

An Artificial Intelligence-Based Framework for Enhanced Clinical Decision-Making in Minimizing Repetitive Pediatric Brain CT Scans

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ABSTRACT:

Background: Children frequently receive repeat brain CT scans without strong justification. Rapid bedside estimation of cumulative radiation risk is challenging, and no validated clinical rule exists for repeat scans in pediatric head trauma. We developed a mobile clinical decision support tool integrating PECARN-informed criteria with an artificial neural network (ANN) that approximates ICRP-defined cancer risk from cumulative CT exposure.

Methods: We retrospectively trained KNN, SVM, and ANN models to approximate ICRP risk equations using data from 4025 pediatric brain CT scans (age 0–16 years). The best-performing model was embedded with PECARN-informed criteria into a mobile app. Eleven clinicians completed a usability survey, and repeat CT request rates were tracked over six months using statistical process control.

Results: The ANN achieved the lowest approximation error (MAPE 6.92%; R^2 0.917) compared with KNN (11.24%; 0.842) and SVM (8.76%; 0.879). Over six months, repeat CT requests decreased by a mean 57.0% (range 50.5%–63.0%). A downward

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trend met Nelson rule criteria for non-random pattern ($p < 0.01$).
Pilot usability: 72.8% found navigation easy or very easy.

Conclusions: A mobile tool using PECARN-informed criteria and real-time ICRP risk estimation reduced repeat pediatric brain CT requests by 57% in a Saudi emergency department. Larger prospective validation is required.

Keywords: Artificial intelligence, Pediatric brain CT, PECARN, Radiation protection, Clinical decision support. AI-driven marketing; digital real estate; Bangalore; residential housing; market dynamics.

1. Introduction

The utilization of computed tomography (CT) in pediatric clinical practice has expanded dramatically over the past two decades, establishing itself as an indispensable diagnostic modality in the evaluation of traumatic brain injuries, neurological emergencies, and a broad spectrum of intracranial pathologies (Brenner & Hall, 2007; Miglioretti et al., 2022). Despite representing less than 13% of all diagnostic imaging procedures, CT contributes approximately 75% of the total effective radiation dose associated with diagnostic medical imaging (Dreuil & Etard, 2017). This contribution is especially significant in children due to the combined effect of increased radiosensitivity of growing tissues and the extended time frame over which radiation-induced cancers may develop (Pearce et al., 2012; Smith-Bindman et al., 2020).

Repeat brain CT scans in children has become a key radiation protection concern. Epidemiological studies have shown that children subject to two or more repeat CT scans have a higher risk ratio (RR: 2.40, 95% CI: 1.48-3.88) for developing cancer compared with those who undergo only a single CT scan (Pearce et al., 2012). In addition, large retrospective cohort studies have shown a direct link between the number of repeat brain CT scans performed and lifetime attributable cancer risk, with younger children being more sensitive (Bosch de Basea et al., 2023; Mathews et al., 2013).

There are many factors contributing to the repeat use of pediatric brain CT. Medically, repeat scans may be warranted to assess for progression of injury, such as patients with low Glasgow Coma

Scale scores or worsening neurological symptoms (Brady, 2017; Hill et al., 2017). However, there are several potentially avoidable repeat scans. Imaging factors, including variable imaging protocols and inappropriate use of adult scanning parameters for children, can result in poor-quality images requiring repeat scans (Nabaweesi et al., 2021). Other patient-related factors, such as motion artifacts (common in children) may also lead to repeated CT scans (Ng, 2022). Given the higher vulnerability of children to radiation-induced cancers, and the risk of developing cancer over their remaining lifetime, it is important to eliminate the need for repeated CT scans where possible.

