XX[th] International Conference on the use of Computers in Radiation therapy

AI for treatment verification in photon external beam radiotherapy

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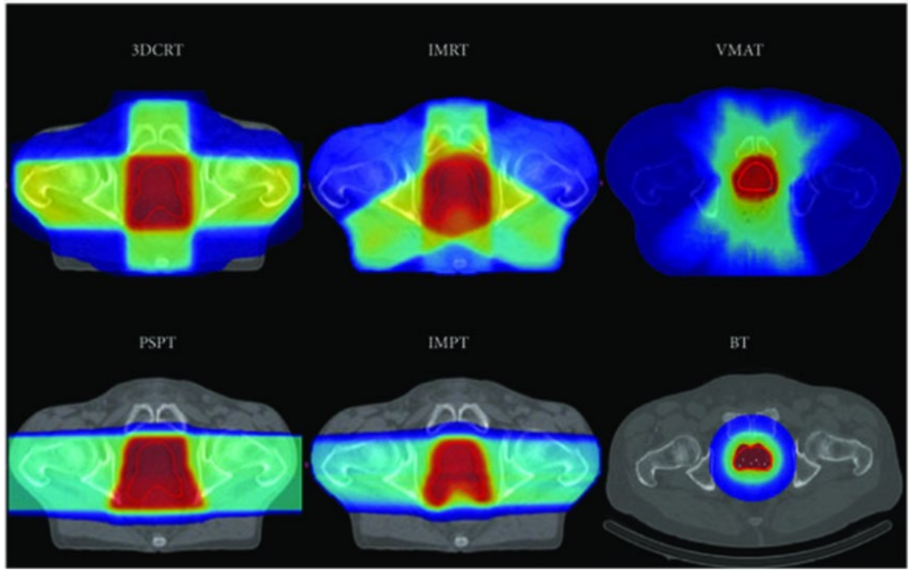
Introduction

- Evolution of radiotherapy (RT)

→ Increased complexity of treatments

→ Increased need for treatment verification



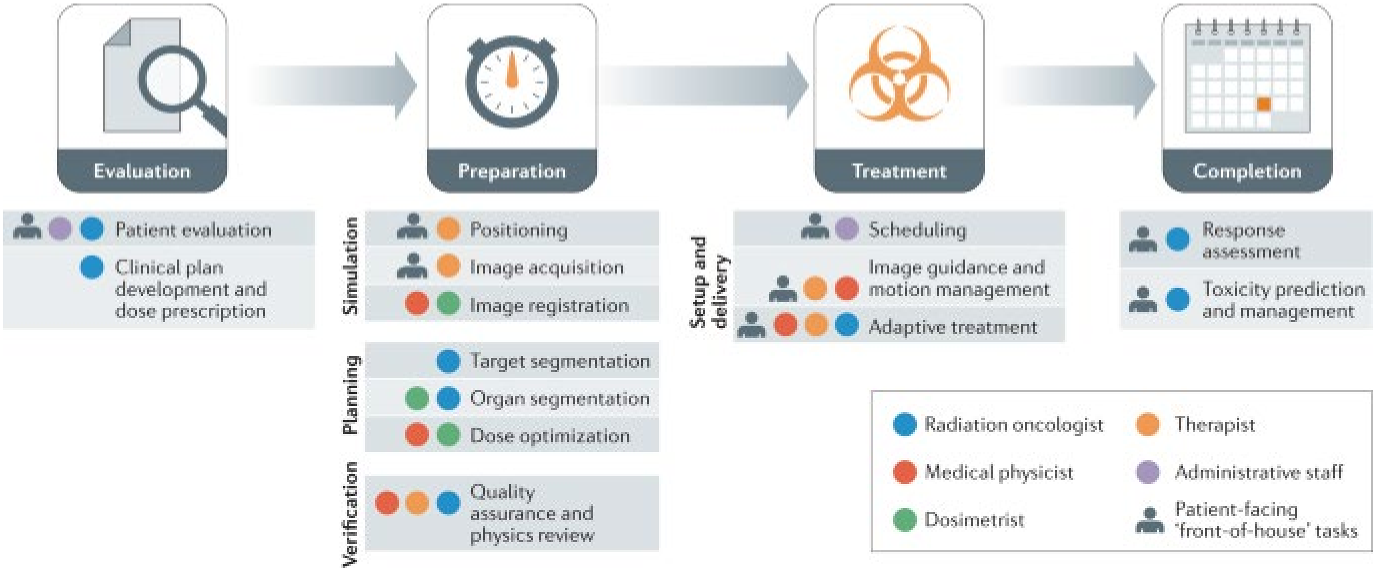
Vanneste et al., *Biomed Res Int*, 2016

- Treatment verification: process of ensuring that the therapy is delivered as planned
  - Critical to prevent errors and ensure that patients receive the intended radiation dose to the correct location

- However, accurate and thorough treatment verification poses a considerable time and labor burden on healthcare professionals

Artificial intelligence (AI)

- Crucial innovation with the potential to substantially reshape the RT workflow



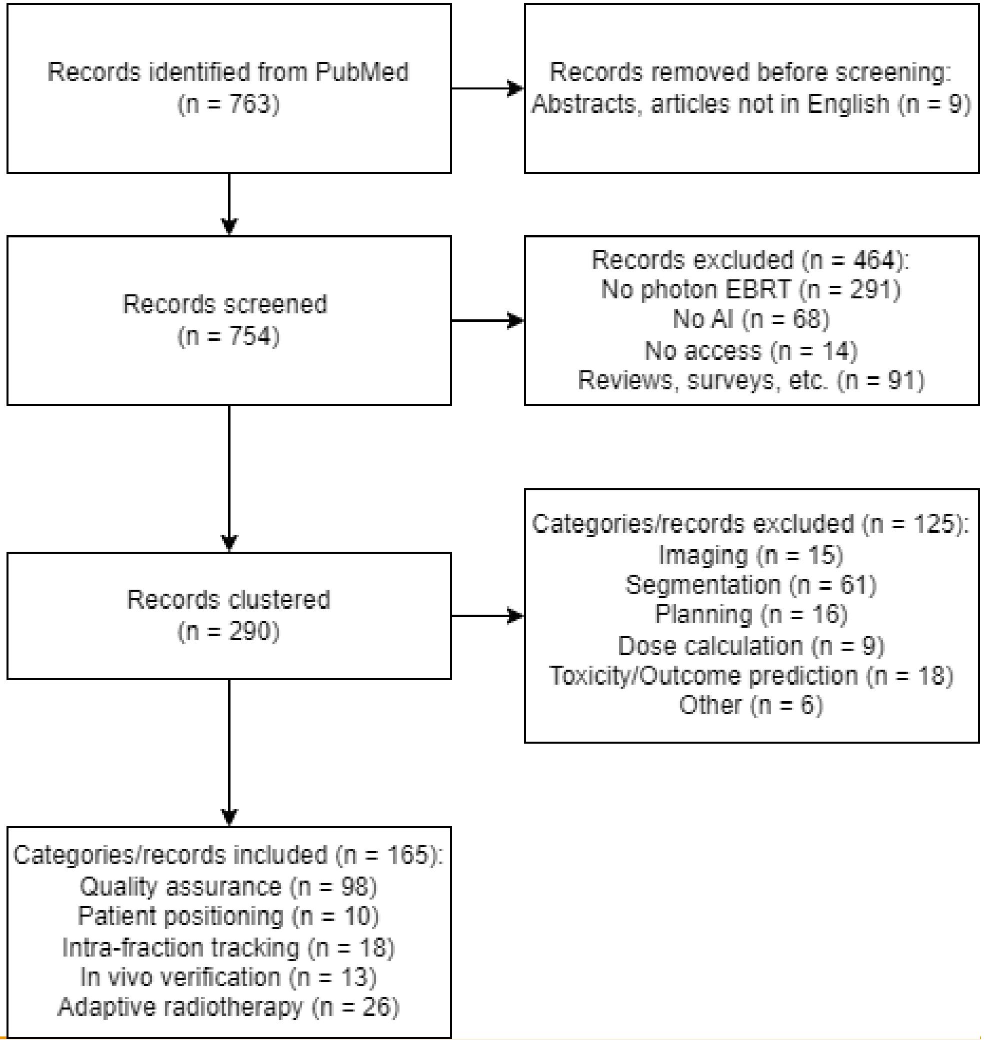
Huynh et al., *Nat Rev Clin Oncol*, 2020

- AI's capability to process and analyze complex datasets rapidly and with high precision offers a promising solution to streamline treatment verification processes
- Mitigates the risk of human error but also contributes to a reduction in the time and labor involved, ultimately leading to improvement in the quality of RT

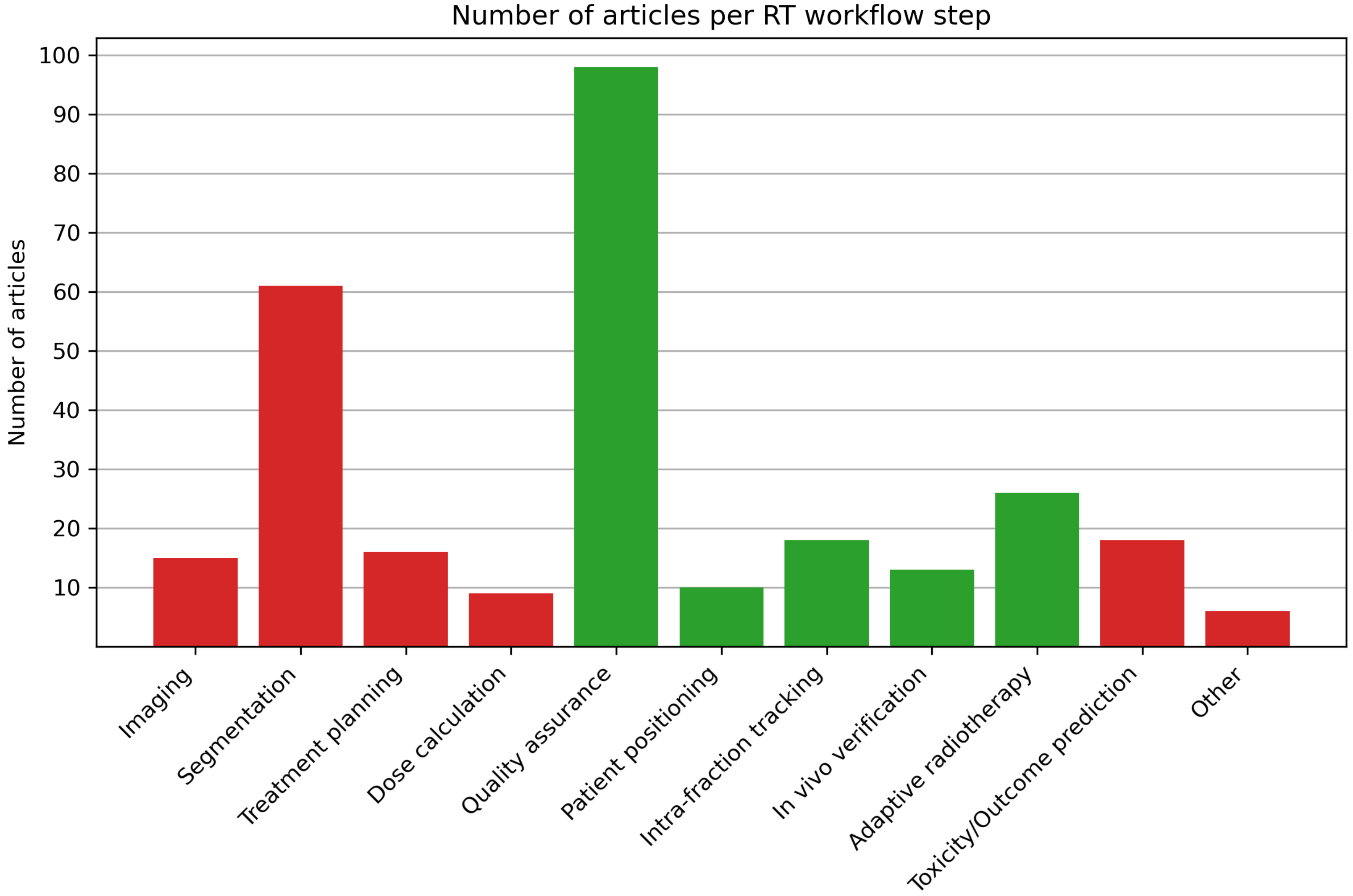
AI for treatment verification

- Literature review to explore the impact of AI for RT treatment verification

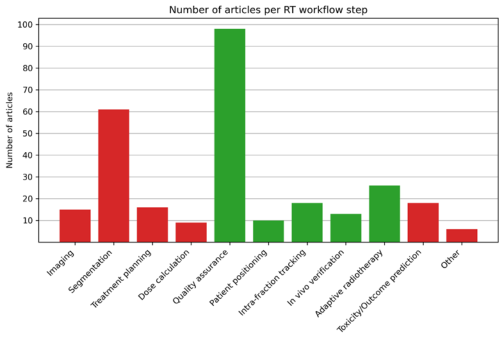
- Literature search on PubMed:
- external beam radiotherapy/artificial intelligence/error detection/treatment verification/quality assurance/patient monitoring



Clustering



Number of articles per RT workflow step
Number of articles
100
90
80
70
60
50
40
30
20
10
Imaging
Segmentation
Treatment planning
Dose calculation
Quality assurance
Patient positioning
Intra-fraction tracking
In vivo verification
Adaptive radiotherapy
Toxicity/Outcome prediction
Other



