

Jornada de Física Médica

18/08/2022



XXIV Congresso da
Sociedade Brasileira de
RADIOTERAPIA

17 A 20 DE AGOSTO | 2022 | FLORIANÓPOLIS/SC

Automação e Inteligência Artificial no QA do tratamento

Doutoranda Jéssica Caroline Lizar

*Programa de Pós Graduação em Física Aplicada à
Medicina e Biologia*

FAMB – USP

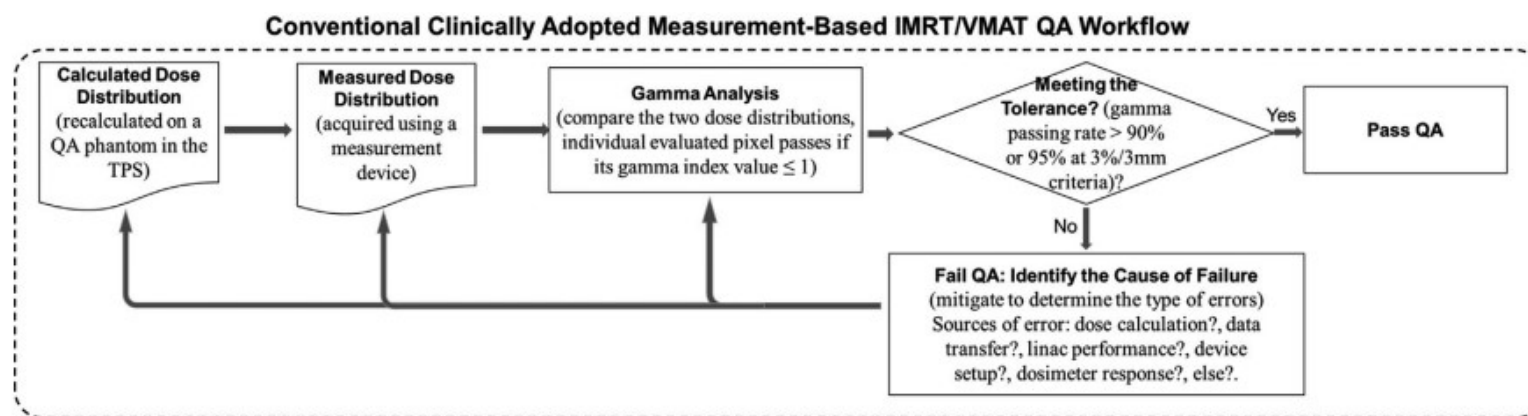
Módulo I
Pesquisa e Prática

Summary

- Introduction
 - Quality Assurance (QA)
- Applications of Machine Learning (ML) and
 - Machine QA
 - Patient-Specific IMRT/VMAT QA (PSQA)
- Clinical applicability
- Questions

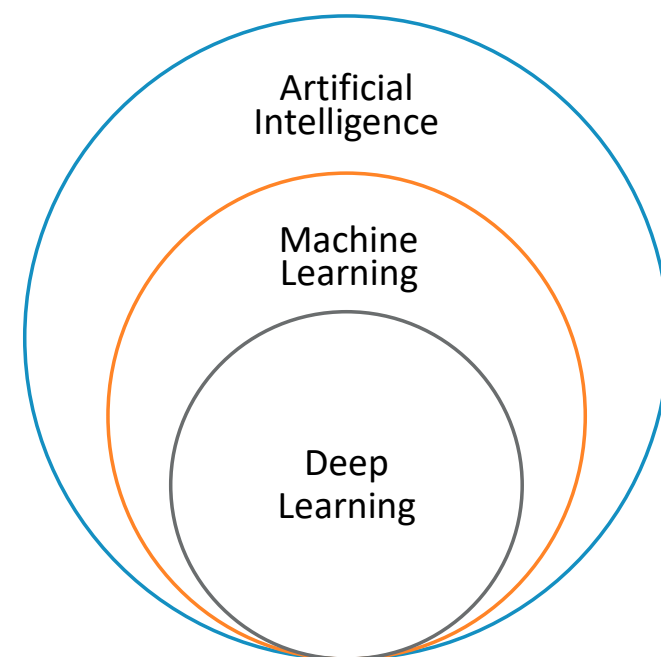
Introduction | Quality Assurance

- Machine and PSQA measurement procedure is recommended by AAPM, to ensure that the treatments can be delivered as planned.
 - The main disadvantages of PSQA
 - it is expensive
 - time-consuming
 - often difficult to identify and correct the cause(s) of failure.