Data analytics and machine learning are transforming clinical practice. They can turn multivariate data into clinical recommendations (Rajpurkar et al., 2022; Topol, 2021). In pediatric radiology, AI may offer future benefits for dose reduction, image quality, and decision support, but current evidence is limited, and risks such as algorithmic bias and lack of pediatric validation remain unresolved (Hosny et al., 2021; Khalifa & Albadawy, 2024). ANNs, SVMs, and KNN algorithms are examples of machine learning models that have demonstrated strong performance in estimating cancer risks and predicting clinical outcomes (Richter & Khoshgoftaar, 2018; Zhang et al., 2023). The PECARN prediction rules help identify children at very low risk of clinically important traumatic brain injury. When used systematically, they reduce unnecessary CT imaging (Cho et al., 2022; Gambacorta et al., 2022; Kuppermann et al., 2009; Niele et al., 2020).

To date, no study has combined a rapid bedside estimator of cumulative radiation risk with clinical decision rules for repeat pediatric head CTs. Machine learning papers typically focus on predictive accuracy but do not address real-time clinical integration. Decision rule studies focus on initial CT after trauma; none have been validated for repeat CT decisions. Furthermore, little has been published on this problem in Middle Eastern healthcare settings. CT use is expanding rapidly in Saudi Arabia (Almohiy et al., 2020; Alzimami et al., 2021), but we could not find a framework tailored to that context.

Important note on PECARN application: The PECARN rules are validated solely for identifying children at very low risk of clinically important traumatic brain injury (cTBI) who can safely avoid an initial CT scan. No equivalent clinical rule exists for repeat CT decisions. We therefore used PECARN criteria pragmatically as an informed screening tool to identify children at very low likelihood of cTBI progression who would also be unlikely to benefit from repeat imaging. This off-label application is a limitation, acknowledged here and addressed further in the Discussion.

We built a three-stage framework: (1) model selection, trained and compared KNN, SVM, and ANN to approximate ICRP-based cancer risk calculations (not to predict individual outcomes) using retrospective data from 4025 cases; (2) decision support integration, embedded PECARN-informed criteria into a decision-tree algorithm inside a mobile application, alongside the ANN risk estimator; (3) pilot assessment, tested the app with 11 clinicians via a usability survey and tracked real-world impact on repeat CT request rates over six months using statistical process control.

2. Methodology

2.1. Design and Overview of Study

This paper used a quantitative research design which involved a multi-stage, comprehensive process to develop an AI-based framework that would reduce repeat pediatric brain CT scans. This methodology was designed as a series of three sequential and mutually dependent steps,

with the development and selection of an optimal supervised machine learning model to estimate cancer risk, integration of proven clinical decision rules into a decision-support mobile application, and validation of the effectiveness, usability, and impact of the application in a clinical context.

2.2. Stage 1: ICRP Risk Approximation Using Machine Learning Models

2.2.1. Data Source and Collection

The data was obtained based on an extensive pediatric imaging database. The sample of 4,025 pediatric cases in 3 large Saudi Arabian hospitals was used, and the variables that were individually related to the repetitive brain CT scans were included. Patient data encompassed demographic data, CT dose report and past CT examination records.

2.2.2. Data Preprocessing

Models were developed using IBM SPSS Modeler v18. Missing numerical values (dose, frequency) were imputed using mean substitution. Outliers in dose-length product (DLP) were identified via boxplots and z-scores. Continuous variables were standardized using z-score transformation; ANN inputs additionally underwent min-max scaling to [0,1]. Categorical variables were label-encoded. Date fields were used to calculate patient age and inter-scan intervals (Collins et al., 2020; Sutton et al., 2020).

2.2.3. Data Partitioning

The dataset was partitioned into training (64%, $n = 2,576$), validation (16%, $n = 644$), and testing (20%, $n = 805$) sets.

2.2.4. Input Variables and Target Variable

Seven input variables were used (Table 1). The target variable was the ICRP-defined lifetime attributable risk (LAR per 100,000), calculated according to ICRP Publication 147 (2021) using age-, sex-, and organ-specific coefficients (ICRP, 2021). This is a deterministic dosimetric calculation, not an observed clinical outcome. Our models were trained to approximate this calculation, enabling real-time bedside estimation.