Treatment verification categories

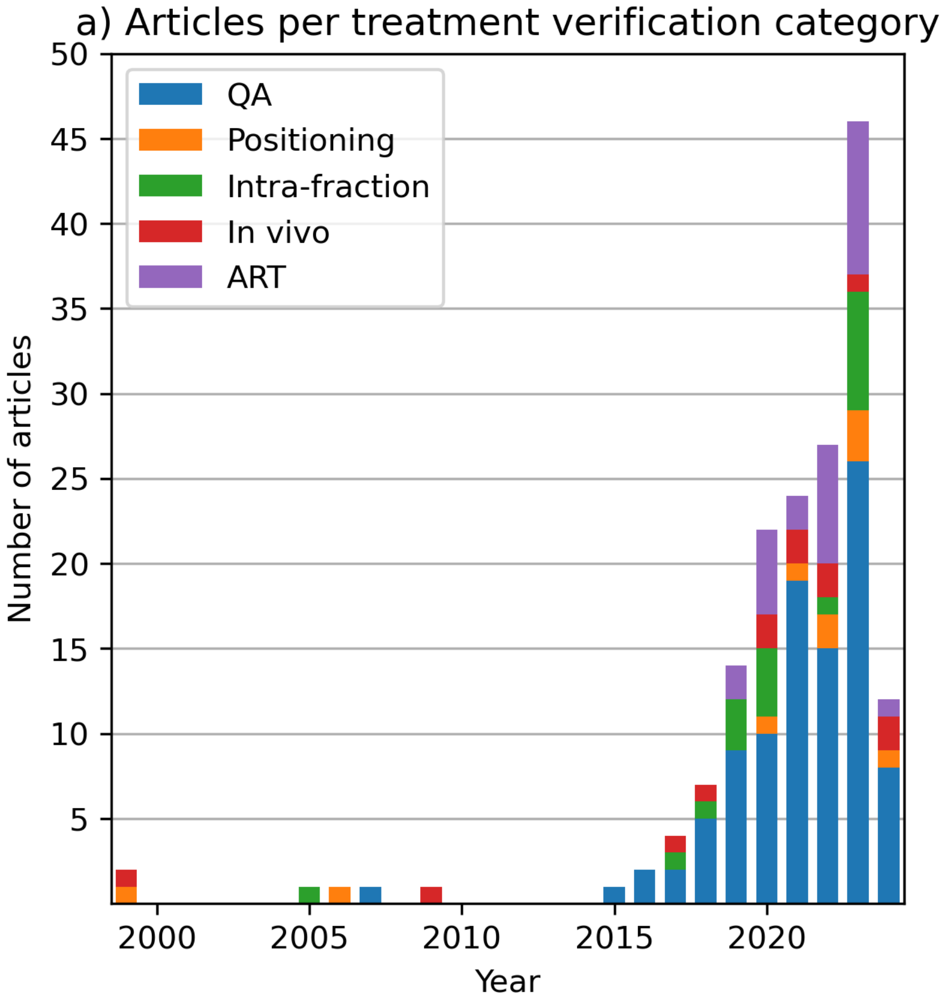
- **Quality assurance**
  - Ensuring correct dose delivery by the linac, i.e. linac QA, dosimetry, plan QA and patient-specific QA (PSQA)
- **Patient positioning**
  - Positioning the patient before delivering the treatment
- **Intra-fraction tracking**
  - Monitoring changes during delivery of treatment using kV imaging or other external devices
- **In vivo verification**
  - Monitoring changes during delivery of treatment using the MV treatment beam itself (e.g. using the electronic portal imaging device (EPID))
- **Adaptive radiotherapy (ART)**
  - Monitoring inter-fractional changes based on imaging and assessing these changes with the purpose of adapting the treatment plan

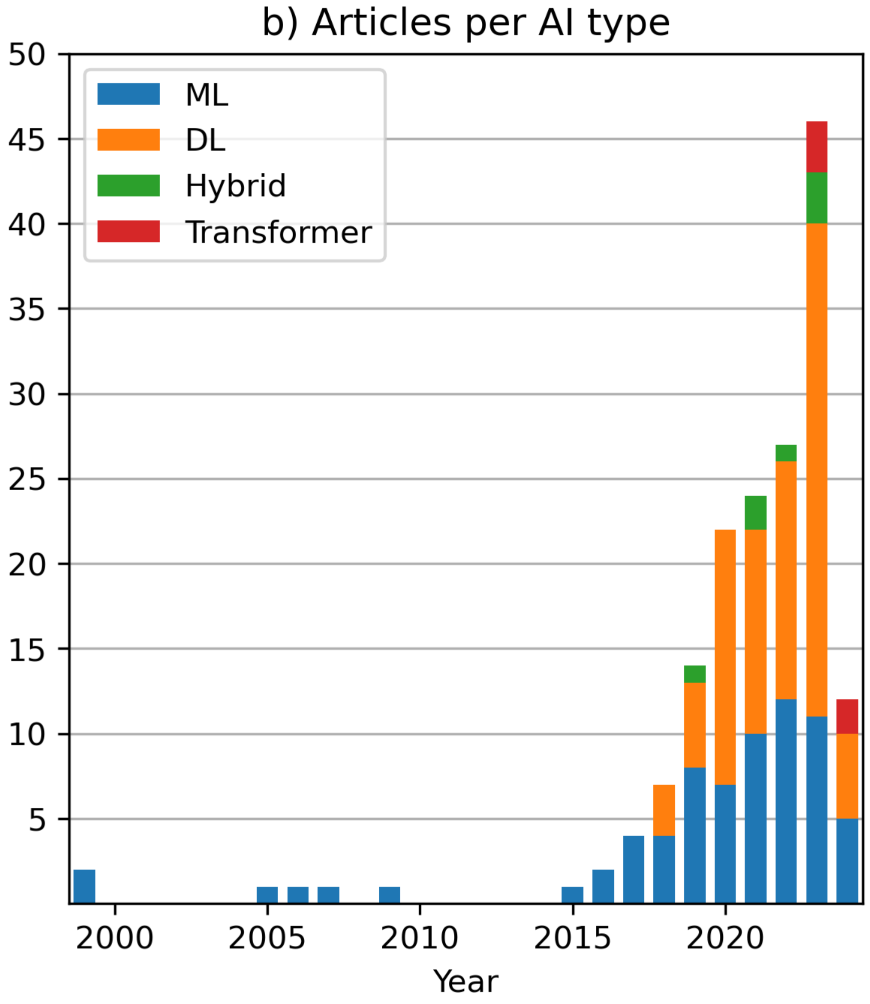
Reading aided by ChatGPT-4

- Asked ChatGPT-4 to extract for each paper:
  - Goal
  - AI task performed (e.g. classification, regression, image-to-image translation)
  - AI model used (incl. if it was a machine learning (ML) or deep learning (DL) model)
  - Data used as AI input and output
  - Treatment site
  - Dataset size
  - Metrics used for evaluating model performance
  - Performance of the model
  - Conclusion

- Sped up reading tremendously, although checking ChatGPT output is crucial!

Overall results

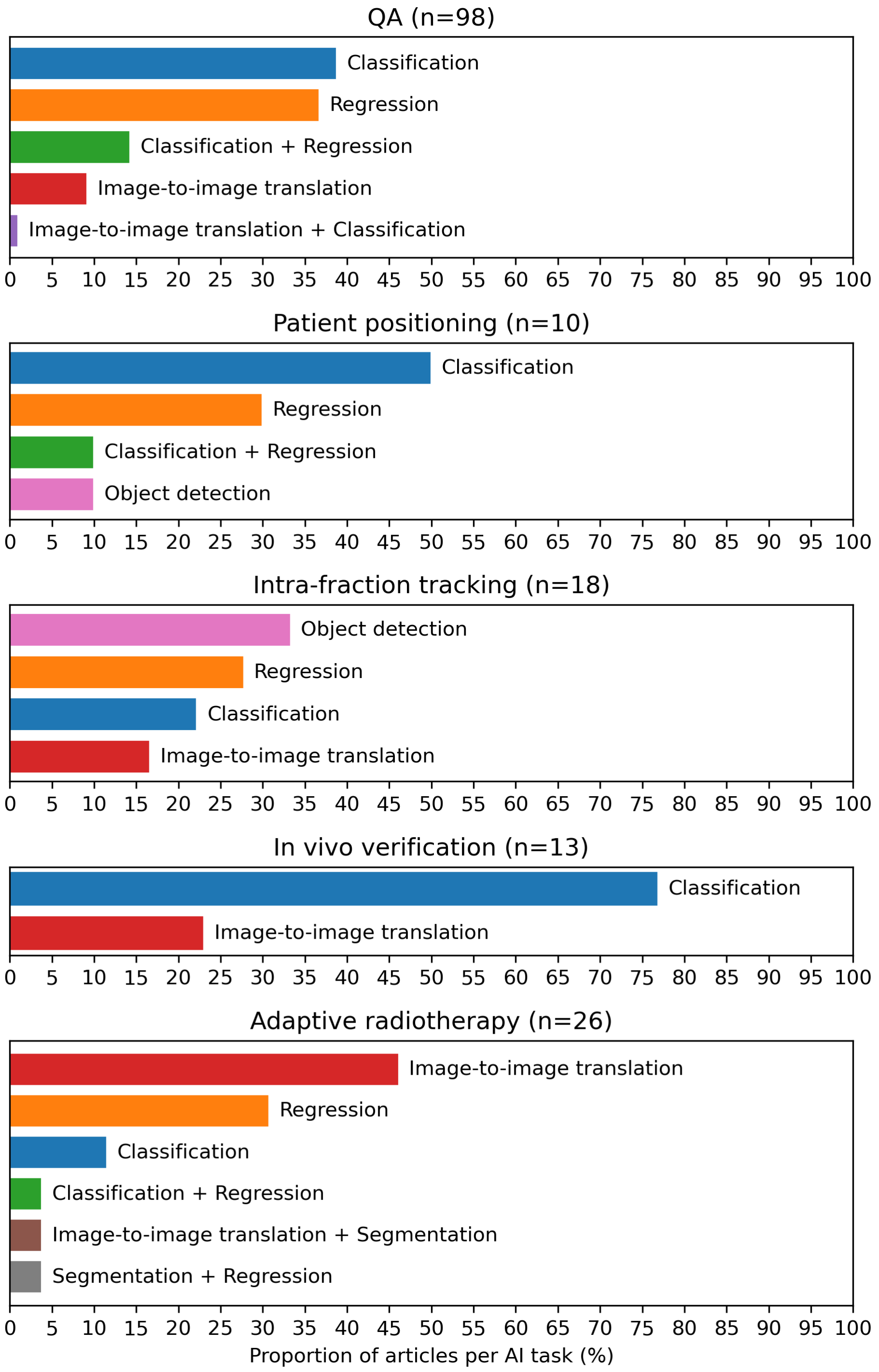




AI tasks per RT category

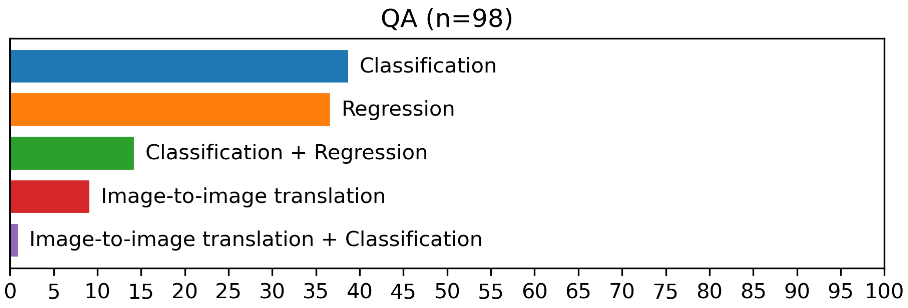
- “Traditional” AI tasks of classification and regression are most prevalent for QA, patient positioning and in vivo verification

- More complex AI tasks such as object detection and image-to-image translation are popular for intra-fraction tracking and ART

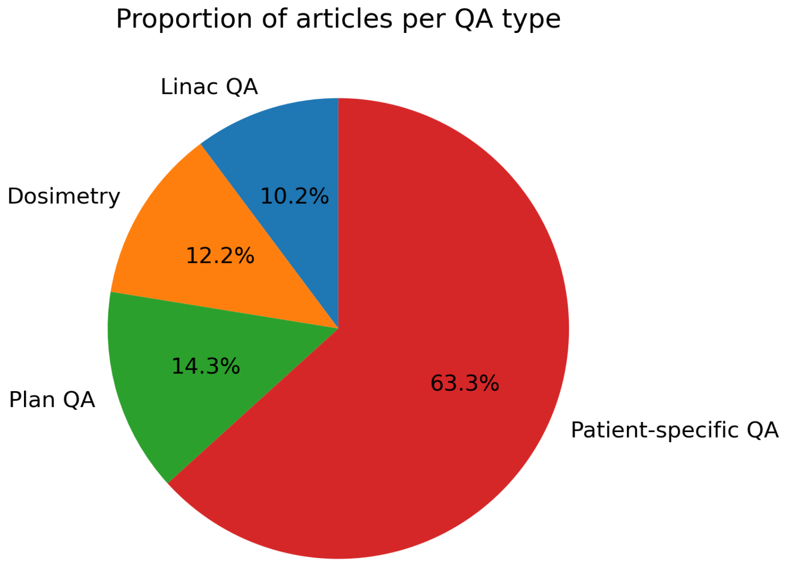


Quality assurance

- Ensuring correct dose delivery by the linac, i.e. linac QA, dosimetry, plan QA and patient-specific QA (PSQA)



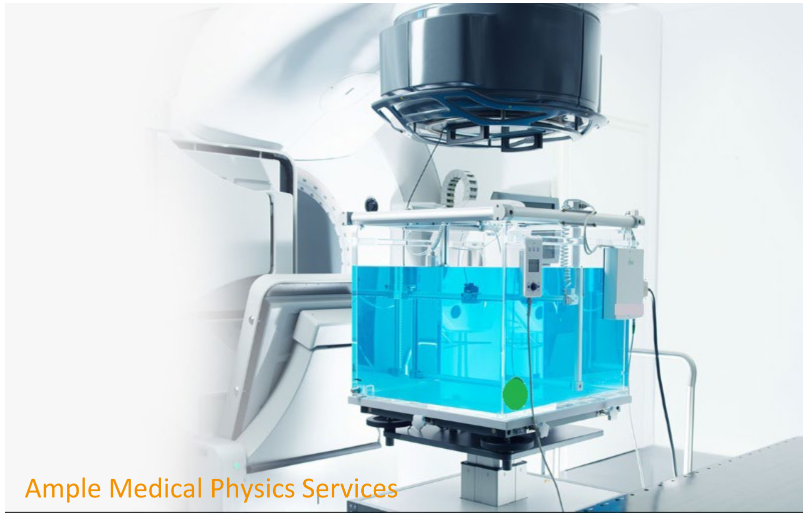
- Largest category
- Labor- and time-intensive workflows with many manual checks and substantial amounts of measurements