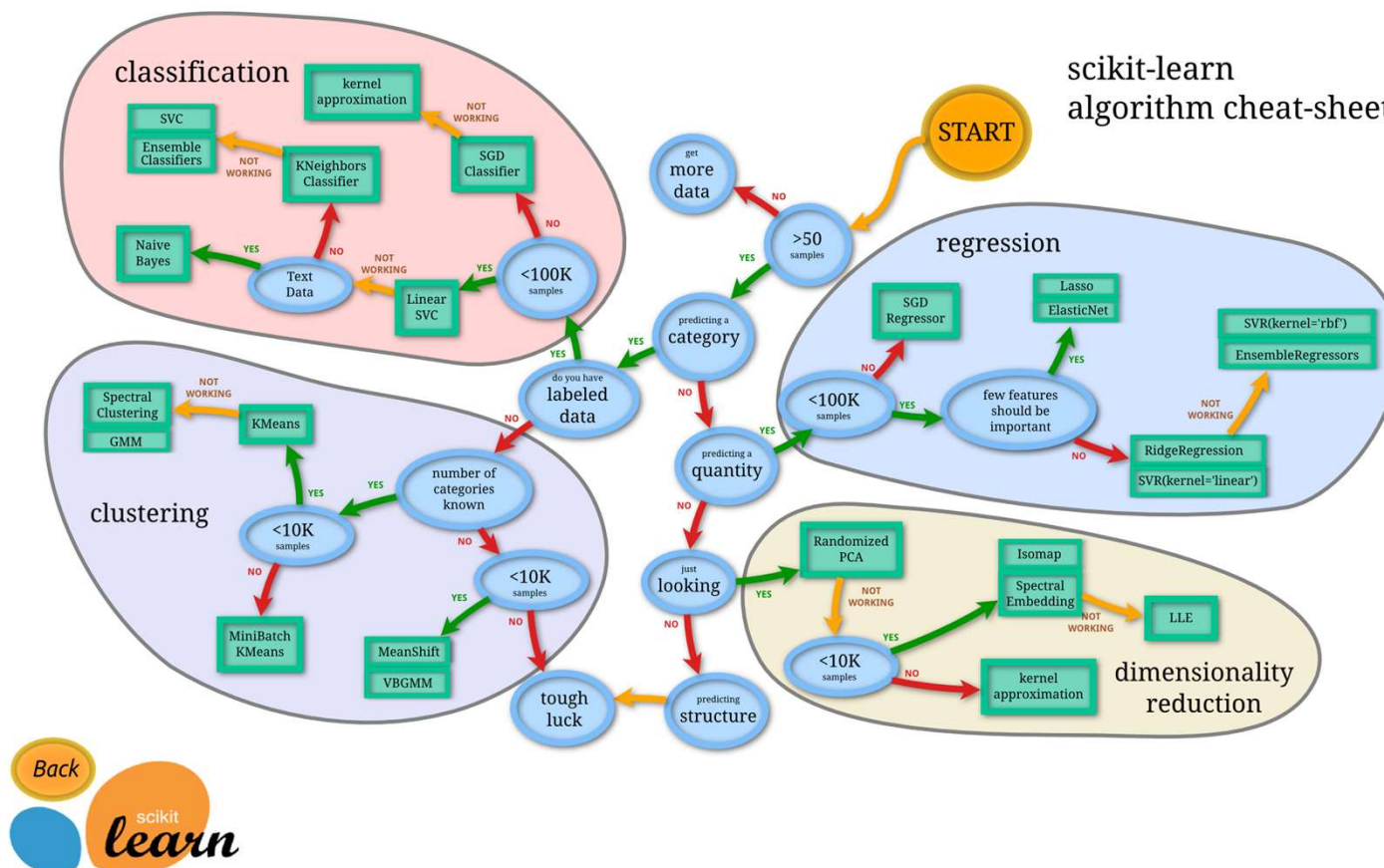


Introduction | Quality Assurance

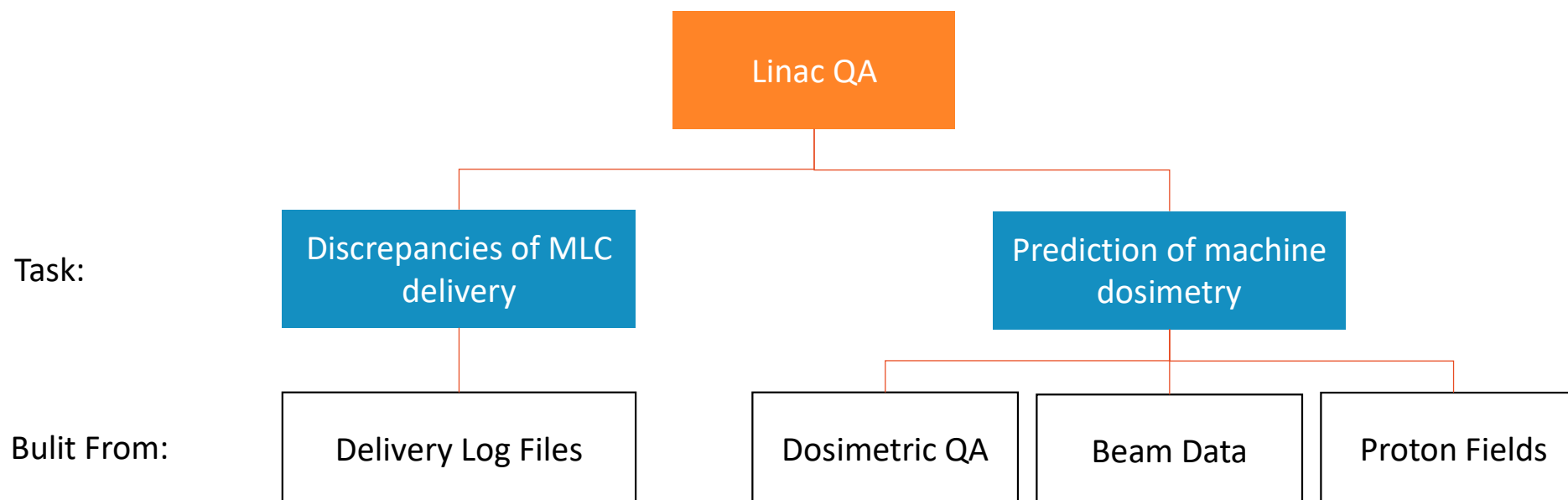
- ML and DL algorithms can produce predictions on new data after being trained on a finite historic dataset.
- Over the past 6 years, ML and DL algorithms have been developed and studied for predicting IMRT/VMAT QA outcome.
 - The developed ML/DL models would significantly reduce the radiation therapy treatment workload.



