

10-11
OTTOBRE
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DOVE L'INTELLIGENZA ARTIFICIALE STA DIVENTANDO REALTÀ: LA DIAGNOSTICA PER IMMAGINI

Lo stato dell'arte dell'intelligenza artificiale nella diagnostica

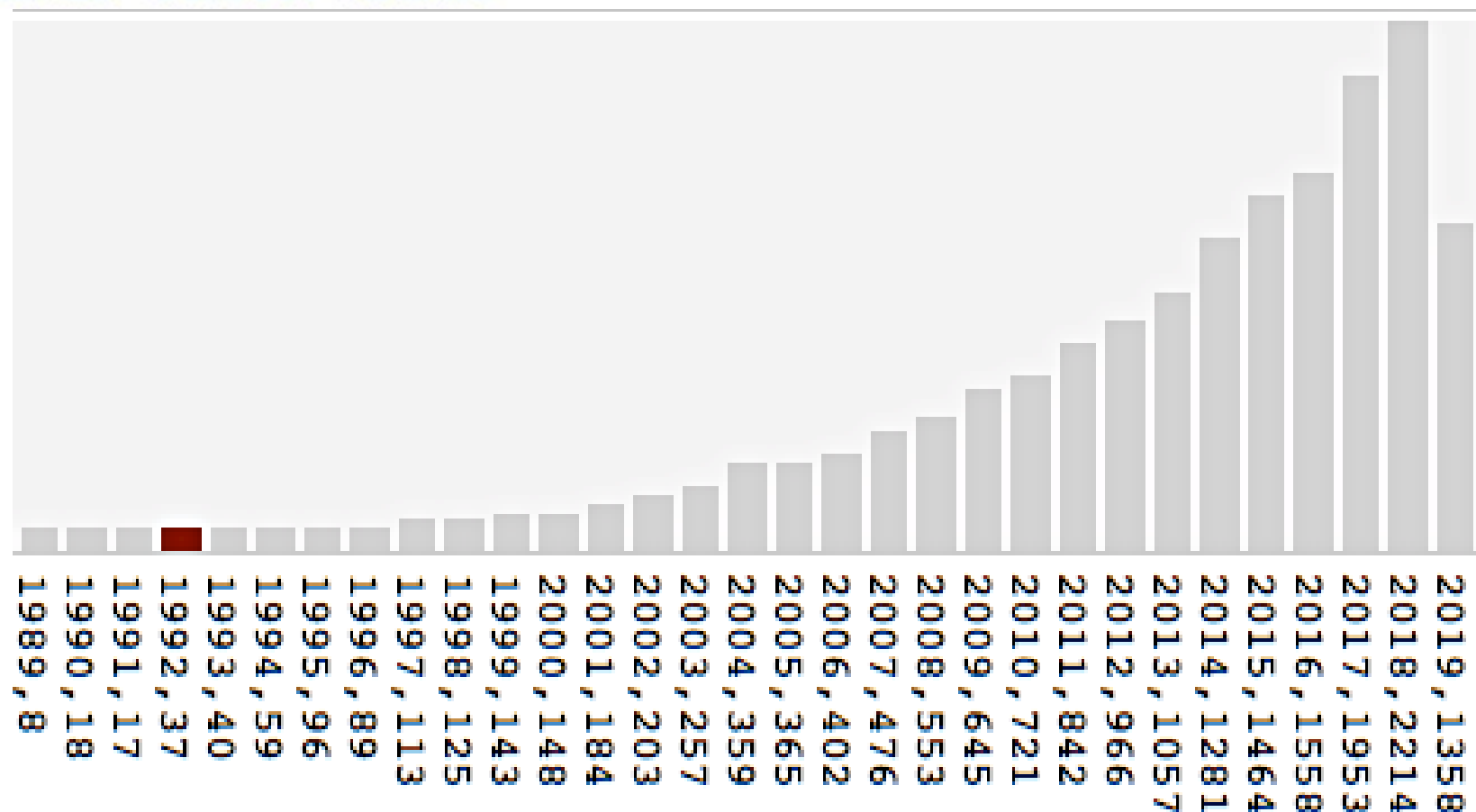
Claudio Maria Berzovini



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((neural network) OR (convolutional neural network)) AND ((radiology) OR (medical imaging))