- Patient-specific QA (PSQA) most researched sub-category

Linac QA

- Maintenance and monitoring of the linac's performance to ensure consistent and precise delivery of RT
- AI for linac QA:
  - *Prediction*: predicting linac output behavior, identifying potential deviations and enabling preemptive corrections
  - *Automation*: automating analysis of measured data and generating data to simplify commissioning procedures



Linac QA - Prediction

- Time-series modeling with artificial neural networks (ANNs) and autoregressive integrated moving average (ARIMA) models
  - Predict linac output behavior based on previous daily linac QA measurements
- Clustering-based machine learning methods
  - Group daily QA parameters
  - Set linac-specific limits and identify deviations
  - Automated detection of operational anomalies in linacs
- Facilitate data-driven decisions, allowing for timely interventions and maintenance responses that enhance treatment reliability and safety

Predictive time-series modeling using artificial neural networks for Linac beam symmetry: an empirical study

Qiongge Li[1,2] and Maria F. Chan[3]

Predictive quality assurance of a linear accelerator based on the machine performance check application using statistical process control and ARIMA forecast modeling

Wayo Puyati[1,2] | Amnach Khawne[1] | Michael Barnes[3,4] | Benjamin Zwan[4,5] | Peter Greer[3,4] | Todsaporn Fuangrod[6]

Machine learning for automated quality assurance in radiotherapy: A proof of principle using EPID data description

Issam El Naqa[a] and Jim Irrer
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Jean M. Moran
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Using KMeans Clustering to Evaluate and Alert for Deviations of Linac Photon Beam Parameters

Narmada Chinnakannan, Punithavelan Nallamuthu*

Linac QA - Automation

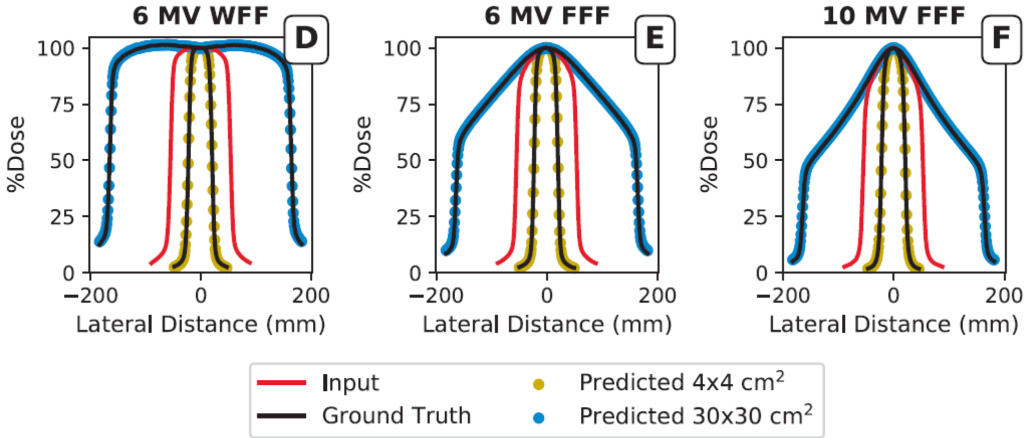
- Regression and implicit neural representation models
  - Predict beam data to alleviate the amount of measurements that need to be performed during commissioning
- Machine and deep learning models
  - To automate analysis of Winston-Lutz tests, detection of dead detector elements, identify phantom types
- Streamline QA processes and contribute to the overall safety and stability of RT

Beam data modeling of linear accelerators (linacs) through machine learning and its potential applications in fast and robust linac commissioning and quality assurance

Wei Zhao[a], Ishan Patil[a], Bin Han[a], Yong Yang[a], Lei Xing[a,*], Emil Schüler[a,b,*]

Modeling linear accelerator (Linac) beam data by implicit neural representation learning for commissioning and quality assurance applications

Lianli Liu[1] | Liyue Shen[2] | Yong Yang[1] | Emil Schüler[1] | Wei Zhao[1] | Gordon Wetzstein[2] | Lei Xing[1,2]



DeepWL: Robust EPID based Winston-Lutz analysis using deep learning, synthetic image generation and optical path-tracing

Michael John James Douglass[a,b,*], James Alan Keal[a]

Efficient quality assurance for isocentric stability in stereotactic body radiation therapy using machine learning

Sana Salahuddin[1,5] · Saeed Ahmad Buzdar[1] · Khalid Iqbal[2] · Muhammad Adeel Azam[3,4] · Lidia Strigari[5]

Dead detector element detection in flat panels using convolutional neural networks

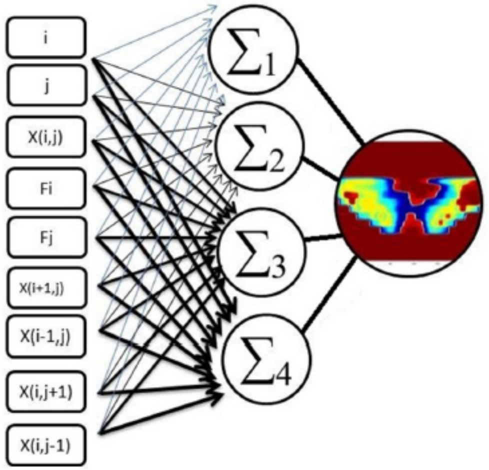
Jon Box[1] | Adam Salazar[2] | Dan Johnson[3] | Isaac Rutel[1]

An AI-based universal phantom analysis method based on XML-SVG wireframes with novel functional object identifiers

Ahmad Sakaamini[1], Alexander Van Slyke[1], Julien Partouche[2], Tianming Wu[2] and Rodney D Wiersma[1,*]

Dosimetry

- AI for conversion of measured signals by a dosimeter or other measurement device into dose values
  - Image-to-image translation
- Conversion of EPID images to planar dose distributions
- Similar approach for other dosimetry systems
- Improve accuracy of measured doses, thereby enhancing accuracy of RT



2D Dose Reconstruction by Artificial Neural Network for Pretreatment Verification of IMRT Fields

Seied Rabie Mahdavi, PhD[a], Mohsen Bakhshandeh, PhD[b], Aram Rostami, PhD[a*] and Ali Jabbary Arfaee, MSc[c]

A convolutional neural network model for EPID-based non-transit dosimetry

Lucas Dal Bosco[1] | Xavier Franceries[2] | Blandine Romain[3] | François Smekens[3] | François Husson[3] | Marie-Véronique Le Lann[1]

Deep learning-enabled EPID-based 3D dosimetry for dose verification of step-and-shoot radiotherapy

Mengyu Jia[†] | Yan Wu[†] | Yong Yang | Lei Wang | Cynthia Chuang | Bin Han | Lei Xing

Use of artificial neural network for pretreatment verification of intensity modulation radiation therapy fields

[1]SEIED RABIE MAHDAVI, [2]ASIEH TAVAKOL, [3]MASTANEH SANEI, [4]SEYED HADI MOLANA, [5]FARSHID ARBABI, [6]ARAM ROSTAMI and [7]SOHRAB BARIMANI

Development of a time-resolved mirrorless scintillation detector

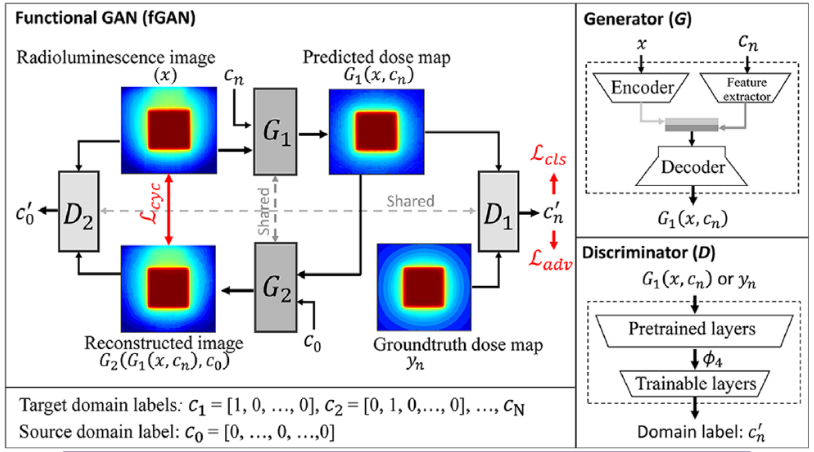
Wonjoong Cheon[1,2], Hyunuk Jung[1,3], Moonhee Lee[1], Jinhyeop Lee[1], Sung Jin Kim[4], Sungkoo Cho[4], Youngyih Han[1,5,*]

Development of a dosimeter prototype with machine learning based 3-D dose reconstruction capabilities

G M Finneman[1], O H Eichhorn[1], N R Meskell[1], T W Caplice[1], A D Benson[1], A S Abu-Halawa[1], G L Ademoski[1], A C Clark[1], D S Gayer[1], K N Hendrickson[1], P A Debbins[2], Y Onel[2], A S Ayan[3] and U Akgun[1,*]

Calibration of the EBT3 Gafchromic Film Using HNN Deep Learning

Liyun Chang,[1] Shyh-An Yeh,[1,2] Sheng-Yow Ho,[3,4] Hueisch-Jy Ding,[1] Pang-Yu Chen,[5] and Tsair-Fwu Lee[6,7]

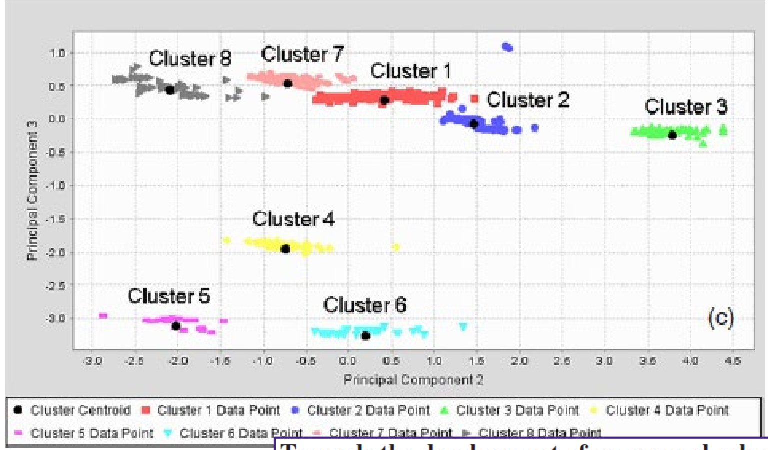


Deep learning-augmented radioluminescence imaging for radiotherapy dose verification

Mengyu Jia | Yong Yang | Yan Wu | Xiaomeng Li | Lei Xing | Lei Wang

Plan QA

- Reviewing and verifying the accuracy and completeness of a patient’s RT treatment plan
- Clustering and supervised ML models
  - To distinguish between acceptable and erroneous treatment plans
- Bayesian networks to indicate the likelihood of errors in RT plans



Guided undersampling classification for automated radiation therapy quality assurance of prostate cancer treatment

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Thomas G. Purdie
Department of Medical Imaging & Physics, Princess Margaret Cancer Centre, University Health Network (UHN), Toronto, Ontario M5G 2M9, Canada
Chris J. McIntosh

SuPART: supervised projective adapted resonance theory for automatic quality assurance approval of radiotherapy treatment plans

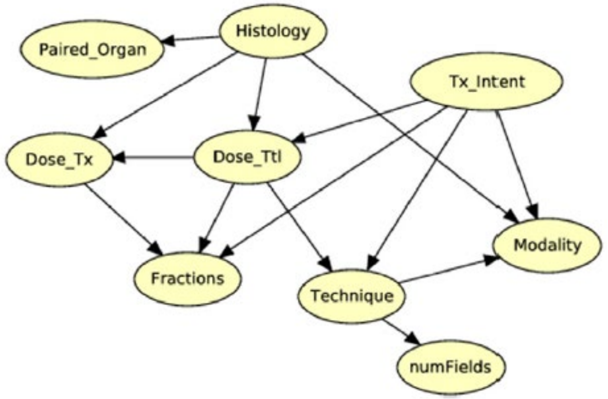
Hootan Kamran[1], Dionne M Aleman[1], Chris McIntosh[2] and Thomas G Purdie[2]

Augmenting Quality Assurance Measures in Treatment Review with Machine Learning in Radiation Oncology

Malvika Pillai, PhD,[a,1,*] John W. Shumway, MD,[b,1] Karthik Adapa, MBBS, MPH, PhD,[a,b] John Dooley, BA,[b] Ross McGurk, PhD,[b] Lukasz M. Mazur, PhD,[b] Shiva K. Das, PhD,[b] and Bhishamjit S. Chera, MD[b]

Towards the development of an error checker for radiotherapy treatment plans: a preliminary study

Fatemeh Azmandian[1], David Kaeli[1], Jennifer G Dy[1], Elizabeth Hutchinson[2], Marek Ancukiewicz[2], Andrzej Niemierko[2] and Steve B Jiang[2,3]



Bayesian network models for error detection in radiotherapy plans

Alan M Kalet[1,2], John H Gennari[2], Eric C Ford[1] and Mark H Phillips[1,2]

Characterization of a Bayesian network-based radiotherapy plan verification model

Samuel M. H. Luk,[a)] Juergen Meyer, Lori A. Young, Ning Cao, and Eric C. Ford
Department of Radiation Oncology, University of Washington Medical Center, Seattle, WA 98195-6043, USA
Mark H. Phillips
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Department of Biomedical Informatics and Medical Education, University of Washington, Seattle, WA 98019-4714, USA
Alan M. Kalet
Department of Radiation Oncology, University of Washington Medical Center, Seattle, WA 98195-6043, USA

Development and Validation of a Bayesian Network Method to Detect External Beam Radiation Therapy Physician Order Errors