Transparency statement: To prevent circularity, LAR values were used exclusively as the target variable and were not included among the input features. All input variables were restricted to clinically available parameters that

would be known at the point of care prior to cancer risk estimation. The ANN estimates population-based ICRP risk for counselling purposes and does not predict individual cancer outcomes.

Table 1. Input variables included in the dataset for model development.

Variable	Type	Description	Values/Coding
Age	Categorical	Patient age group	0 = 0–5 years; 1 = 6–16 years
Date of Birth	Date	Patient birth date	yyyy-mm-dd
Gender	Categorical	Biological sex	1 = Male; 2 = Female
Dose of CT Scan	Continuous	Dose-length product (DLP)	Numerical value (mGy·cm)
Frequency of Repetition	Continuous	Number of prior CT scans	Numerical value (count)
Exam Date	Date	Date of CT examination	yyyy-mm-dd
Target Organ	Categorical	Anatomical region scanned	0 = Nonspecific; 1 = Brain; 2 = Other Protocols

Note: All patient data were retrospectively collected and de-identified. DLP = dose-length product.

2.2.5. Machine Learning Algorithms

We used three supervised regression algorithms.

K-Nearest Neighbours (KNN): Initial setting of 3 nearest neighbours (Euclidean distance), k was later optimized (Zhang et al., 2023).

Support Vector Machine (SVM): Linear SVM using LAR as the target field. Epsilon automatically tuned (Nakamura et al., 2020).

Artificial Neural Network (ANN): Multilayer perceptron (MLP) with 7 inputs, 2 hidden layers (second layer: 9 neurons), hyperbolic tangent activation, and sigmoid output. Learning rate = 0.01 (Table 3).

2.2.6. Model Evaluation Metrics

Performance was assessed using MSE, RMSE, MAE, MAPE, SMAPE, MAAPE, and R^2 . Feature importance used mean dropout loss (50 permutations).

2.3. Stage 2: Decision-Making Support Using PECARN-Informed Tree Algorithm

PECARN-informed criteria were integrated into a mobile decision tree. For children under 2 years: scalp hematomas (excluding frontal), loss of consciousness >5 seconds, severe mechanism, palpable skull fracture, altered mental status, abnormal behavior. For children aged 2 years and older: headache, vomiting, loss of consciousness, severe mechanism, basilar skull fracture signs, altered mental status. High-risk features lead to CT recommendation; low-risk features lead to observation or alternative management strategies.

2.4. Stage 3: Pilot Assessment and Effectiveness Evaluation

2.4.1. Clinician Pilot Usability Survey (n = 11)

Survey assessed effectiveness, usability (Likert scale), and impact. Data were collected from physicians at a military hospital emergency department in Saudi Arabia. Descriptive statistics (frequencies, percentages) with Cronbach's alpha were calculated. Due to the small sample (n = 11), inferential statistics are not reported; results are considered preliminary.

2.4.2. Operational Effectiveness Assessment

An I-MR control chart was applied to statistical process control (SPC). The data was the monthly percentage decrease in CT brain requests for six months (March to August 2024). The UCL and LCL were set at ± 3 standard deviations from the mean. Further, Nelson rule #2 (six or more consecutive decreasing points) was used to test for non-randomness.

2.5. Ethical Considerations

This study received ethical approval from the King Saud University Institutional Review Board (Approval No. 18-36+). All patient data were de-identified. Informed consent was obtained from all survey participants.

3. Results

3.1. Machine Learning Model Selection

3.1.1. KNN Regression

Effective dose was found to be the most important feature (dropout loss 0.022) followed

by DLP (0.018) and K factor (0.013) in feature importance analysis (Table 4). With $k = 3$, MAPE was 11.24% ($R^2 = 0.842$). After optimization (with $k = 2$), the KNN model's final model evaluation (Table 2) produced an R^2 of 0.842 and a MAPE of 11.24%.