Introduction



Applications in Machine QA

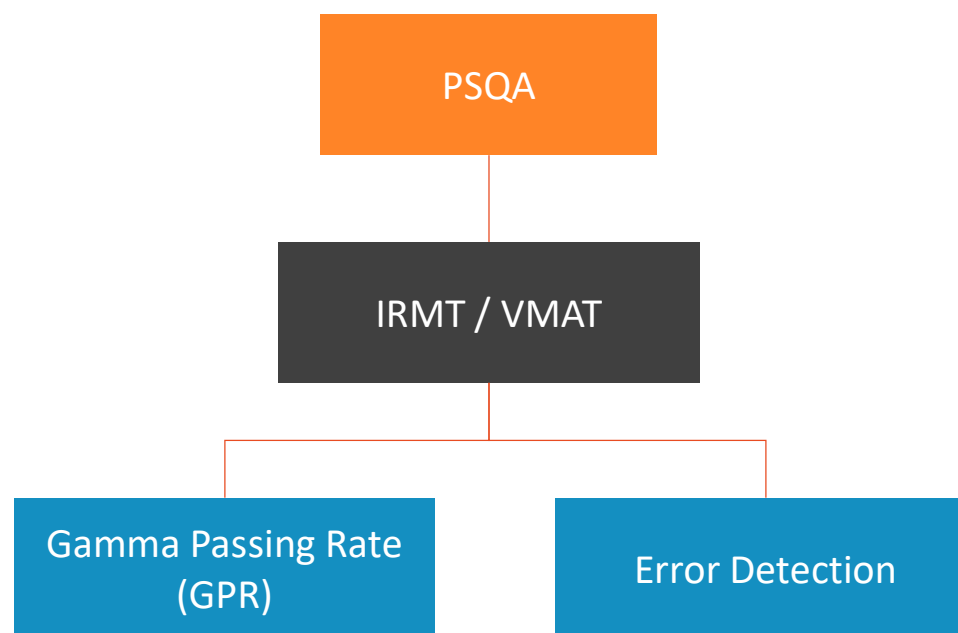


Linac QA | MLC delivery

References	QA Source	Data Source	ML Model	Task
Carlson et al. (2016)	DICOM_RT, Dynalog files	74 VMAT plans	Regression, Random Forest, Cubist	MLC Position Errors Detection
Li and Chan (2017)	Daily QA Device	5-year Daily QA Data	ANN Time-Series, ARIMA Models	Symmetry Prediction
Sun et al. (2018)	Ion Chamber	1,754 Proton Fields	Random Forrest, XGBoost, Cubist	Output for Compact Proton Machine
El Naqa et al. (2019)	EPID	119 Images from 8 Linacs	Support Vector Data Description, Clustering	Gantry Sag, Radiation Field Shift, MLC Offset
Grewal et al. (2020)	Ion Chamber	4,231 Proton Fields	Gaussian Processes, Shallow NN	Output and Patient QA Proton Machine
Osman et al. (2020)	log files	400 machine delivery log files	ANN	MLC Discrepancies during Delivery & Feedback
Chuang et al. (in press)	Trajectory log files	116 IMRT plans, 125 VMAT plans	Boosted Tree Outperformed LR	MLC Discrepancies during Delivery & Feedback
Zhao et al. (in press)	Water Tank Measurement	43 Truebeam PDD, Profiles	Multivariate Regression (Ridge)	Modeling of Beam Data Linac Commissioning

Chan MF, Witztum A, Valdes G. Integration of AI and Machine Learning in Radiotherapy QA. *Front Artif Intell.* 2020 Sep 29;3:577620. doi: 10.3389/frai.2020.577620. PMID: 33733216; PMCID: PMC7861232. <https://www.frontiersin.org/articles/10.3389/frai.2020.577620/full>

Applications in Patient-Specific QA



Osman, Alexander FI, and Nabil M. Maalej. "Applications of machine and deep learning to patient-specific IMRT/VMAT quality assurance." *Journal of Applied Clinical Medical Physics* 22.9 (2021): 20-36.