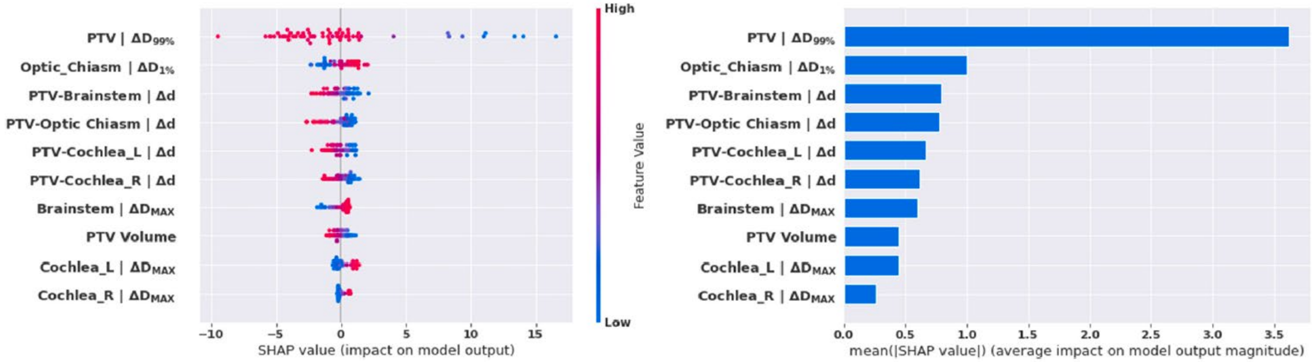
Xiao Chang, PhD,* H. Harold Li, PhD,* Alan M. Kalet, PhD,† and Deshan Yang, PhD*

Automatic quality assurance of radiotherapy treatment plans using Bayesian networks: A multi-institutional study

Petros Kalendralis[1*†], Samuel M. H. Luk[2†], Richard Canters[1], Denis Eyssen[1], Ana Vaniqui[1], Cecile Wolfs[1], Lars Murrer[1], Wouter van Elmpt[1], Alan M. Kalet[3], Andre Dekker[1,4], Johan van Soest[1,4], Rianne Fijten[1], Catharina M. L. Zegers[1] and Inigo Bermejo[1†]

Explainable AI (XAI) for Plan QA

- XAI: methods and techniques that provide human-understandable explanations for the decisions and actions taken by AI systems
- Shapley additive explanation (SHAP)
- Local interpretable model-agnostic explanations (LIME)
- Feature selection

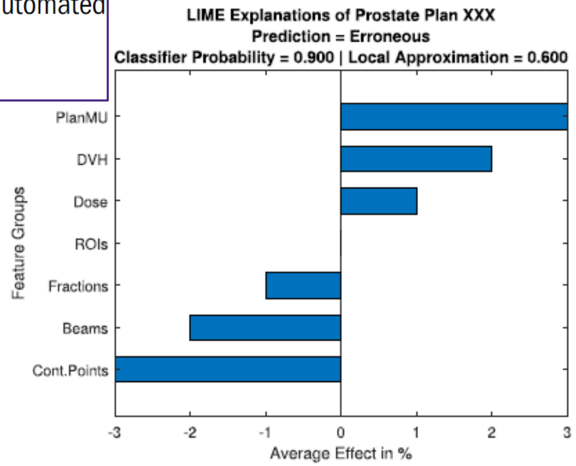


Machine learning for dose-volume histogram based clinical decision-making support system in radiation therapy plans for brain tumors

Pawel Siciarz [a,b,*], Salem Alfaifi [c], Eric Van Uytven [c], Shrinivas Rathod [c,d], Rashmi Koul [d,e], Boyd McCurdy [d,f,b]

Understanding machine learning classifier decisions in automated radiotherapy quality assurance

Yunsheng Chen[1], Dionne M Aleman[1], Thomas G Purdie[2,3] and Chris McIntosh[2,3]



Feature Engineering for Interpretable Machine Learning for Quality Assurance in Radiation Oncology

Malvika Pillai[a], Karthik Adapa[a,b], John W Shumway[b], John Dooley[b], Shiva K Das[b], Bhishamjit S Chera[b], Lukasz Mazur[b]

Maastro · GROW School for Oncology & Developmental Biology · Maastricht University · Maastricht UMC+

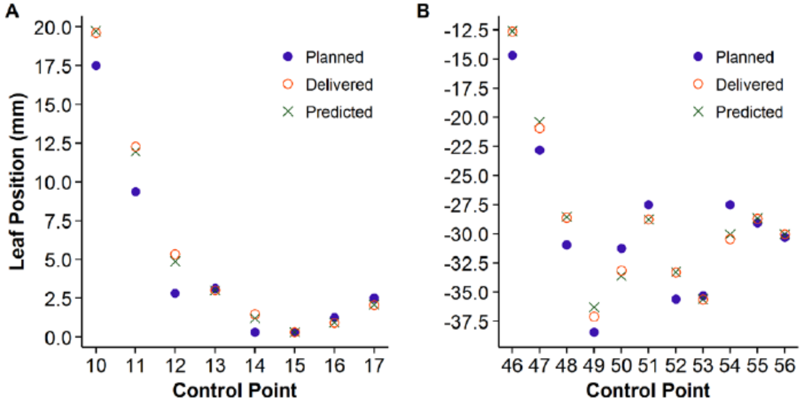
Patient-specific Quality Assurance (PSQA)

- Ensuring that each treatment is tailored to the individual patient's anatomy and tumor characteristics and that the treatment plan is deliverable by the linac

- AI for PSQA:
  - *Error prediction*: verifying the machine delivery parameters by predicting potential deviations or errors in machine parameter values before they occur
  - *Error classification*: analysis of measured dose distributions and/or dose comparison images with the aim of detecting and identifying errors
  - *Virtual QA*: predicting dose deviations before performing PSQA measurements to facilitate selection of plans that need measurements

PSQA - Error prediction

- Regression machine learning models
  - To predict discrepancies between planned and delivered parameter values based on log files
- Generative models
  - To predict MLC aperture and MUs and verify the treatment plan



A machine learning approach to the accurate prediction of multi-leaf collimator positional errors

Joel N K Carlson[1,2], Jong Min Park[2,3,4,5], So-Yeon Park[2,3,4,6], Jong In Park[1,2], Yunseok Choi[6,7] and Sung-Joon Ye[1,2,3,4,5,6]

Prediction of the individual multileaf collimator positional deviations during dynamic IMRT delivery *priori* with artificial neural network

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Department of Physics, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

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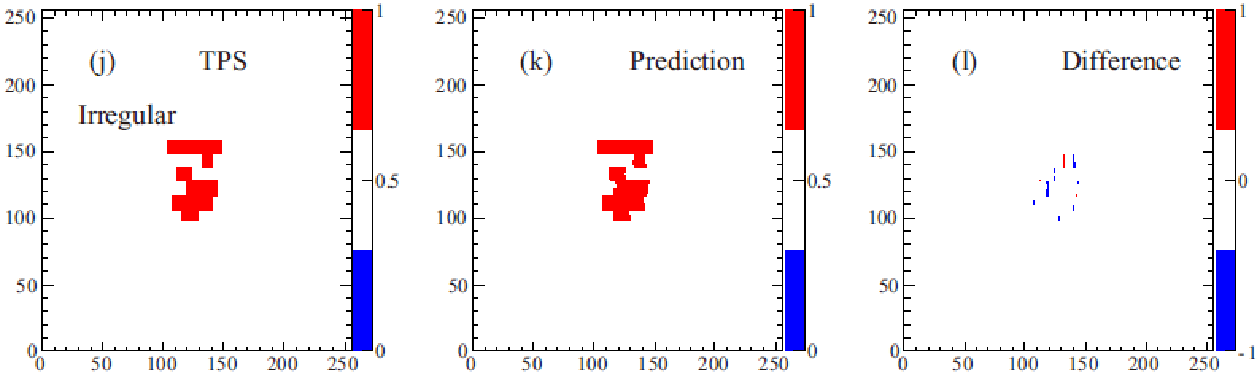
Department of Radiation Oncology, American Hospital Dubai, Dubai, United Arab Emirates



A tool for patient-specific prediction of delivery discrepancies in machine parameters using trajectory log files

Kai-Cheng Chuang
Medical Physics Graduate Program, Duke University, Durham, North Carolina, USA
Medical Physics Graduate Program, Duke Kunshan University, Kunshan, China

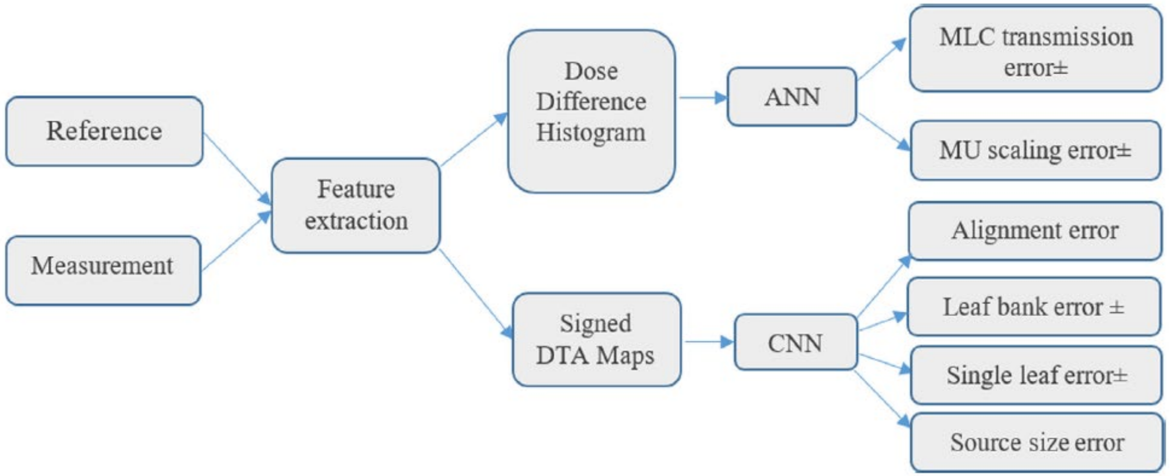
William Giles and Justus Adamson[a)]
Department of Radiation Oncology, Duke University Medical Center, Durham, North Carolina, USA

Verification of the machine delivery parameters of a treatment plan via deep learning

Jiawei Fan[1,2], Lei Xing[1], Ming Ma[1], Weigang Hu[2] and Yong Yang[1]

PSQA – Error classification

- ML and DL models
  - To detect MLC and/or MU errors in pre-treatment measurements
  - Various studies using different AI models and input data



Error detection and classification in patient-specific IMRT QA with dual neural networks

Nicholas J. Potter*, Karl Mund*, Jacqueline M. Andreozzi, Jonathan G. Li, Chihray Liu, and Guanghua Yan[a)]
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Deep learning for patient-specific quality assurance: Identifying errors in radiotherapy delivery by radiomic analysis of gamma images with convolutional neural networks

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Department of Industrial Engineering, University of Arkansas, Fayetteville, AR, USA

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W. Art Chaovalitwongse
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Department of Radiology, University of Washington, Sea

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

Landon S. Wootton, PhD,* Matthew J. Nyflot, PhD,*,† W. Art Chaovalitwongse, PhD,†,‡ and Eric Ford, PhD*

Error detection using a convolutional neural network with dose difference maps in patient-specific quality assurance for volumetric modulated arc therapy

Yuto Kimura[a,b], Noriyuki Kadoya[a,*], Seiji Tomori[a,c], Yohei Oku[b], Keiichi Jingu[a]

Error detection model developed using a multi-task convolutional neural network in patient-specific quality assurance for volumetric-modulated arc therapy

Yuto Kimura[1,2] | Noriyuki Kadoya[1] | Yohei Oku[2] | Tomohiro Kajikawa[1,3] | Seiji Tomori[1,4] | Keiichi Jingu[1]

What is the optimal input information for deep learning-based pre-treatment error identification in radiotherapy?

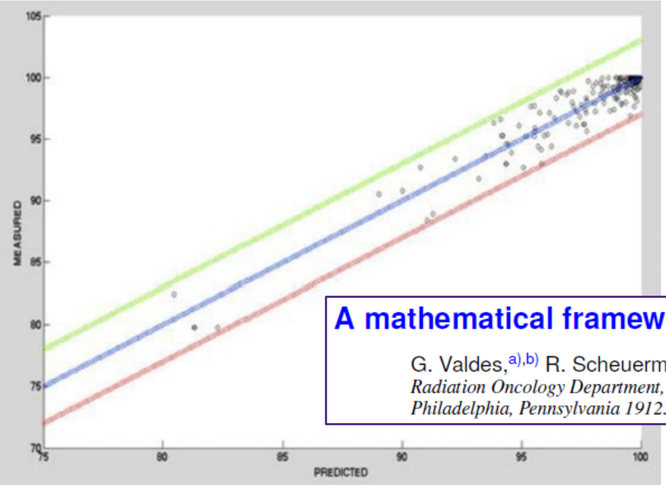
Cecile J.A. Wolfs *, Frank Verhaegen

Error detection using a multi-channel hybrid network with a low-resolution detector in patient-specific quality assurance

Bing Yan[1,2] | Jun Shi[3] | Xudong Xue[4] | Hu Peng[1] | Aidong Wu[2] | Xiao Wang[5] | Chi Ma[5]

PSQA – Virtual QA

- ML and DL models
  - To predict gamma pass rates or other dose evaluation metrics
  - To predict dose evaluation metrics and classify as pass or fail
  - To directly classify as pass or fail
  - To predict a measured dose or gamma distribution



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

Yannet Interian* and Vincent Rideout*
MS in Analytics Program, University of San Francisco, San Francisco, CA, USA
Vasant P. Kearney, Efstathios Gennatas, Olivier Morin, Joey Cheung, Timothy Solberg, and Gilmer Valdes[a)]
Department of Radiation Oncology, Un

Patient-specific quality assurance prediction models based on machine learning for novel dual-layered MLC linac