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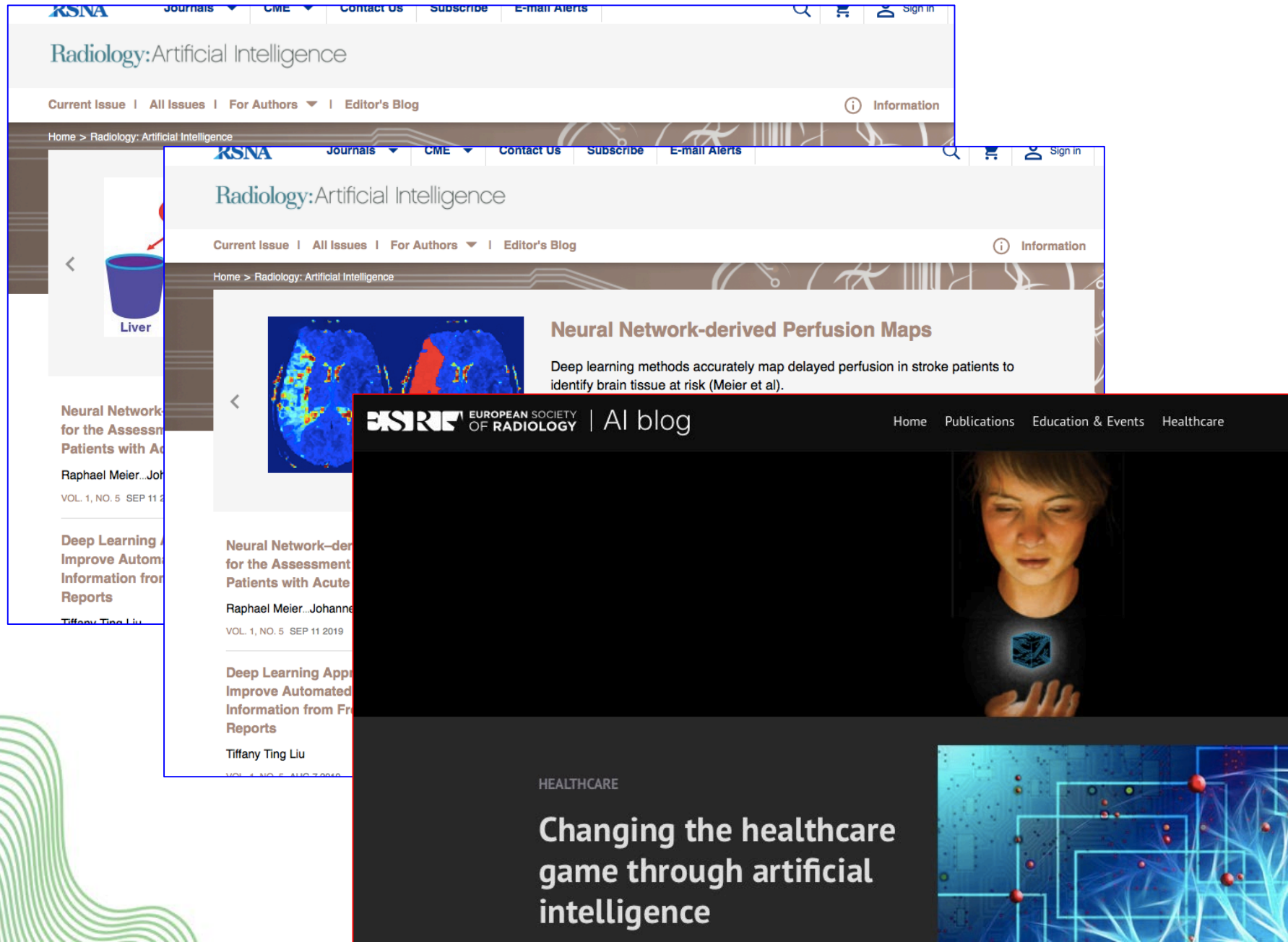