Applications in Patient-Specific QA

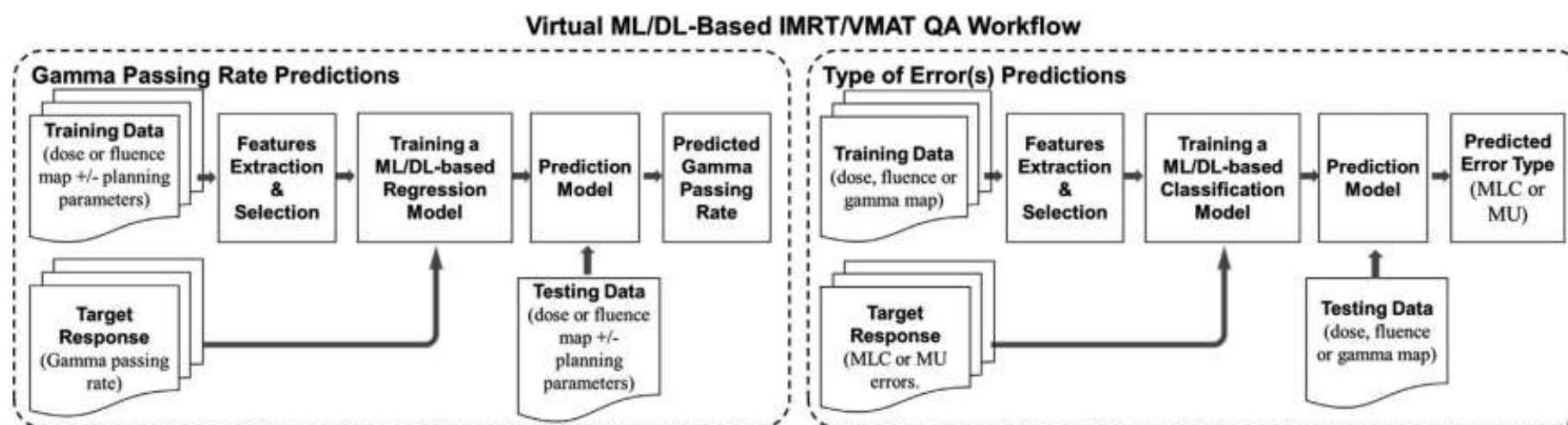


FIGURE 2 A typical flow diagram of patient-specific intensity modulated radiation therapy/volumetric-arc radiation therapy (IMRT/VMAT) quality assurance (QA).

PSQA | Input Features

Built From:

Machine Parameters
and Plan Properties

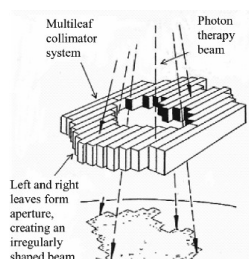
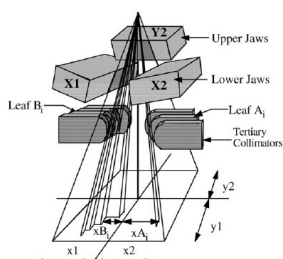
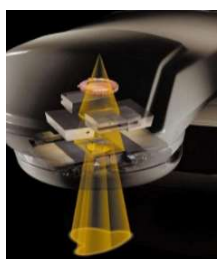
Features:

Plan Complexity
Metrics (PCMs)

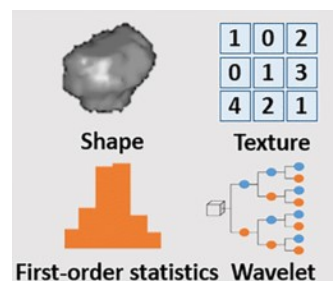
Dose, Fluence and
Gamma Images

Radiomics

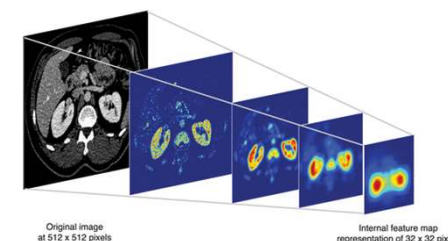
CNN features



KLEIN, Eric E. et al. Validation of calculations for electrons modulated with conventional photon multileaf collimators. *Physics in Medicine & Biology*, v. 53, n. 5, p. 1183, 2008.



Wu et al. (2021). Structural and functional radiomics for lung cancer. *European Journal of Nuclear Medicine and Molecular Imaging*. 48. 1-14. [10.1007/s00259-021-05242-1](https://doi.org/10.1007/s00259-021-05242-1).



Chartrand, Gabriel, et al. "Deep learning: a primer for radiologists." *Radiographics* 37.7 (2017): 2113-2131. <https://pubs.rsna.org/doi/full/10.1148/rg.2017170077>

PSQA | Input Features

Built From:

Machine Parameters
and Plan Properties

Features:

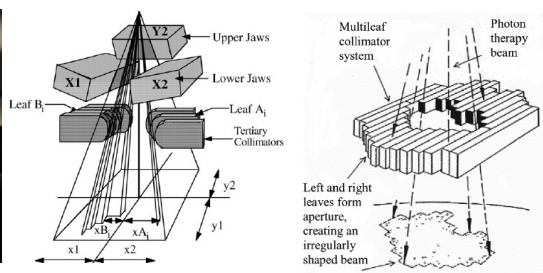
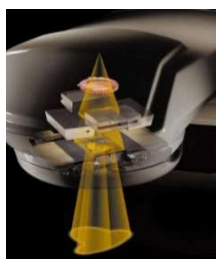
Plan Complexity
Metrics (PCMs)

+

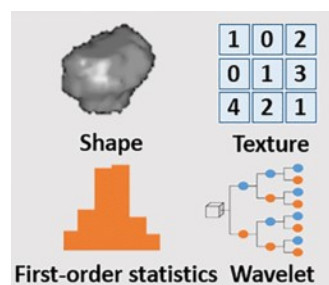
Radiomics

+

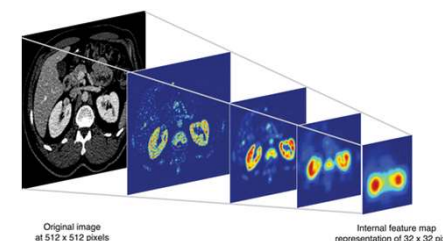
CNN features



KLEIN, Eric E. et al. Validation of calculations for electrons modulated with conventional photon multileaf collimators. *Physics in Medicine & Biology*, v. 53, n. 5, p. 1183, 2008.



Wu et al. (2021). Structural and functional radiomics for lung cancer. *European Journal of Nuclear Medicine and Molecular Imaging*. 48. 1-14. 10.1007/s00259-021-05242-1.



Chartrand, Gabriel, et al. "Deep learning: a primer for radiologists." *Radiographics* 37.7 (2017): 2113-2131. <https://pubs.rsna.org/doi/full/10.1148/rg.2017170077>

TABLE 3 Summary of features used as inputs to ML/DL models for IMRT/VMAT QA outcome predictions.