Heling Zhu | Qizhen Zhu | Zhiqun Wang | Bo Yang | Wenjun Zhang | Jie Qiu

Machine Learning for Patient-Specific Quality Assurance of VMAT: Prediction and Classification Accuracy

Jiaqi Li, MS,* Le Wang, PhD,[†,‡] Xile Zhang, MS,* Lu Liu, MS,* Jun Li, PhD,* Maria F. Chan, PhD,[§] Jing Sui, PhD,[†,‡] and Ruijie Yang, PhD*

Pretreatment patient-specific quality assurance prediction based on 1D complexity metrics and 3D planning dose: classification, gamma passing rates, and DVH metrics

Liyuan Chen[1†], Huanli Luo[1†], Shi Li[1], Xia Tan[1], Bin Feng[1], Xin Yang[1], Ying Wang[1] and Fu Jin[1*]

Predicting VMAT patient-specific QA results using a support vector classifier trained on treatment plan characteristics and linac QC metrics

Dal A Granville[1,4], Justin G Sutherland[1,2,3], Jason G Belec[1,2] and Daniel J La Russa[1,2,3]

Efficient dose–volume histogram–based pretreatment patient-specific quality assurance methodology with combined deep learning and machine learning models for volumetric modulated arc radiotherapy

Changfei Gong[1,2] | Kecheng Zhu[2] | Chengyin Lin[2] | Ce Han[2] | Zhongjie Lu[3] | Yuanhua Chen[3] | Changhui Yu[4] | Liqiao Hou[4] | Yongqiang Zhou[2] | Jinling Yi[2] | Yao Ai[2] | Xiaojun Xiang[1] | Congying Xie[2,5] | Xiance Jin[2,6]

A mathematical framework for virtual IMRT QA using machine learning

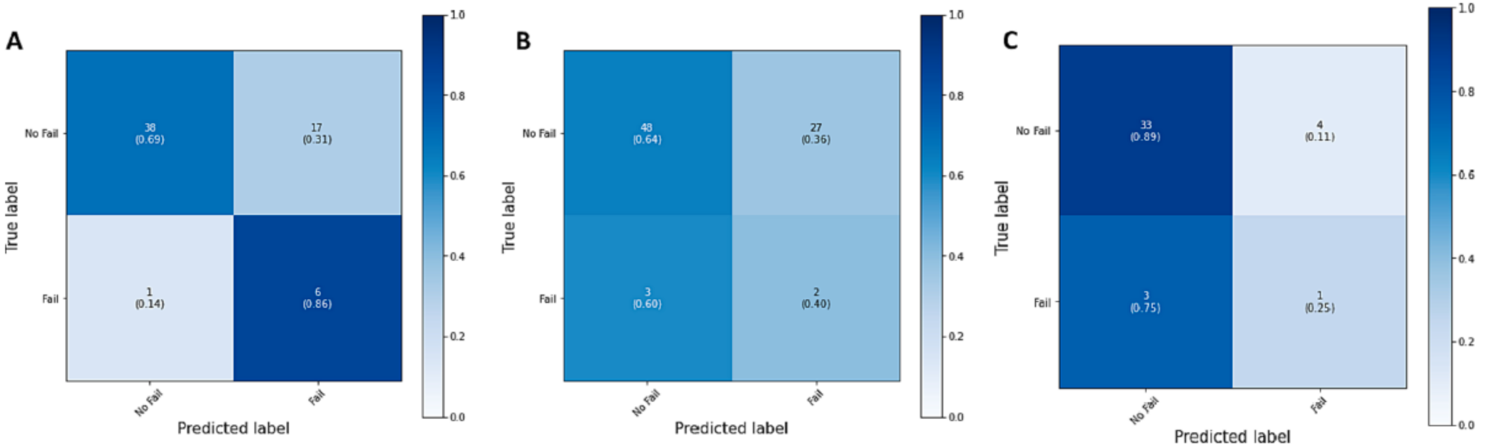
G. Valdes,[a),b)] R. Scheuermann,[a)] C. Y. Hung, A. Olszanski, M. Bellerive, and T. D. Solberg
Radiation Oncology Department, Perelman Center for Advanced Medicine, University of Pennsylvania, Philadelphia, Pennsylvania 19123

A synthesized gamma distribution-based patient-specific VMAT QA using a generative adversarial network

Takaaki Matsuura[1,2] | Daisuke Kawahara[2] | Akito Saito[3] | Kiyoshi Yamada[1] | Shuichi Ozawa[1,2] | Yasushi Nagata[1,2]

PSQA – Virtual QA

- Due to large interest in virtual QA, research is emerging on:
  - Multi-centric validation
  - Implementation in clinical practice



Multi-institutional generalizability of a plan complexity machine learning model for predicting pre-treatment quality assurance results in radiotherapy

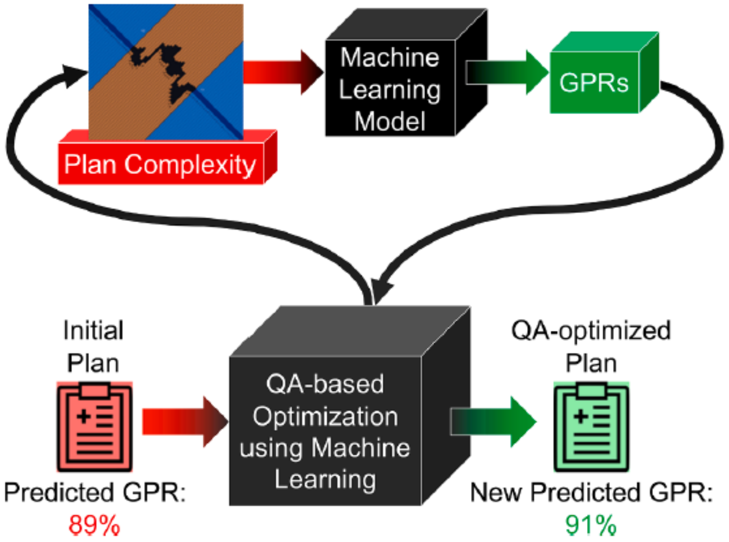
Michaël Claessens [a,b,*], Geert De Kerf [a], Verdi Vanreusel [a,b,c], Isabelle Mollaert [a], Victor Hernandez [d], Jordi Saez [e], Núria Jornet [f], Dirk Verellen [a,b]

IMRT QA using machine learning: A multi-institutional validation

Gilmer Valdes [1,3,a] | Maria F. Chan [2,a] | Seng Boh Lim [2] | Ryan Scheuermann [3] | Joseph O. Deasy [2] | Timothy D. Solberg [1,3]

Multicentric evaluation of a machine learning model to streamline the radiotherapy patient specific quality assurance process

Nicola Lambri [a,b], Victor Hernandez [c], Jordi Sáez [d], Marco Pelizzoli [a,e], Sara Parabicoli [a,e], Stefano Tomatis [a], Daniele Loiacono [f], Marta Scorsetti [a,b], Pietro Mancosu [a,*]



Prospective Clinical Validation of Virtual Patient-Specific Quality Assurance of Volumetric Modulated Arc Therapy Radiation Therapy Plans

Phillip D.H. Wall, PhD, MS, Emily Hirata, PhD, Olivier Morin, PhD, Gilmer Valdes, PhD, and Alon Witztum

A TPS integrated machine learning tool for predicting patient-specific quality assurance outcomes in volumetric-modulated arc therapy

Caroline Noblet [*], Mathis Maunet, Marie Duthy, Frédéric Coste, Matthieu Moreau

Quality assurance-based optimization (QAO): Towards improving patient-specific quality assurance in volumetric modulated arc therapy plans using machine learning

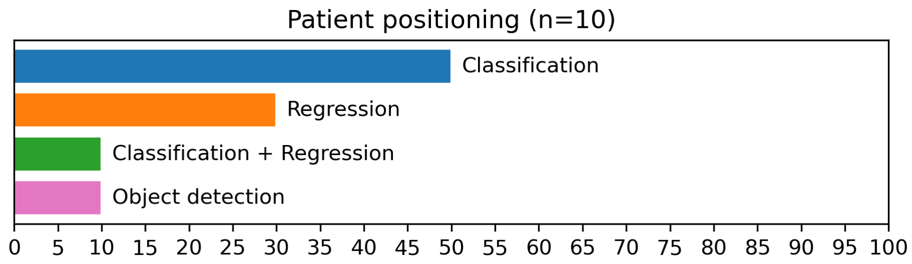
Phillip D.H. Wall [a,*], Jonas D. Fontenot [a,b]

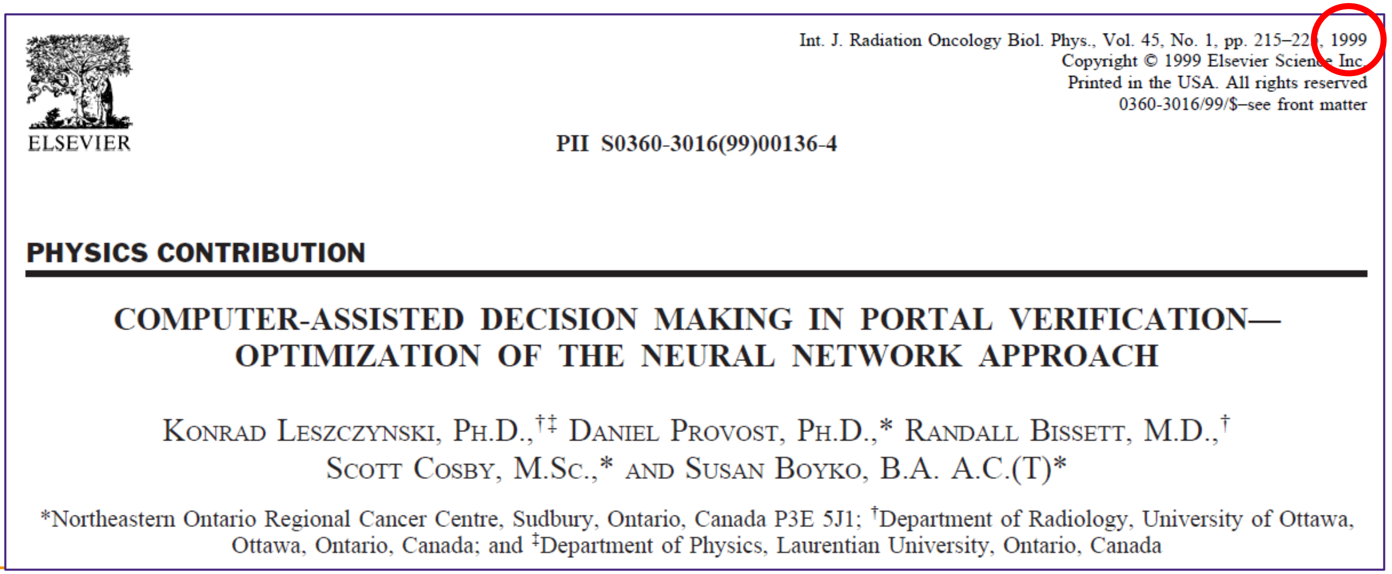
Patient positioning

- Positioning the patient before delivering the treatment

- Smallest category
- AI is not often used yet to optimize and assist

- Early application of AI in RT
- Artificial neural networks to evaluate portal set-up images





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0360-3016/99/$–see front matter

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PII S0360-3016(99)00136-4

PHYSICS CONTRIBUTION

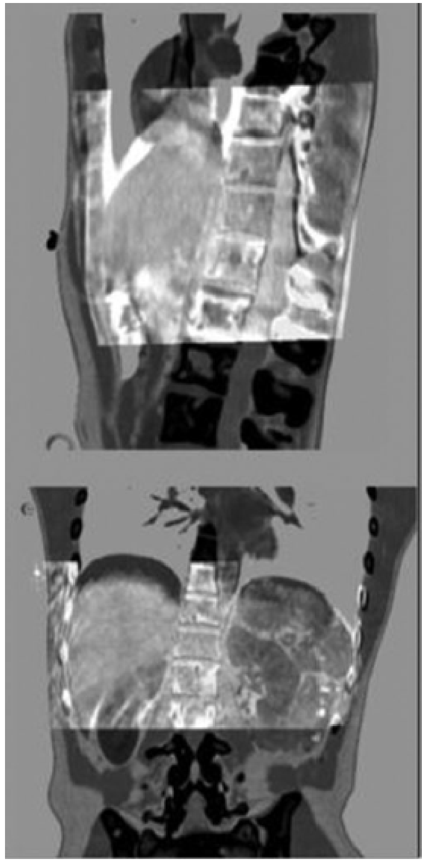
COMPUTER-ASSISTED DECISION MAKING IN PORTAL VERIFICATION—OPTIMIZATION OF THE NEURAL NETWORK APPROACH

KONRAD LESZCZYNSKI, PH.D.,†‡ DANIEL PROVOST, PH.D.,* RANDALL BISSETT, M.D.,† SCOTT COSBY, M.SC.,* AND SUSAN BOYKO, B.A. A.C.(T)*

*Northeastern Ontario Regional Cancer Centre, Sudbury, Ontario, Canada P3E 5J1; †Department of Radiology, University of Ottawa, Ottawa, Ontario, Canada; and ‡Department of Physics, Laurentian University, Ontario, Canada

Patient positioning

- Different applications
- Object (positioning device) detection
- Detection of vertebral misalignment
- Surface guidance



Machine learning-based treatment couch parameter prediction in support of surface guided radiation therapy

Geert De Kerf[a,*], Michaël Claessens[a,b], Isabelle Mollaert[a], Wim Vingerhoed[a], Dirk Verellen[a,b]

Technical Note: Deep Learning approach for automatic detection and identification of patient positioning devices for radiation therapy

David H. Thomas[a)], Leah K. Schubert, Yevgeniy Vinogradskiy, Sameer Nath, Brian Kavanagh, Moyed Miften, and Bernard Jones
Department of Radiation Oncology, University of Colorado, Aurora, CO, USA

Proof-of-concept study of artificial intelligence-assisted review of CBCT image guidance

Jack Neylon[1] | Dishane C. Luximon[1] | Timothy Ritter[2] | James M. Lamb[1]