3.1.2. SVM Regression

Feature importance analysis (Table 5) identified effective dose as the highest-ranked predictor (dropout loss 0.027), followed by DLP (0.006) and K factor (0.005). The linear SVM model achieved a MAPE of 8.76% and R^2 of 0.879 (Table 2).

3.1.3. ANN Regression

Effective dose was the most important feature (dropout loss 0.048) (Table 6), followed by DLP (0.032) and K factor (0.027). Effective dose was assigned the highest weight to the MLP input layer. Training and validation errors carried through the generations with the validation error approaching 0.0005 after the fourth generation, suggesting good model training with no overfitting. The ANN model achieved a MAPE of 6.92% and R^2 of 0.917 (Table 2).

3.1.4. Model Comparison and Ranking

Comparing the three models (Table 2), the ANN model had the smallest error for all measures: MAPE (6.92%), SMAPE (6.73%), MAAPE (3.87%) and MAE (0.0581). The highest R^2 (0.917) was also recorded by the ANN. The ANN was chosen to be incorporated into the framework based on this comparison.

Table 2. Head-to-head performance comparison of KNN, SVM, and ANN regression models.

Metric	KNN (k=2)	SVM (linear)	ANN (MLP)
MSE	0.0187	0.0142	0.0098
RMSE	0.1368	0.1192	0.0990
MAE / MAD	0.0893	0.0724	0.0581
MAPE	11.24%	8.76%	6.92%

Metric	KNN (k=2)	SVM (linear)	ANN (MLP)
SMAPE	10.98%	8.51%	6.73%
MAAPE	6.21%	4.93%	3.87%
R ²	0.842	0.879	0.917

Note: Bold indicates best performance per metric. MSE = Mean Squared Error; RMSE = Root Mean Squared Error; MAE = Mean Absolute Error; MAD = Mean Absolute Deviation; MAPE = Mean Absolute

Percentage Error; SMAPE = Symmetric Mean Absolute Percentage Error; MAAPE = Mean Arctangent Absolute Percentage Error; R² = Coefficient of determination.

Table 3. Artificial Neural Network (ANN) architecture specifications.

Parameter	Value
Network Architecture	
Network type	Multilayer Perceptron (MLP)
Number of input nodes	7
Number of hidden layers	2
Neurons in hidden layer 1	Automatically determined by SPSS Modeler
Neurons in hidden layer 2	9
Number of output nodes	1
Activation Functions	
Hidden layers	Hyperbolic tangent (tanh)
Output layer	Logistic sigmoid
Training Parameters	
Learning rate	0.01

Parameter	Value
Optimizer	Default SPSS Modeler (scaled conjugate gradient)
Batch size	Default (automatic)
Epochs	Trained until convergence
Early stopping	Implicit via validation set monitoring
Loss function	Mean Squared Error (MSE)
Data Preprocessing	
Normalization	Min-max scaling to [0,1]
Standardization	Z-score transformation
Data Partitioning	
Training set	64% (n = 2,576)
Validation set	16% (n = 644)
Test set	20% (n = 805)

Note: Full weight matrices available from corresponding author upon reasonable request.

Table 4. KNN feature importance metrics (corrected, without LAR).

Item	Mean Dropout Loss
Effective Dose	0.022
DLP	0.018
K Factor	0.013
Frequency of Repetition	0.006

Item	Mean Dropout Loss
CED	0.006
Age/Year	0.005
Gender	0.004

Note: Based on 50 permutations. LAR was not included as an input variable to prevent circularity.

Table 5. SVM feature importance metrics (corrected, without LAR).

Item	Mean Dropout Loss
Effective Dose	0.027
DLP	0.006
K Factor	0.005
Age/Year	0.003
Gender	0.003
CED	0.003

Note: Based on 50 permutations. LAR was not included as an input variable to prevent circularity.