Input features	QA technique	Feature selection technique	Important features	Reference
Plan complexity features	2D array detector	LASSO	4 features: MU factor, aperture score, irregularity factor, and fraction of the plan delivered at the corners of a 40 × 40 cm ² field	Valdes et al. ³³
	2D array detector and EPID	LASSO	7 features: irradiated area outline, Jaw position, fraction of the area receiving dose from penumbra, Duty cycle, irregularity factor, and others	Valdes et al. ³⁴
	Film dosimetry	Dropout technique	4 features: MU values, the PTV volume, the rectum volume, and the overlapping region volume	Tomori et al. ³⁵
	3D array detector	Pearson's correlation coefficient	28 features: plan complexity parameters ($n = 18$), machine type ($n = 4$), and photon beam energy ($n = 6$).	Ono et al. ⁴⁶
	3D array detector	SVM recursive feature elimination	30 features: Linac output, MU factor, total number of control points, and others	Granville et al. ⁴⁷
	2D array detector	Manually	54 features: MU value, union aperture area, plan area/irregularity/modulation, average leaf gap/dose rate/travel distance, modulation index of leaf speed/acceleration, and others	Li et al. ⁴⁵
	EPID	Manually	10 features: modulation complexity score, beam irregularity, MUs/control point in a beam, maximum of x–y jaw positions, edge metric, and others	Lam et al. ³⁸
	3D array detector	Manually	54 features: plan modulation-complexity and delivery-characteristics	Wang et al. ⁵¹
	2D array detector	Extra-trees, mutual information, and linear regression	100 features: aperture score, MU factor, edge metric, leaf gap/travel/motion, plan irregularity, plan modulation, and others	Wall and Fontenot ⁴⁸
	2D array detector	Manually	6 features: leaf position, instantaneous velocity, movement away/toward the center, leaf movement status, the control point number, and the leaf bank	Carlson et al. ⁴⁴
	EPID	Manually	14 features: leaf previous/current/next positions, dose fraction, gantry angle, leaf speed/acceleration, leaf gap, leaf movement status, and others	Osman et al. ⁴¹
	EPID	Manually	7 features: leaf velocity, acceleration, control point, dose rate, gravity vector, gantry velocity (VMAT), and gantry acceleration (VMAT)	Chuang et al. ⁴³

PSQA

Radiomics features	EPID	Wilcoxon rank-sum Test	13 features: radiomics features (size zone metric) and intensity histogram metrics derived from gamma map images	Wootton et al. ³⁷
	2D array detector	Dropout technique	CNN features derived from fluence map images	Interian et al. ³⁶
	2D array detector	Dropout technique	CNN features derived from dose distribution images	Tomori et al. ⁵⁰
	EPID	SVM recursive feature elimination	11 features: radiomics features e.g. contrast, uniformity, zone entropy, and others	Ma et al. ⁴⁰
	3D array detector	Dropout technique	CNN features derived from dose difference or gamma map images	Kimura et al. ⁵²
	EPID	Random forest regression	11 features: radiomics intensity histogram features and the texture features derived from fluence difference map images	Sakai et al. ⁴²
Combined features	EPID	Principal component analysis, and triplet networks	81 features: 17 texture features (hand-crafted) from intensity histograms and size zone matrices) and 64 CNN features derived from gamma map images	Nyflot et al. ³⁹
	3D array detector	Random forest	502 features: plan complexity features (e.g. aperture area/perimeter/irregularity, and others), radiomics features (shape, statistical information, and texture features), and clinical parameters (treatment site/machine, beam energy, and dose calculation algorithm)	Hirashima et al. ⁴⁹

PSQA | ML GPR - PCMs

► Med Phys. 2016 Jul;43(7):4323. doi: 10.1118/1.4953835.

A mathematical framework for virtual IMRT QA using machine learning

G Valdes¹, R Scheuermann¹, C Y Hung¹, A Olszanski¹, M Bellerive¹, T D Solberg¹

Affiliations + expand

PMID: 27370147 DOI: 10.1118/1.4953835

- 498 IMRT plans
- 78 PCMs
- 5 AL
- Poisson Regression

TABLE I. The five most important features for each model. Features are different for each of the different Linac groups, suggesting that separate models may be needed at each specific institution.

Group	Features
Clinacs 1, 3, and 4	1. Weighted average irregularity factor 2. Weighted out of circle fractional area 40 cm 3. MU factor 4. SAS 5 mm 5. Leaf gap moment 4
Clinac 2	1. MU factor 2. SAS 5 mm 3. Weighted out of circle fractional area 25 cm 4. Out of circle fractional area 30 cm 5. SAS 10 mm
TrueBeam	Average perimeter Infield area 1 Infield area 4 Out of circle fractional area 25 cm Infield area 5

PSQA | ML GPR - PCMs

► Med Phys. 2016 Jul;43(7):4323. doi: 10.1118/1.4953835.