Results of an Artificial Intelligence–Based Image Review System to Detect Patient Misalignment Errors in a Multi-institutional Database of Cone Beam Computed Tomography–Guided Radiation Therapy

Dishane C. Luximon, MS,* Jack Neylon, PhD,* Timothy Ritter, PhD,† Nzhde Agazaryan, PhD,* John V. Hegde, Michael L. Steinberg, MD,* Daniel A. Low, PhD,* and James M. Lamb, PhD*

Development and multi-institutional validation of a convolutional neural network to detect vertebral body mis-alignments in 2D x-ray setup images

Rachel Petragallo[1] | Pascal Bertram[2] | Per Halvorsen[3] | Ileana Iftimia[3] | Daniel A. Low[1] | Olivier Morin[4] | Ganesh Narayanasamy[5] | Daniel L. Saenz[6] | Kevinraj N. Sukumar[7] | Gilmer Valdes[4] | Lauren Weinstein[8] | Michelle C. Wells | Benjamin P. Ziemer[4] | James M. Lamb[1]

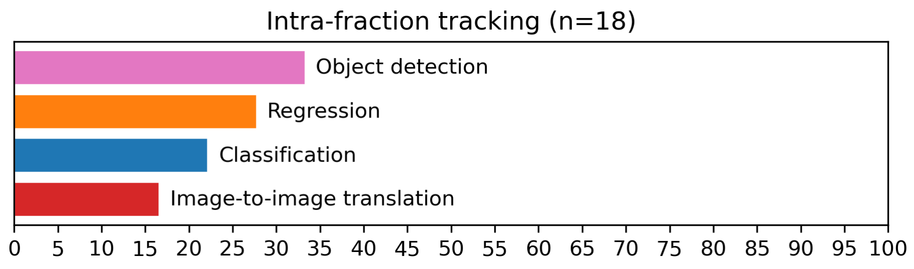
Development and interinstitutional validation of an automatic vertebral-body misalignment error detector for cone-beam CT-guided radiotherapy

Dishane C. Luximon[1] | Timothy Ritter[2] | Emma Fields[2] | John Neylon[1] | Rachel Petragallo[1] | Yasin Abdulkadir[1] | John Charters[1] | Daniel A. Low[1] | James M. Lamb[1]

Intra-fraction tracking

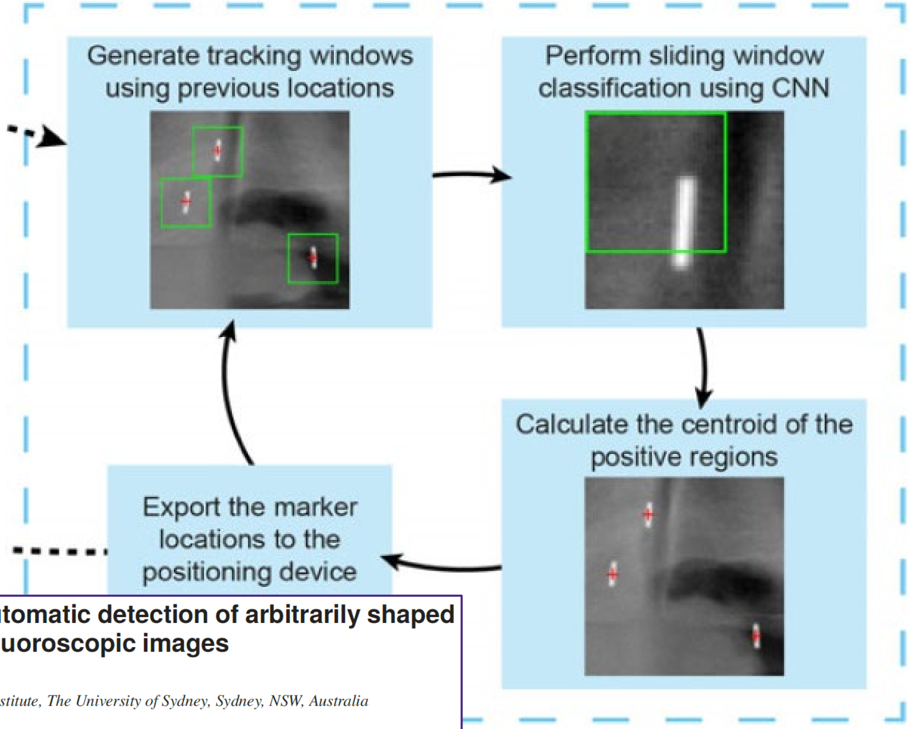
- Monitoring changes during delivery of treatment using kV imaging or other external devices

- Object detection tasks
    - Monitoring of the tumor or an anatomical target during the delivery of radiation



Anatomical monitoring

- Tracking methods evolved over time
  - External markers
  - Fiducial (implanted) markers
  - Markerless



On using an adaptive neural network to predict lung tumor motion during respiration for radiotherapy applications

Marcus Isaksson and Joakim Jalden
Department of Electrical Engineering, Stanford University, Stanford, California 94036
Martin J. Murphy[a)]
Department of Radiation Oncology, Virginia Commonwealth University, Richmond, Virginia 23298

A deep learning framework for automatic detection of arbitrarily shaped fiducial markers in intrafraction fluoroscopic images

Adam Mylonas, and Paul J. Keall
Faculty of Medicine and Health, ACRF Image X Institute, The University of Sydney, Sydney, NSW, Australia
Jeremy T. Booth
Royal North Shore Hospital, Northern Sydney Cancer Centre, St Le
Chun-Chien Shieh
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Royal North Shore Hospital, Northern Sydney Cancer Centre, St Le
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Doan Trang Nguyen[a)]
Faculty of Medicine and Health, ACRF Image X Institute, The University of Sydney, Sydney, NSW, Australia
School of Biomedical Engineering, University of Techn

A feasibility study on the development and use of a deep learning model to automate real-time monitoring of tumor position and assessment of interfraction fiducial marker migration in prostate radiotherapy patients*

Ryan Motley[1,2], Prabhakar Ramachandran[1,2] and Andrew Fielding[1]

Simultaneous object detection and segmentation for patient-specific markerless lung tumor tracking in simulated radiographs with deep learning

Lili Huang[1,2] | Christopher Kurz[1] | Philipp Freislederer[1] | Farkhad Manapov[1] | Stefanie Corradini[1] | Maximilian Niyazi[1] | Claus Belka[1,3,4] | Guillaume Landry[1] | Marco Riboldi[2]

Evaluation of deep learning based implanted fiducial markers tracking in pancreatic cancer patients

Abdella M Ahmed[1,3], Maegan Gargett[1,3], Levi Madden[1,2], Adam Mylonas[2], Danielle Chrystall[1,4], Ryan Brown[1], Adam Briggs[5], Trang Nguyen[2], Paul Keall[2], Andrew Kneebone[1,6], George Hruby[1,6] and Jeremy Booth[1,4]

Deep learning-based markerless lung tumor tracking in stereotactic radiotherapy using Siamese networks

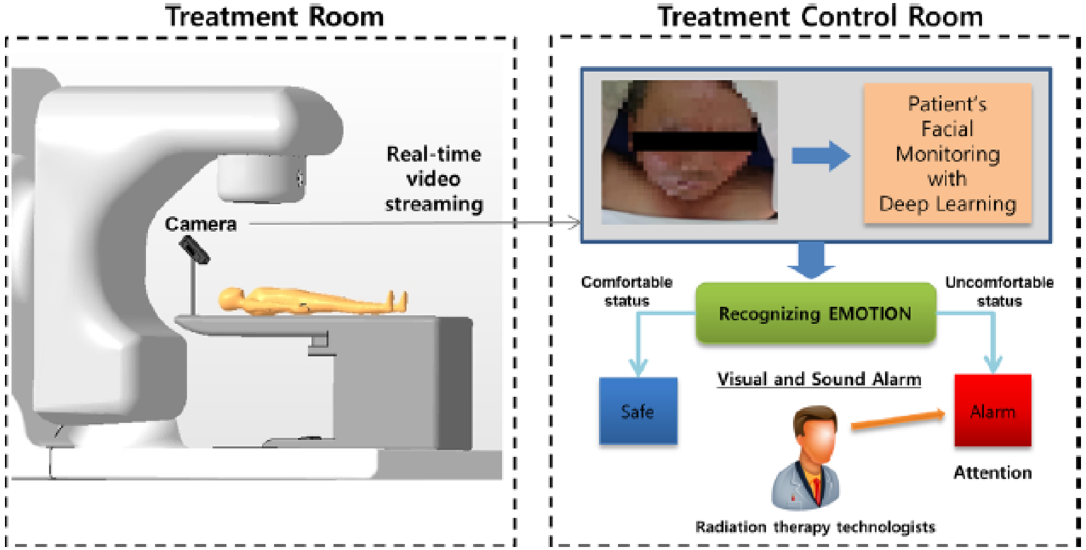
Dragos Grama[1] | Max Dahele[1] | Ward van Rooij[1] | Ben Slotman[1] | Deepak K. Gupta[2] | Wilko F. A. R. Verbakel[1]

Deep Learning model for markerless tracking in spinal SBRT

Toon Roggen*, Mislav Bobic, Nasim Givehchi, Stefan G. Scheib

Other tracking applications

- Surface guidance
  - Selection of ROI, correlation between internal and external movement
- Image improvement
  - kV image quality, volumetric imaging, image decomposition
- Patient movement
  - Monitoring facial expressions

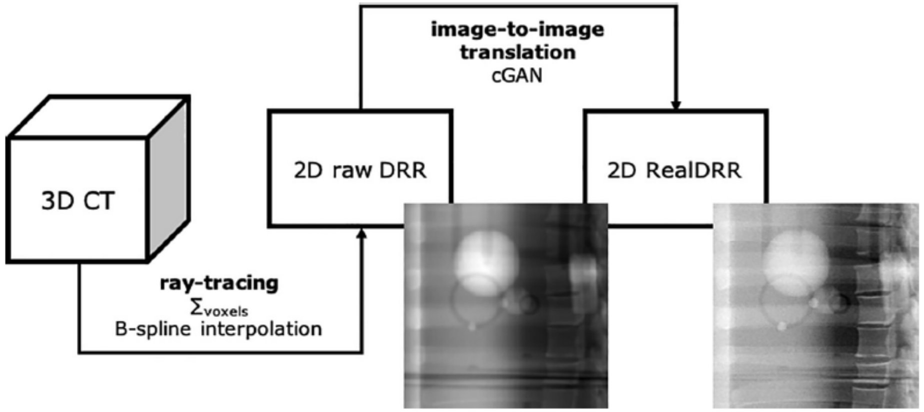


Automatic prediction model for online diaphragm motion tracking based on optical surface monitoring by machine learning

Zhenhui Dai[1^], Qiang He[1], Lin Zhu[1], Bailin Zhang[1], Huaizhi Jin[1], Geng Yang[1], Chunya Cai[1], Xiang Tan[1], Wanwei Jian[1], Yao Chen[2], Hua Zhang[3], Jian Wu[2], Xuetao Wang[1]

Deep-learning based surface region selection for deep inspiration breath hold (DIBH) monitoring in left breast cancer radiotherapy

Haibin Chen[1,2], Mingli Chen[2], Weiguo Lu[2], Bo Zhao[2], Steve Jiang[2], Linghong Zhou[1], Nathan Kim[2], Ann Spangler[2], Asal Rahimi[2], Xin Zhen[1] and Xuejun Gu[2]



RealDRR – Rendering of realistic digitally reconstructed radiographs using locally trained image-to-image translation

Jennifer Dhont[a,b,c,*], Dirk Verellen[d,e], Isabelle Mollaert[d], Verdi Vanreusel[d], Jef Vandemeulebroucke[a,b]

Deep learning-based real-time volumetric imaging for lung stereotactic body radiation therapy: a proof of concept study

Yang Lei[1,2], Zhen Tian[1,2], Tonghe Wang[1], Kristin Higgins[1], Jeffrey D Bradley[1], Walter J Curran[1], Tian Liu[1] and Xiaofeng Yang[1,*]

Patient specific prior cross attention for kV decomposition in paraspinal motion tracking

Xiuxiu He[1] | Weixing Cai[1] | Feifei Li[1] | Qiyong Fan[1] | Pengpeng Zhang[1] | John J. Cuaron[2] | Laura I. Cerviño[1] | Jean M. Moran[1] | Xiang Li[1] | Tianfang Li[1]

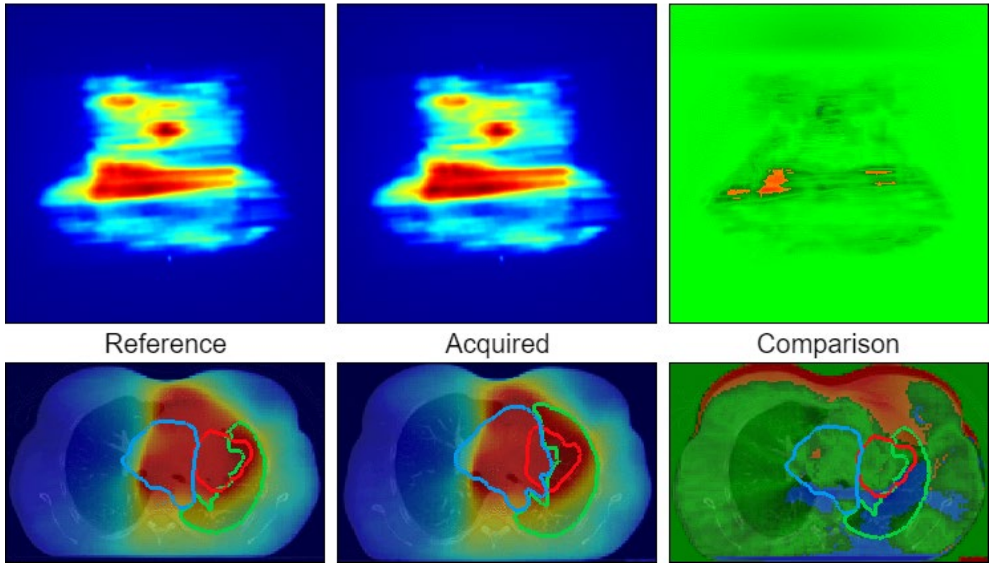
Facial expression monitoring system for predicting patient's sudden movement during radiotherapy using deep learning

