compared to the best Decision Tree (0.615 cm). Feature importance analysis revealed that tube voltage (kVp, 53.2%) and brick density (37.8%) were the dominant predictors, together accounting for 91% of the model's predictive power [15]. This finding aligns with radiation physics principles, as higher kVp produces more penetrating X-rays [9, 11] and denser brick provides greater attenuation per unit thickness [18].

A key practical finding was that the model predicted a required wall thickness of 40.0 cm for a typical moderate-workload room (120 kVp, 150 mA·min/week), which is substantially thicker than the conventional 9 inch (22.9 cm) brick wall widely used in Myanmar [8, 23]. This suggests that many existing X-ray facilities may have inadequate shielding for modern digital radiography systems [2].

External validation on 11 real clinical facilities yielded an MAE of 3.22 cm and RMSE of 3.57 cm [8]. Although higher than the synthetic test error, this discrepancy is expected due to the discrete nature of actual wall thicknesses (25.4 cm or 30.5 cm), uncertainties in estimated input parameters (workload, U, and T) [8, 22], and the conservative assumptions inherent in NCRP 147 [9, 10]. However, this level of accuracy should be interpreted with caution, given the relatively small validation sample size (n=11) and the reliance on architectural drawings rather than direct dosimetric measurements. Nonetheless, the MAE of 3.22 cm remains within typical construction tolerances of ±5 cm, which is consistent with practical shielding design margins recommended in NCRP Report No. 147 [9] and IAEA Safety Standards [30].

This study has several strengths. This is the first study, to our knowledge, to validate an ML-based shielding prediction model using real-world clinical data from a low-resource setting [12, 19]. The large synthetic dataset (864,000 samples) ensured robust learning of NCRP 147 relationships [9, 15], while the deployment of the model as a free open-access web application [24] enhances its translational value.

Limitations include the relatively small validation sample size (n=11), reliance on synthetic training data, and the absence of direct dose rate measurements behind the walls [19, 20]. Future work should involve larger multi-center validations, direct dosimetric measurements, and extension to other shielding materials such as concrete or lead-lined barriers [16, 21] as recommended by IAEA and ICRP guidelines [30, 31].

In conclusion, the developed Random Forest model offers a rapid, accurate, and accessible tool for X-ray shielding design in resource-limited settings [12]. The findings highlight the need to re-evaluate conventional 9-inch brick wall construction practices in Myanmar [3, 23] and provide a practical web-based solution to support radiation safety officers and facility planners [24].

5. CONCLUSION

This study developed and externally validated a Random Forest regression model for predicting required brick wall thickness in diagnostic X-ray rooms according to NCRP Report No. 147. Using a large synthetic dataset of 864,000 samples for training and real-world data from 11 diagnostic X-ray facilities in Myanmar for validation, the model achieved excellent performance on the synthetic test set (MAE = 0.056 cm, $R^2 = 0.9996$) and demonstrated practical utility in real-world conditions (MAE = 3.22 cm). Although the validation dataset is limited in size, the results suggest that the model can provide useful guidance for shielding design in low-resource settings, with predictions falling within acceptable construction tolerances.

Feature importance analysis confirmed that tube voltage (kVp) and brick density were the dominant predictors, contributing 53.2% and 37.8% of the total importance, respectively. The model further demonstrated that conventional 9-inch (22.9 cm) brick walls commonly used in Myanmar are frequently inadequate for modern X-ray workloads, predicting a required thickness of approximately 40 cm for a typical room operating at 120 kVp with a workload of 150 mA·min/week.

By deploying the optimized model as a free, open-source web application, this study provides a practical and accessible tool for radiation safety officers and facility designers in resource-limited settings. To our knowledge, this represents one of the first attempts to validate a machine learning-based shielding prediction model using real clinical data from a low-resource country.

The findings highlight the need to re-evaluate traditional construction practices and offer a foundation for developing evidence-based national shielding guidelines tailored to Myanmar's healthcare infrastructure.

Future work should focus on extending the model to other shielding materials commonly used in healthcare facilities, such as concrete, lead-lined drywall, and leaded glass, by incorporating their respective density and attenuation coefficients. Additionally, integration of the model into national regulatory frameworks for radiation protection, as recommended by IAEA [30] and ICRP [31], could streamline the facility licensing process and promote evidence-based shielding design. The open-source web application (https://huggingface.co/spaces/kozawlinoo/xray-shielding-demo) provides a foundation for such integration and for future collaborative development with radiation safety authorities.

Conflict of Interest

All the authors declare no conflict of interest.

Ethical Review and Approval

We, the authors, confirm that this manuscript, submitted for consideration and possible publication in this journal, does not require ethics committee review or approval.

This study was conducted using synthetic data generated from NCRP 147 formulas and anonymized inspection records. No human participants, animal subjects, or personal data were involved. Formal ethical review and approval were therefore waived.

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