Table 6. ANN feature importance metrics (corrected, without LAR).

Item	Mean Dropout Loss
Effective Dose	0.048
DLP	0.032
K Factor	0.027
CED	0.018
Frequency of Repetition	0.016

Item	Mean Dropout Loss
Age/Year	0.012

Note: Based on 50 permutations. LAR was not included as an input variable to prevent circularity.

3.2. The AI-Based Framework

The AI-based approach to reduce repeated brain CT scans in children produced considerable improvements in the three stages of its implementation.

The initial stage (screening) of the emergency department was effective in deciding the need for brain CT scans by visual inspection and clinical judgement of emergency room doctors. Standardised clinical processes were used in this stage to overcome concerns about over-imaging with CT scans, while complying with guidelines for the management of children with head trauma.

The decision-making stage, which included PECARN-based criteria in the decision tree algorithm, provided excellent outcome in the classification of patients in terms of risk for traumatic brain injury and CT scans. This stage of the process was successful in addressing concerns about over-imaging in the emergency department, as CT scans were recommended only when traumatic brain injury was at risk, based on the patient's age.

The prediction stage, using the ANN model, led to significant improvements in the prediction of cancer risk for patients with repeated CT scans. This model has been demonstrated to be accurate in assessing the cancer risk according to radiation dose exposure and can help doctors in the decision-making process for using imaging methods.

3.3. Pilot Assessment Results

3.3.1. Clinician Pilot Usability Survey (n = 11)

Eleven experienced clinicians participated (54.5% doctoral; 81.8% >10 years). Cronbach's alpha for questions 3-6 was 0.7. Descriptive results only (preliminary, hypothesis-generating).

Usability: 36.4% (4/11) rated the app as "Easy" and another 36.4% as "Very Easy"; 18.2% were neutral, and 9.1% found it difficult. **Perceived effectiveness:** 45.5% (5/11) rated the app as "Very accurate (85-95%)" and no one rated it as inaccurate. **Anticipated effect:** 45.5% (5/11) predicted a significant reduction (more than 50%) in unnecessary paediatric CT scans. **Confidence:** 54.5% (6/11) showed high confidence in the AI-based framework.

Due to the small sample size (n = 11), inferential statistics are not reported; these results are considered preliminary and hypothesis-generating.

3.3.2. Operational Effectiveness and SPC Trend Analysis

Mean reduction in repeat CT requests was 57.0% (March: 63.0%, April: 60.5%, May: 58.0%, June: 57.0%, July: 53.0%, August: 50.5%). The I-MR control chart showed UCL = 69.7% and LCL = 44.3%. A downward trend across six consecutive months met Nelson rule #2 (non-random pattern, $p < 0.01$), indicating waning of the intervention effect over time. All data points remained within the 3-sigma limits.

4. Discussion

This AI-based framework for minimizing repeat paediatric brain CT scans integrates clinical assessment with machine learning to reduce unnecessary radiation exposure while preserving diagnostic capability.

Clarification of AI role and PECARN application. Our ANN approximates ICRP population-based risk (MAPE 6.92%) and does not predict individual cancer outcomes. We used PECARN criteria off label for repeat CT decisions, as no validated rule exists for this scenario. Readers should interpret our 57% reduction in the context of this pragmatic, unvalidated extension.

Our 57% reduction is meaningful. Other studies show PECARN rules alone can reduce unnecessary imaging (Gambacorta et al., 2022; Niele et al., 2020), but those were for initial CTs, not repeat CT decision support. Our app provides both a yes/no recommendation and a numerical estimate of population-based cancer risk from cumulative radiation exposure.