Kwang Hyeon Kim | Kyeongyun Park | Haksoo Kim | Byungdu Jo | Sang Hee Ahn | Chankyu Kim | Myeongsoo Kim | Tae Ho Kim | Se Byeong Lee | Dongho Shin | Young Kyung Lim | Jong Hwi Jeong

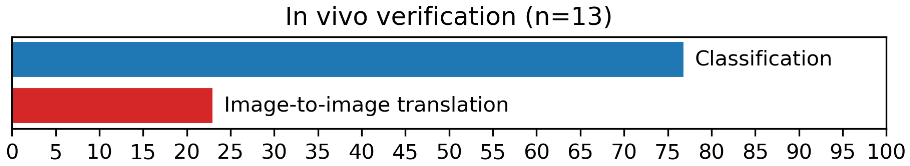
Maastricht UMC+

In vivo verification

- Monitoring changes during delivery of treatment using the MV treatment beam itself (e.g. using the electronic portal imaging device (EPID))



- Classification tasks:
  - *Error detection*: aim is to detect whether or not any error is present
  - *Error identification*: aim is to detect which type of error is present
- Image-to-image translation
  - Improve or convert (dose) measurements performed during treatment



In vivo verification – Error detection

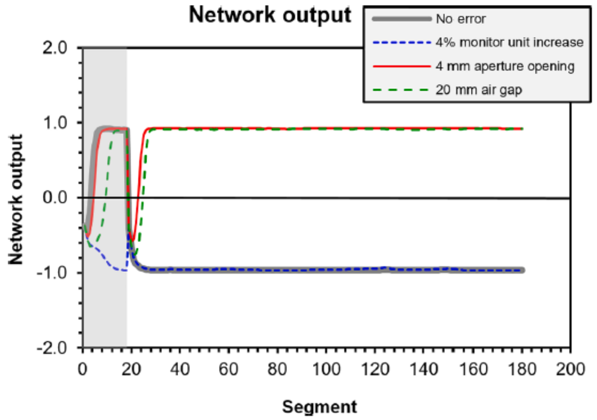
- Detect whether or not an error is present
- Early applications in portal verification
- Hidden Markov models and clustering
  - To identify anatomical changes
- Recurrent neural networks
  - To detect errors in real time during a treatment fraction

Application of a fuzzy pattern classifier to decision making in portal verification of radiotherapy

Konrad Leszczynski†‡§, Scott Cosby, Randall Bissett§, Daniel Provost, Susan Boyko, Stephen Loose‡ and Eding Mvilongo‡

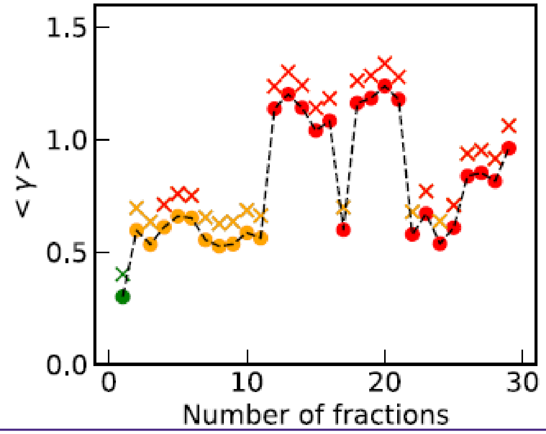
A feasibility study of treatment verification using EPID cine images for hypofractionated lung radiotherapy*

Xiaoli Tang[1,2], Tong Lin[1,3] and Steve Jiang[1]



A recurrent neural network for rapid detection of delivery errors during real-time portal dosimetry

James L. Bedford*, Ian M. Hanson[1]



Classification of changes occurring in lung patient during radiotherapy using relative γ analysis and hidden Markov models

Nicolas Varfalvy
Département de Radio-oncologie, CHU de Québec, 11 Côte du Palais, Québec, QC, Canada

Ophelie Piron
Département de Radio-oncologie, CHU de Québec, 11 Côte du Palais, Québec, QC, Canada
Physics Department, Université Laval, Québec City, QC, Canada

Marc François Cyr
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Anne Dagnault
Département de Radio-oncologie, CHU de Québec, 11 Côte du Palais, Québec, QC, Canada

Louis Archambault[a)]
Département de
Physics Departm

External validation of a hidden Markov model for gamma-based classification of anatomical changes in lung cancer patients using EPID dosimetry

Cecile J. A. Wolfs[a)]
Department of Radiation Oncology (Maastro), GROW School for Oncology, Maastricht University Medical Centre+, Maastricht, The Netherlands

Nicolas Varfalvy
Département de Radio-oncologie, CHU de Québec, Québec, QC, Canada

Richard A. M. Canters, Sebastiaan M. J. J. G. Nijsten, and Djoya Hattu
Department of Radiation Oncology (Maastro), GROW School for Oncology, Maastricht University Medical Centre+, Maastricht, The Netherlands

Louis Archambault*
Département de Radio-oncologie, CHU de Québec, Québec, QC, Canada
Physics Department, Université Laval, Québec City, QC, Canada

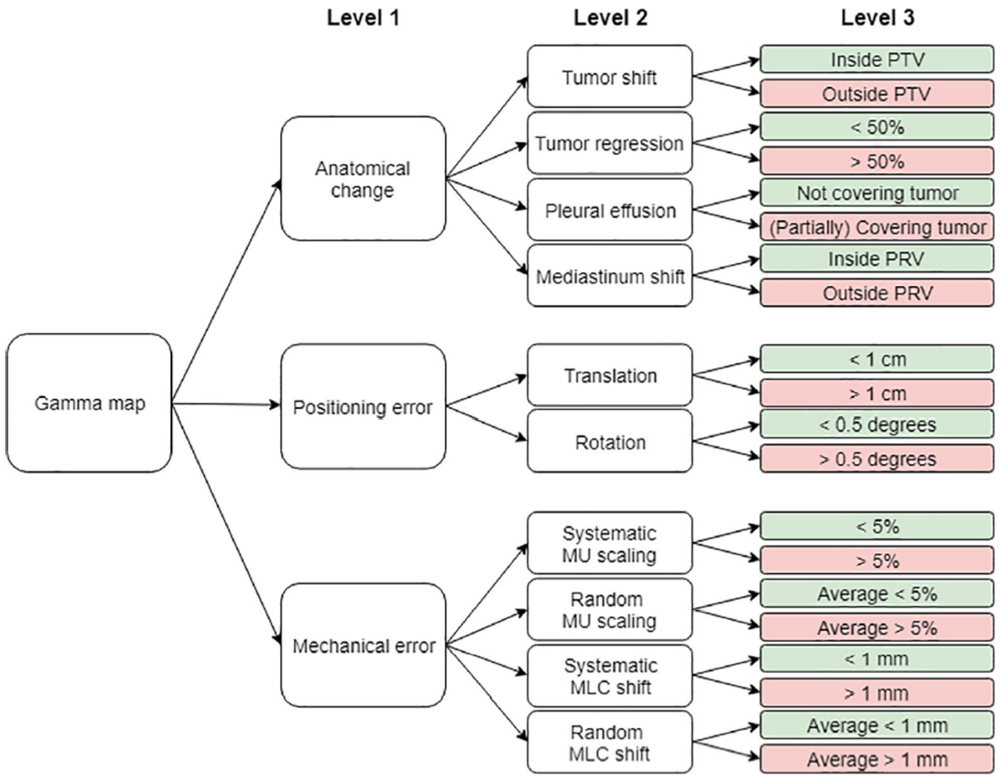
Frank Verhaegen*

Establishing action threshold for change in patient anatomy using EPID gamma analysis and PTV coverage for head and neck radiotherapy treatment

Ophélie Piron[a)], Nicolas Varfalvy, and Louis Archambault
Department de Radio-oncologie, CHU de Quebec, 11 Côte du Palais, Quebec, QC, Canada
Université Laval, 2325 Rue de l'Université, Ville de Québec, QC G1V 0A6, Canada

In vivo verification – Error identification

- Determine which error occurred
- Convolutional neural networks
  - To classify error type and magnitude
- Autoencoder U-Net
  - To distinguish between generic and plan-specific deviations



Deep learning-based tools to distinguish plan-specific from generic deviations in EPID-based in vivo dosimetry

Igor Olaciregui-Ruiz | Rita Simões | Sonke Jan-Jakob

Identification of treatment error types for lung cancer patients using convolutional neural networks and EPID dosimetry

Cecile J.A. Wolfs, Richard A.M. Canters, Frank Verhaegen*

Analysis of EPID Transmission Fluence Maps Using Machine Learning Models and CNN for Identifying Position Errors in the Treatment of GO Patients

Guyu Dai[1†], Xiangbin Zhang[1†], Wenjie Liu[2], Zhibin Li[1], Guangyu Wang[1], Yaxin Liu[1], Qing Xiao[1], Lian Duan[1], Jing Li[1], Xinyu Song[1], Guangjun Li[1] and Sen Bai[1*]*

A 3D transfer learning approach for identifying multiple simultaneous errors during radiotherapy

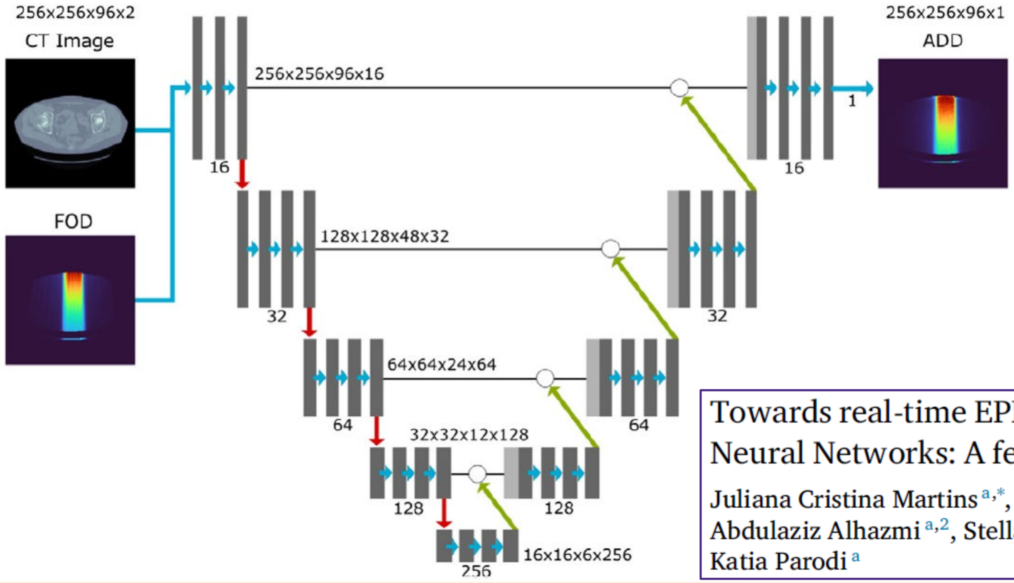
Kars van den Berg[1], Cecile J A Wolfs[2,*] and Frank Verhaegen[2]

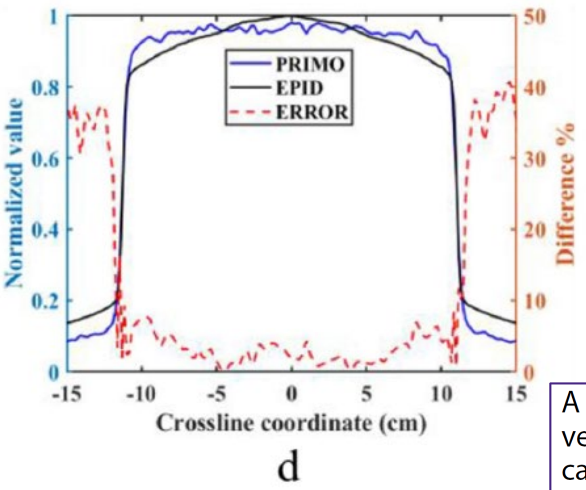
Radiomics analysis of EPID measurements for patient positioning error detection in thyroid associated ophthalmopathy radiotherapy

Xiangbin Zhang[1], Guyu Dai[1], Renming Zhong, Li Zhou, Qing Xiao, Xuetao Wang, Jialu Lai, Jianling Zhao, Guangjun Li[*], Sen Bai[*]

In vivo verification – I2I

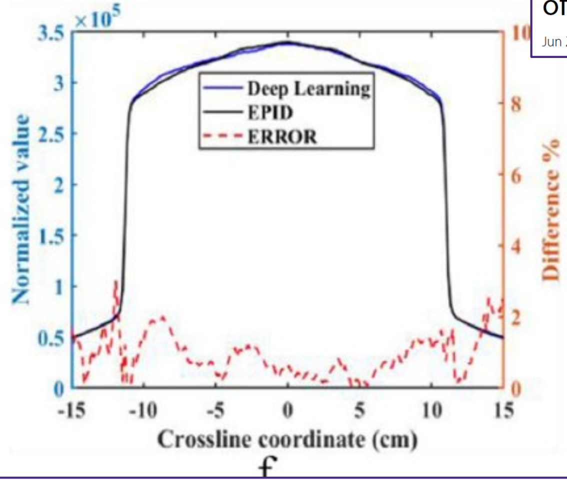
- Improve or convert (dose) measurements performed during treatment
- U-Net
  - To predict 2D or 3D dose distributions from EPID measurements





A feasibility study for in vivo treatment verification of IMRT using Monte Carlo dose calculation and deep learning-based modelling of EPID detector response

Jun Zhang[1*], Zhibiao Cheng[1], Ziting Fan[1], Qilin Zhang[2], Xile Zhang[2], Ruijie Yang[2] and Junhai Wen[1*]