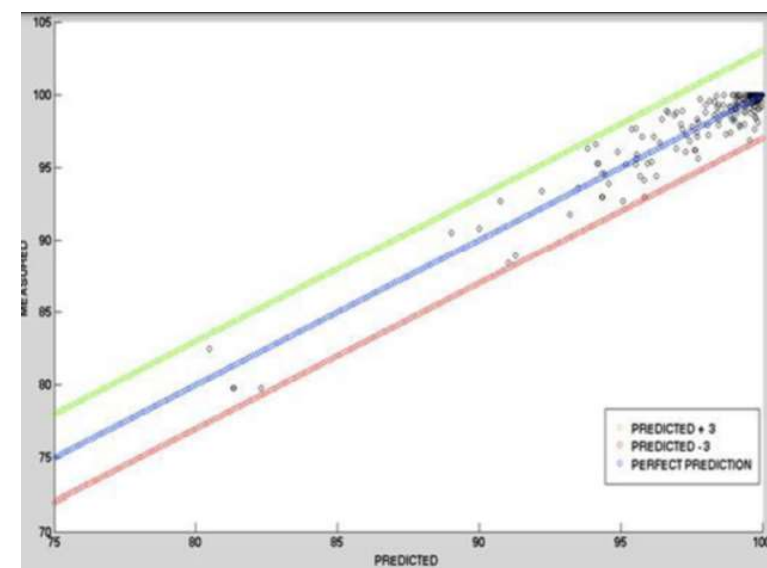
A mathematical framework for virtual IMRT QA using machine learning

G Valdes¹, R Scheuermann¹, C Y Hung¹, A Olszanski¹, M Bellerive¹, T D Solberg¹

Affiliations + expand

PMID: 27370147 DOI: 10.1118/1.4953835

- MU factor (MU per Gy)
- Small Aperture Score
- Irregularity factor
- Fraction of the plan delivered at the corners of a 40x40 cm field
 - to determine that the profiles of one Linac was different from our beam model at the periphery of a 40x40 cm² field.



PSQA | DL GPR - CNN

Comparative Study > Med Phys. 2018 Jun;45(6):2672-2680. doi: 10.1002/mp.12890.

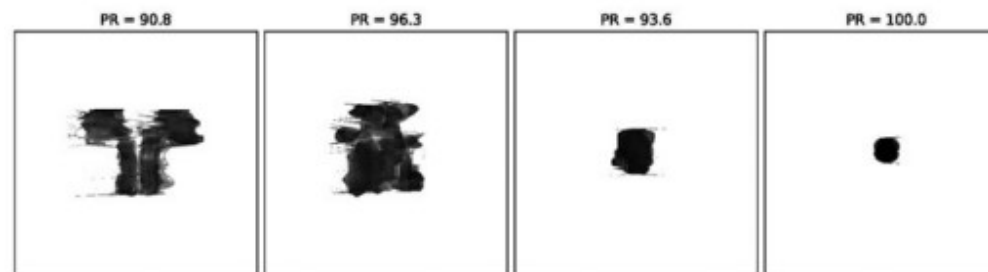
Epub 2018 Apr 18.

Deep nets vs expert designed features in medical physics: An IMRT QA case study

Yannet Interian¹, Vincent Rideout¹, Vasant P Kearney², Efstathios Gennatas², Olivier Morin²,
Joey Cheung², Timothy Solberg², Gilmer Valdes²

Affiliations + expand

PMID: 29603278 DOI: [10.1002/mp.12890](https://doi.org/10.1002/mp.12890)



PSQA | DL GPR - CNN

Comparative Study > [Med Phys.](#) 2018 Jun;45(6):2672-2680. doi: 10.1002/mp.12890.

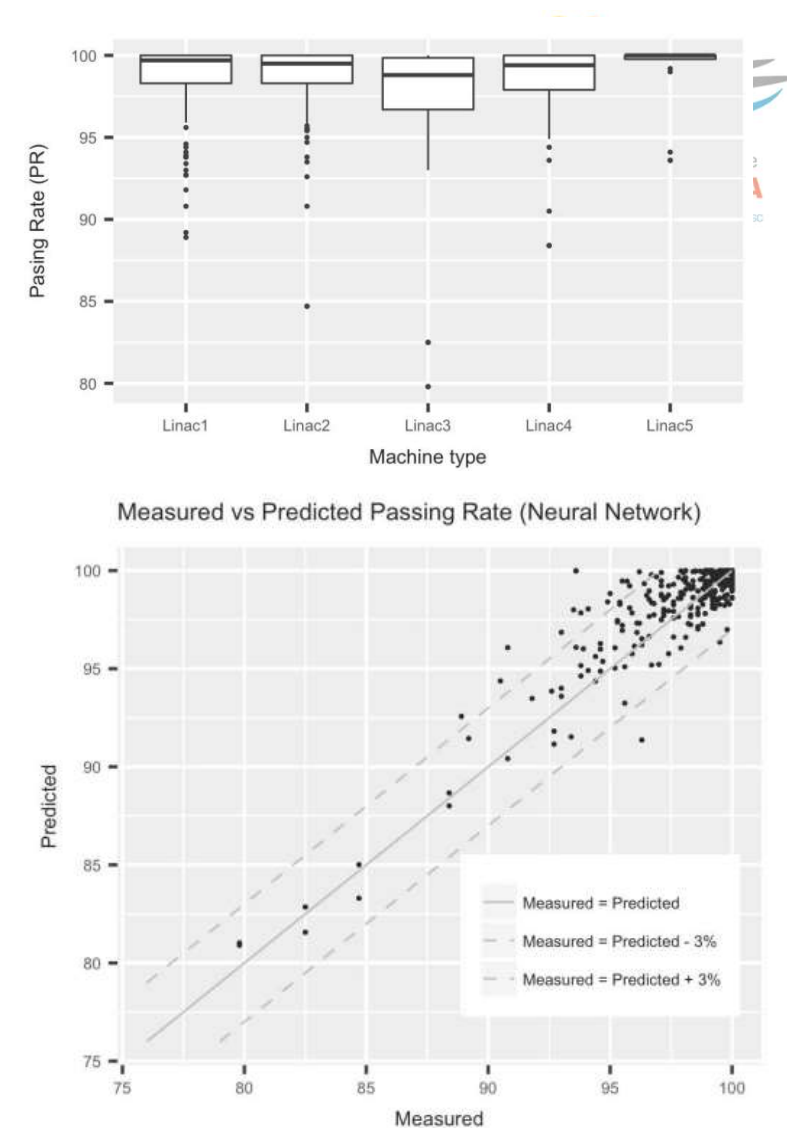
Epub 2018 Apr 18.