The superior performance of the ANN across error-based measures (MAPE 6.92%, R^2 0.917) indicates its applicability in this domain. The finding of effective dose and DLP as the most significant predictors is consistent with radiobiological knowledge that cancer risk from CT exposure is primarily influenced by the magnitude and cumulative quality of radiation doses (Brenner, 2002; Pearce et al., 2012).

The decreasing trend in SPC. The reduction in percentage over six months from 63.0% to 50.5% (Nelson rule #2, $p < 0.01$) is of great concern as it indicates that the intervention effect wanes over time. Possible explanations include novelty effect, case mix variation, app fatigue (45-60 seconds per use), and seasonal staffing. We have implemented three countermeasures: (1) monthly refresher training, (2) in-app usage reminders at 45-day intervals, and (3) a clinician feedback dashboard. These will be evaluated over the subsequent six months.

The positive reception (72.8% rating navigation easy/very easy) suggests strong face validity, but the small sample size ($n = 11$) constrains generalizability.

4.1. Limitations

This study has several important limitations:

1. **PECARN off-label use:** We applied PECARN criteria to repeat CT decisions, for which it has not been validated. A dedicated rule for repeat pediatric head CTs is urgently needed.
2. **AI scope:** Our ANN estimates ICRP dosimetric calculations; it does not make predictions on individual cancer outcomes. Future validation against cancer registries should be done.
3. **Survey sample:** 11 clinicians responded to the survey, sufficient for pilot testing but not for making conclusions.
4. **SPC trend:** The 6-month decreasing effect (63% to 50.5%) is not random and suggests loss of efficacy.
5. **Single country:** May not be generalizable to other countries.
6. **Retrospective training data:** Prospective data would be optimal.
7. **No cancer outcomes:** We did not track cancer in children.
8. **Technology limitations:** Not tested on iOS, old devices, or low bandwidth.
9. **Safety metric not reported:** We did not measure whether the app ever recommended against a repeat CT that later proved clinically necessary.

4.2. Clinical Implications

Despite limitations, the framework is evidence-informed, easy to use (72.8% found navigation easy/very easy), and reduced radiation requests without documented adverse outcomes. However, readers should interpret the 57% reduction cautiously given the uncontrolled before-after design and declining trend.

5. Conclusion

We developed and piloted a mobile clinical decision support tool that combines PECARN-informed criteria with a real-time ANN approximator of ICRP-based radiation risk. When implemented in a Saudi emergency department, the tool reduced repeat pediatric brain CT requests by an average of 57% over six months, although a significant waning effect was observed. The ANN accurately emulated ICRP risk calculations (MAPE 6.92%, R^2 0.917). Pilot usability feedback from 11 clinicians was positive but preliminary. The off-label application of PECARN to repeat CT decisions remains a limitation. While our framework is feasible and shows promise, readers should interpret the 57% reduction cautiously given the uncontrolled before-after design and the declining trend.

Immediate next steps include external prospective validation, development of a dedicated repeat-CT clinical rule, and a fully powered usability study.

Immediate next steps for future direction include:

(1) external prospective validation in 3–5 Saudi

hospitals, (2) development of a dedicated clinical rule for repeat pediatric head CTs, (3) a fully powered usability study ($n \geq 50$ clinicians), (4) an audit of clinically necessary CTs that the tool would have withheld, (5) an iOS version, (6) integration with hospital EMRs, and (7) cost-effectiveness analysis.

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Declaration

Ethics Statement

This study received ethical approval from the King Saud University Institutional Review Board (Approval No. 18-36+). All procedures performed involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. All patient data were retrospectively collected and de-identified prior to analysis. Informed consent was obtained from all individual participants (clinicians) who completed the usability survey in the validation phase of this study. For the retrospective pediatric imaging data, patient consent was waived by the IRB due to the de-identified nature of the data. All authors have reviewed and approved the final version of the manuscript and consent to its publication. Informed consent for publication of survey findings was obtained from all clinician participants.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. The data are not publicly available due to institutional privacy restrictions related to patient imaging records.