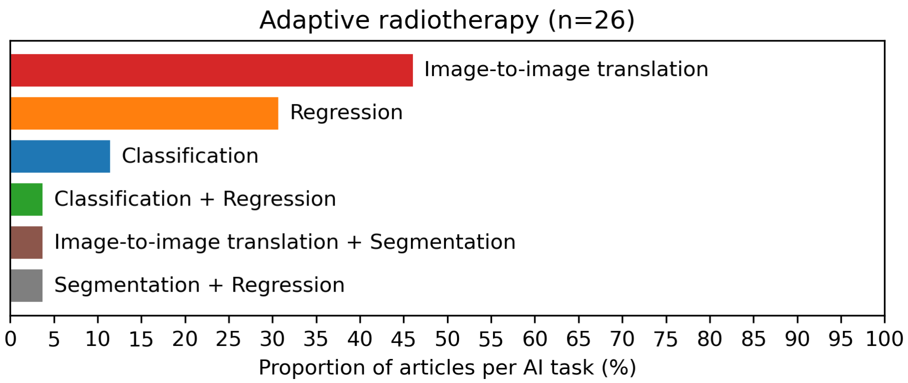
Towards real-time EPID-based 3D in vivo dosimetry for IMRT with Deep Neural Networks: A feasibility study

Juliana Cristina Martins [a,*], Joscha Maier [b], Chiara Gianoli [a], Sebastian Neppl [c,1], George Dedes [a], Abdulaziz Alhazmi [a,2], Stella Veloza [a,3], Michael Reiner [c], Claus Belka [c], Marc Kachelrieß [b,d], Katia Parodi [a]

Adaptive radiotherapy (ART)

- Monitoring inter-fractional changes based on imaging and assessing these changes with the purpose of adapting the treatment plan

- Image-to-image translation tasks
  - CBCT to CT conversion
- Regression and classification tasks
  - Prediction of anatomical changes

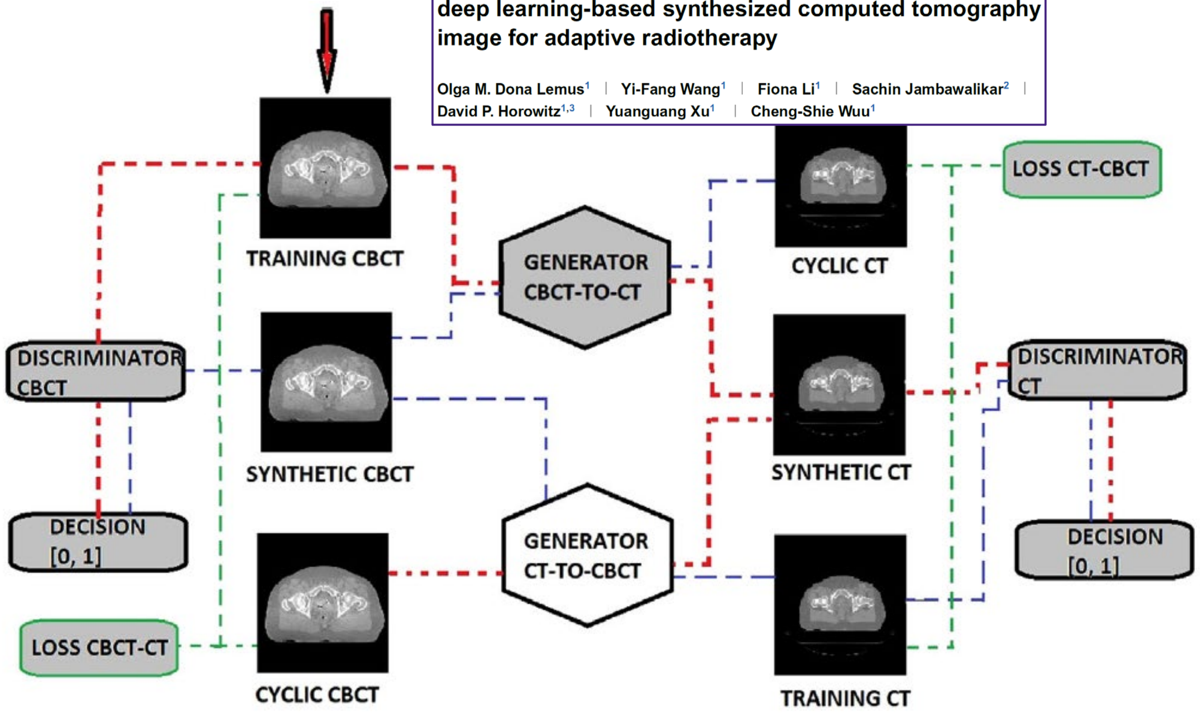


ART – I2I

- Improve image quality for improved assessment of changes
- CycleGAN
  - To convert CBCT to CT
- Other applications
  - CBCT correction, image registration

Dosimetric assessment of patient dose calculation on a deep learning-based synthesized computed tomography image for adaptive radiotherapy

Olga M. Dona Lemus[1] | Yi-Fang Wang[1] | Fiona Li[1] | Sachin Jambawalikar[2] | David P. Horowitz[1,3] | Yuanguang Xu[1] | Cheng-Shie Wuu[1]



A convolutional neural network for estimating cone-beam CT intensity deviations from virtual CT projections

Branimir Rusanov[1], Martin A Ebert[1,2], Godfrey Mukwada[2], Ghulam Mubashar Hassan[1] and Mahsheed Sabet[1,2]

Seq2Morph: A deep learning deformable image registration algorithm for longitudinal imaging studies and adaptive radiotherapy

Donghoon Lee | Sadegh Alam | Jue Jiang | Laura Cervino | Yu-Chi Hu | Pengpeng Zhang

Inter-fraction deformable image registration using unsupervised deep learning for CBCT-guided abdominal radiotherapy

Huiqiao Xie[1], Yang Lei, Yabo Fu[1,2], Tonghe Wang[1,2], Justin Roper[1], Jeffrey D Bradley[1], Pretesh Patel[1], Tian Liu[1,3] and Xiaofeng Yang[1,*]

CBCT correction using a cycle-consistent generative adversarial network and unpaired training to enable photon and proton dose calculation

Christopher Kurz[1,2,3,5], Matteo Maspero[2], Mark H F Savenije[2], Guillaume Landry[1,3], Florian Kamp[1], Marco Pinto[3], Minglun Li[1], Katia Parodi[3], Claus Belka[1,4] and Cornelis A T van den Berg[2]

Generating synthesized computed tomography (CT) from cone-beam computed tomography (CBCT) using CycleGAN for adaptive radiation therapy

Xiao Liang[1,2], Liyuan Chen[1,2], Dan Nguyen[1], Zhiguo Zhou[1], Xuejun Gu[1], Ming Yang[1], Jing Wang[1] and Steve Jiang[1]

A single neural network for cone-beam computed tomography-based radiotherapy of head-and-neck, lung and breast cancer

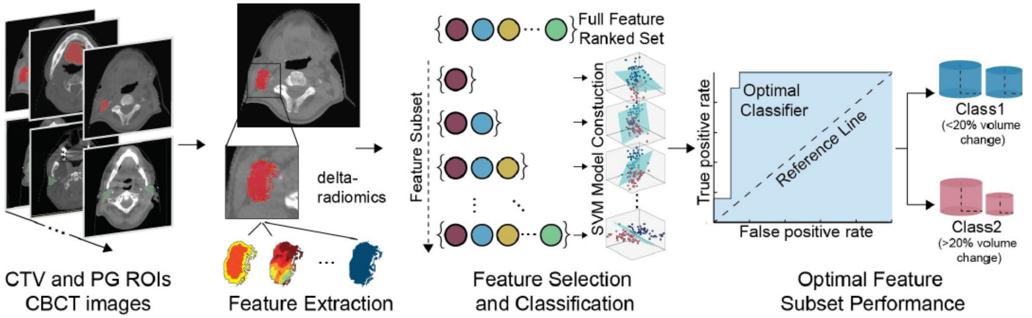
Matteo Maspero[a,b,*], Antonetta C. Houweling[a], Mark H.F. Savenije[a,b], Tristan C.F. van Heijst[a], Joost J.C. Verhoeff[a], Alexis N.T.J. Kotte[a], Cornelis A.T. van den Berg[a,b]

Transformer CycleGAN with uncertainty estimation for CBCT based synthetic CT in adaptive radiotherapy

Branimir Rusanov[1,2,3,*], Ghulam Mubashar Hassan[1], Mark Reynolds[1], Mahsheed Sabet[1,2,3], Pejman Rowshanfarzad[1,3], Nicholas Bucknell[2], Suki Gill[2], Joshua Dass[2] and Martin Ebert[1,2,3,4,5]

ART – Prediction of changes

- Predict changes so patients can be monitored more closely
- Feature extraction & ML models
  - To predict volume changes
- DL models
  - To predict geometric or dosimetric changes based on full images

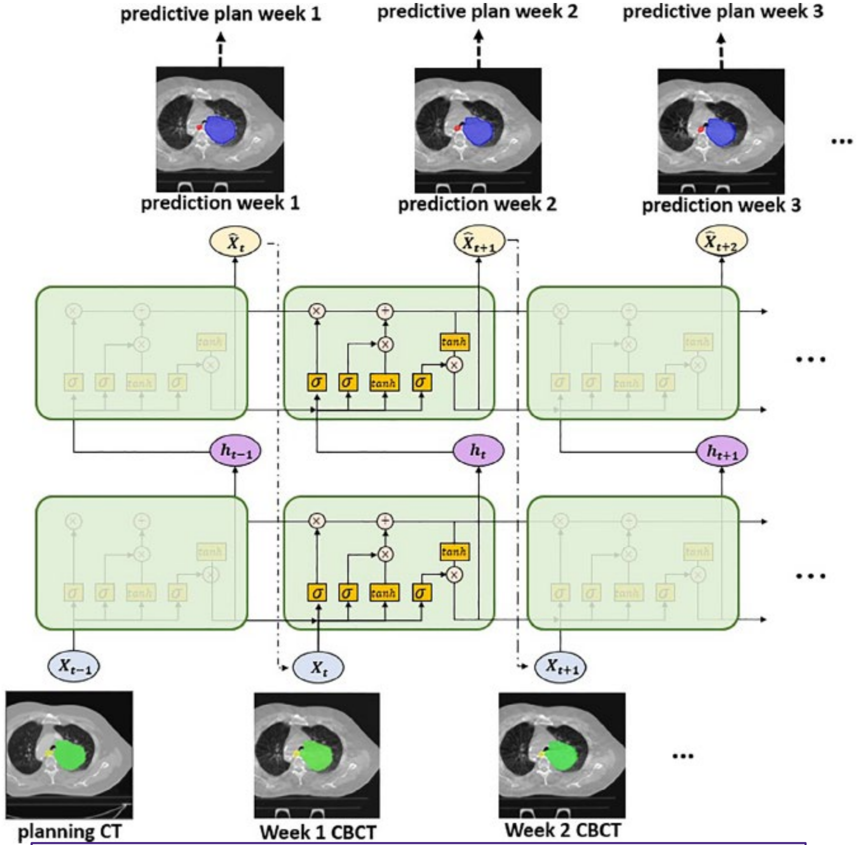


Early Prediction of Planning Adaptation Requirement Indication Due to Volumetric Alterations in Head and Neck Cancer Radiotherapy: A Machine Learning Approach

Vasiliki Iliadou [1,*], Ioannis Kakkos [1,2], Pantelis Karaiskos [3], Vassilis Kouloulias [4], Kalliopi Platoni [4], Anna Zygogianni [5] and George K. Matsopoulos [1]

A prediction model for dosimetric-based lung adaptive radiotherapy

Chaoqiong Ma [1,2,#] | Zhen Tian [2,3,#] | Ruoxi Wang [1] | Zhongsu Feng [1] | Fan Jiang [1] | Qiaoqiao Hu [1] | Fang Yang [1,4] | Anhui Shi [1] | Hao Wu [1,5]



Deep learning driven predictive treatment planning for adaptive radiotherapy of lung cancer

Donghoon Lee [a], Yu-chi Hu [a], Licheng Kuo [a], Sadegh Alam [a], Ellen Yorke [a], Anyi Li [a], Andreas Rimner [b], Pengpeng Zhang [a,*]

Prediction of inter-fractional radiotherapy dose plans with domain translation in spatiotemporal embeddings

Andrei Svecic [a], David Roberge [b], Samuel Kadoury [a,c,*]

Dynamic stochastic deep learning approaches for predicting geometric changes in head and neck cancer

Julia M Pakela [1,2], Martha M Matuszak [2], Randall K Ten Haken [2], Daniel L McShan [2] and Issam El Naqa [1,2]

Predictive dose accumulation for HN adaptive radiotherapy

Donghoon Lee, Pengpeng Zhang, Saad Nadeem, Sadegh Alam, Jue Jiang, Amanda Caringi, Natasha Allgood, Michalis Aristophanous, James Mechalakos and Yu-Chi Hu

Purposes of AI for treatment verification

- Streamline workflows
  - Automated analysis of (measured) data
  - AI could mean a considerable leap forward in analyzing the complex multi-dimensional datasets common in RT treatment verification
  - Save time and resources, reduce human error

- Enhance precision and reliability
  - AI-based enhancement of imaging and dosimetry
  - Improve precision and reliability of data used for treatment verification

- Preemptive verification
  - Predictive models anticipate deviations and detect anomalies
  - Precautionary adjustments to maintain consistency of treatment delivery

Challenges and future research

- Multi-center validation
  - Needed to ensure generalizability and robustness
  - Not commonly taken into account in studies
  - No conclusive results from the multi-center studies that have been performed

- Integration of AI tools in clinical workflows
  - Complexities of regulatory approvals and clinical acceptance
  - Understanding of and trust in AI decisions is paramount
  - Need for XAI methods
    - XAI currently usually added as another layer on top of the AI model

Take-home messages

- AI has the potential to revolutionize RT treatment verification through improved efficiency, precision, and safety

- Continued development and integration of AI into RT treatment verification workflows hold great promise for enhancing RT treatment and thereby patient outcomes, underscoring the need for ongoing research, collaboration, and innovation

- Crucial to address the challenges of validation, implementation and explanation to fully realize the potential of AI for treatment verification in a clinical setting

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AI for treatment verification in photon external beam radiotherapy

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