Deep nets vs expert designed features in medical physics: An IMRT QA case study

Yannet Interian ¹, Vincent Rideout ¹, Vasant P Kearney ², Efstathios Gennatas ², Olivier Morin ², Joey Cheung ², Timothy Solberg ², Gilmer Valdes ²

Affiliations + expand

PMID: 29603278 DOI: [10.1002/mp.12890](#)



PSQA | ML Error Detection - Radiomcs

► [Int J Radiat Oncol Biol Phys](#). 2018 Sep 1;102(1):219-228. doi: 10.1016/j.ijrobp.2018.05.033.
Epub 2018 May 19.

Error Detection in Intensity-Modulated Radiation Therapy Quality Assurance Using Radiomic Analysis of Gamma Distributions

Landon S Wootton ¹, Matthew J Nyflot ², W Art Chaovalitwongse ³, Eric Ford ⁴

Affiliations + expand

PMID: 30102197 DOI: [10.1016/j.ijrobp.2018.05.033](#)

- 186 IMRT beams from 23 patients
- EPID device
- Head and Neck, Lung and Rectal Cancer
- Logistic Regression

PSQA | ML Error Detection - Radiomcs

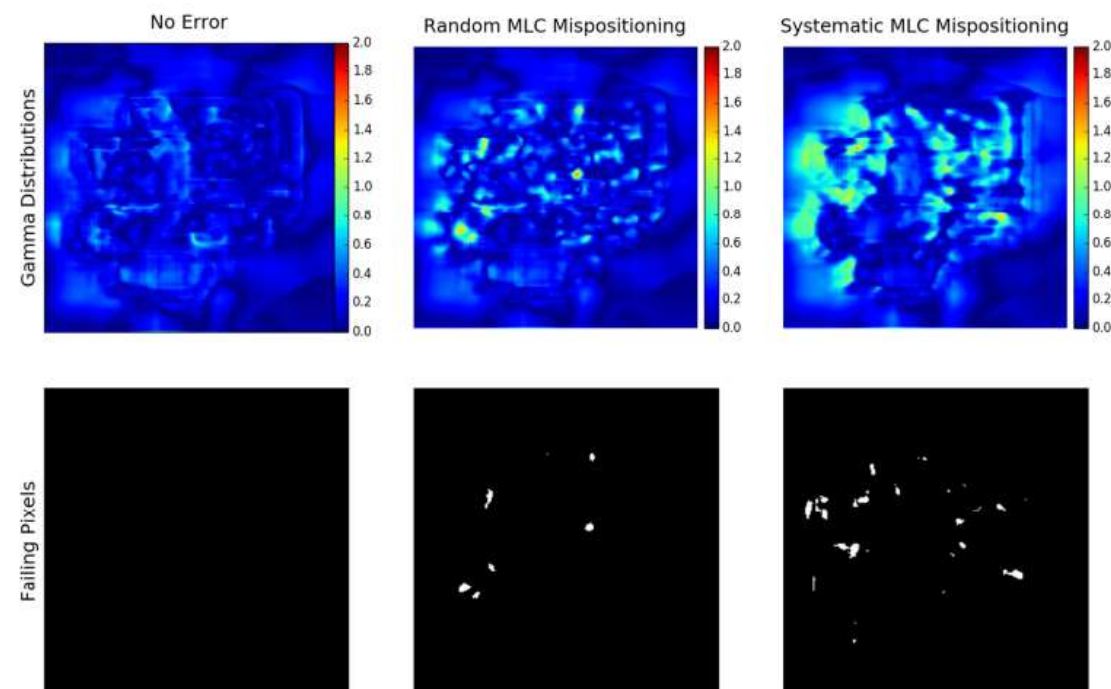
Int J Radiat Oncol Biol Phys. 2018 Sep 1;102(1):219-228. doi: 10.1016/j.ijrobp.2018.05.033
Epub 2018 May 19.

Error Detection in Intensity-Modulated Therapy Quality Assurance Using Radio of Gamma Distributions

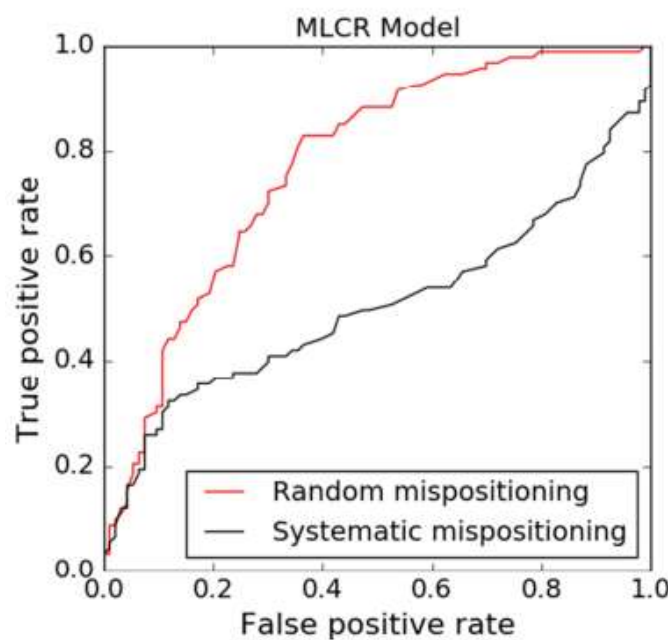
Landon S Wootton¹, Matthew J Nyflot², W Art Chaovalitwongse³, Eric Fo

Affiliations + expand

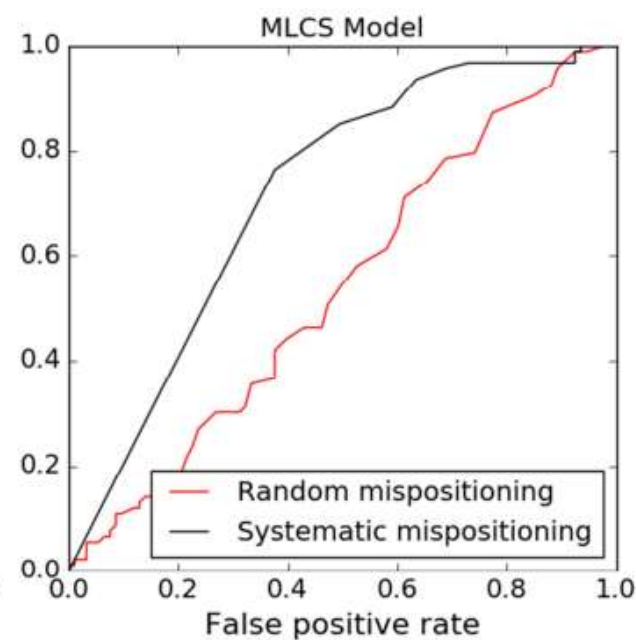
PMID: 30102197 DOI: 10.1016/j.ijrobp.2018.05.033



PSQA | ML Error Detection - Radiomcs



0.772 AUC



0.717 AUC

PSQA | ML Error Detection - Radiomics

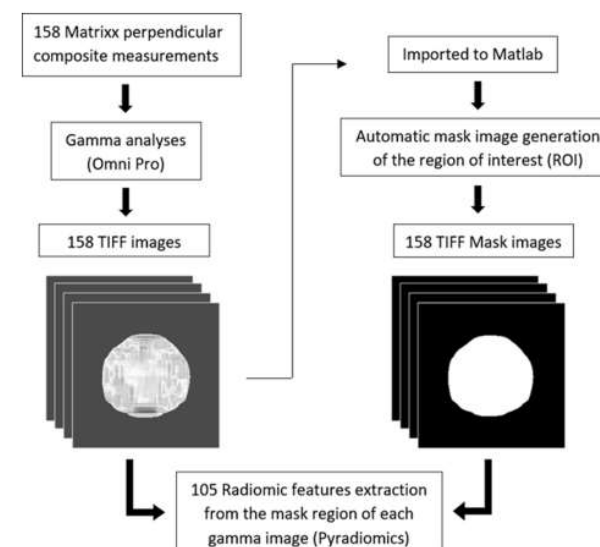
> *Phys Med.* 2021 Feb;82:100-108. doi: 10.1016/j.ejmp.2021.01.071. Epub 2021 Feb 17.

Patient-specific IMRT QA verification using machine learning and gamma radiomics

Jéssica Caroline Lizar¹, Carolina Cariolatto Yaly², Alexandre Colello Bruno²,
Gustavo Arruda Viani², Juliana Fernandes Pavoni³

Affiliations + expand

PMID: 33607523 DOI: 10.1016/j.ejmp.2021.01.071



PSQA | ML Error Detection - Radiomics

► [Phys Med.](#) 2021 Feb;82:100-108. doi: 10.1016/j.ejmp.2021.01.071. Epub 2021 Feb 17.

Patient-specific IMRT QA verification using machine learning and gamma radiomics

Jéssica Caroline Lizar ¹, Carolina Cariolatto Yaly ², Alexandre Colello Bruno ²,
Gustavo Arruda Viani ², Juliana Fernandes Pavoni ³

Affiliations [+](#) expand

PMID: 33607523 DOI: [10.1016/j.ejmp.2021.01.071](#)

ML III confusion matrix, evaluation parameters, and accuracy using the test set from dataset A and the additional dataset B.

Data	Confusion matrix			Evaluation parameters			Accuracy
Test set	True Label	Predicted Label		Precision	Recall	f1-score	0.99
		0 1					
	0	42 1	1.00	0.98	0.99		
Dataset B	1	1 37	0.97	1.00	0.99		
	True Label	Predicted Label	Precision	Recall	f1-score	0.98	
		0 1					
	0	27 0	0.96	1.00	0.98		
	1	1 22	1.00	0.96	0.98		

Conclusions | ML DL QA Clinical applicability

- PSQA IMRT/VMAT QA
 - GPR ML and DL models within 3% errors
 - lack the generalizability → were trained on institution-specific dataset
- For errors detection of IMRT/VMAT plans that fail the QA
 - Deep learning has shown the potential for accurate error detection
 - development of an ML/DL model that could accurately identify all potential sources of errors is required for effective clinical application.

Jornada de Física Médica

18/08/2022



XXIV Congresso da
Sociedade Brasileira de
RADIOTERAPIA

17 A 20 DE AGOSTO | 2022 | FLORIANÓPOLIS/SC

Módulo I

Pesquisa e Prática

Obrigada



jclizar@usp.br

Automação e
Inteligência Artificial
no QA do tratamento