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Lunedì 30 Settembre 2019
Dalle 08.00 alle 18.00
Aula Magna - IRCCS Policlinico San Donato (MI)

Intelligenza artificiale in radiologia: istruzioni per l'uso



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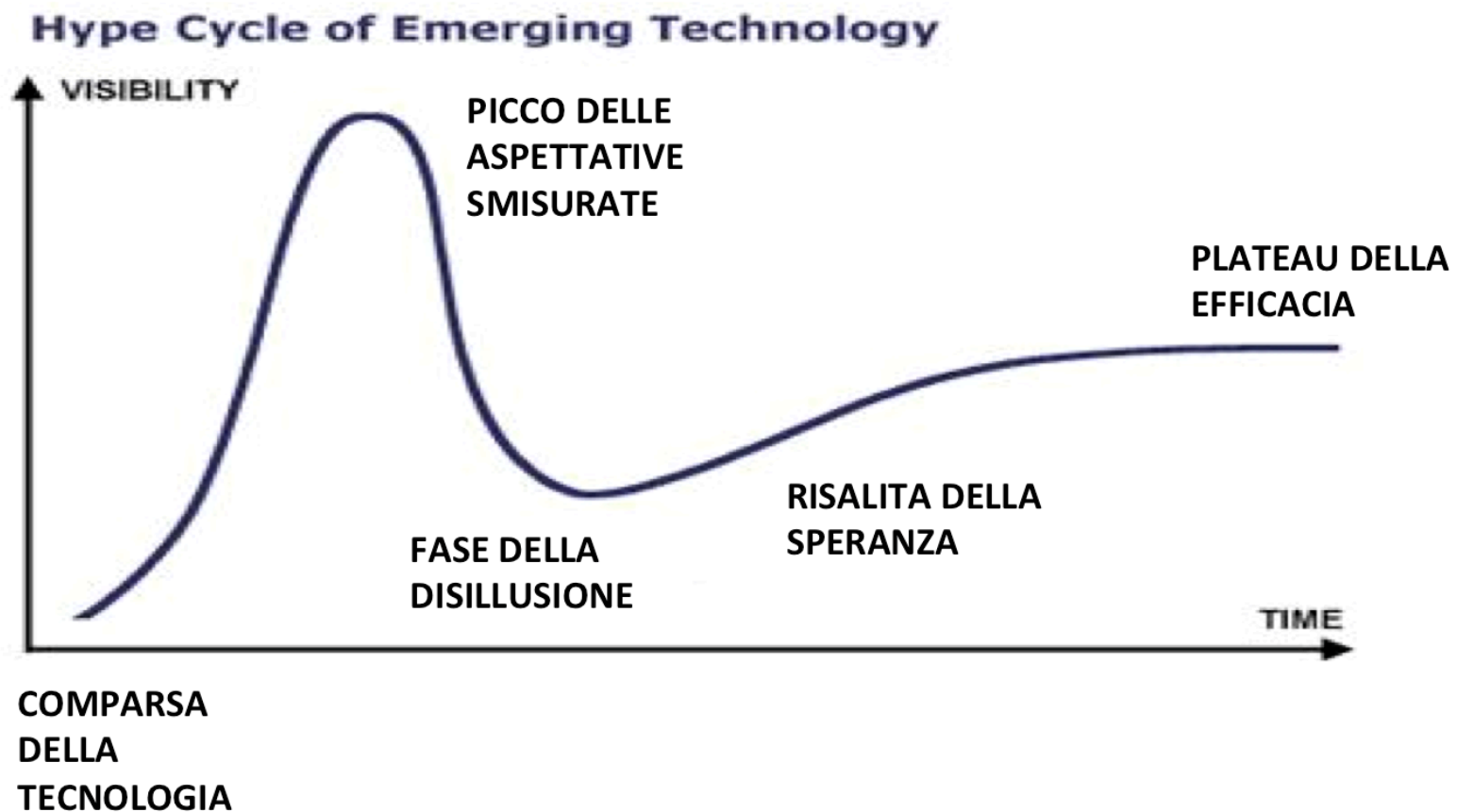
 **CONVEGNO NAZIONALE**
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Dott.ssa Francesca Coppola



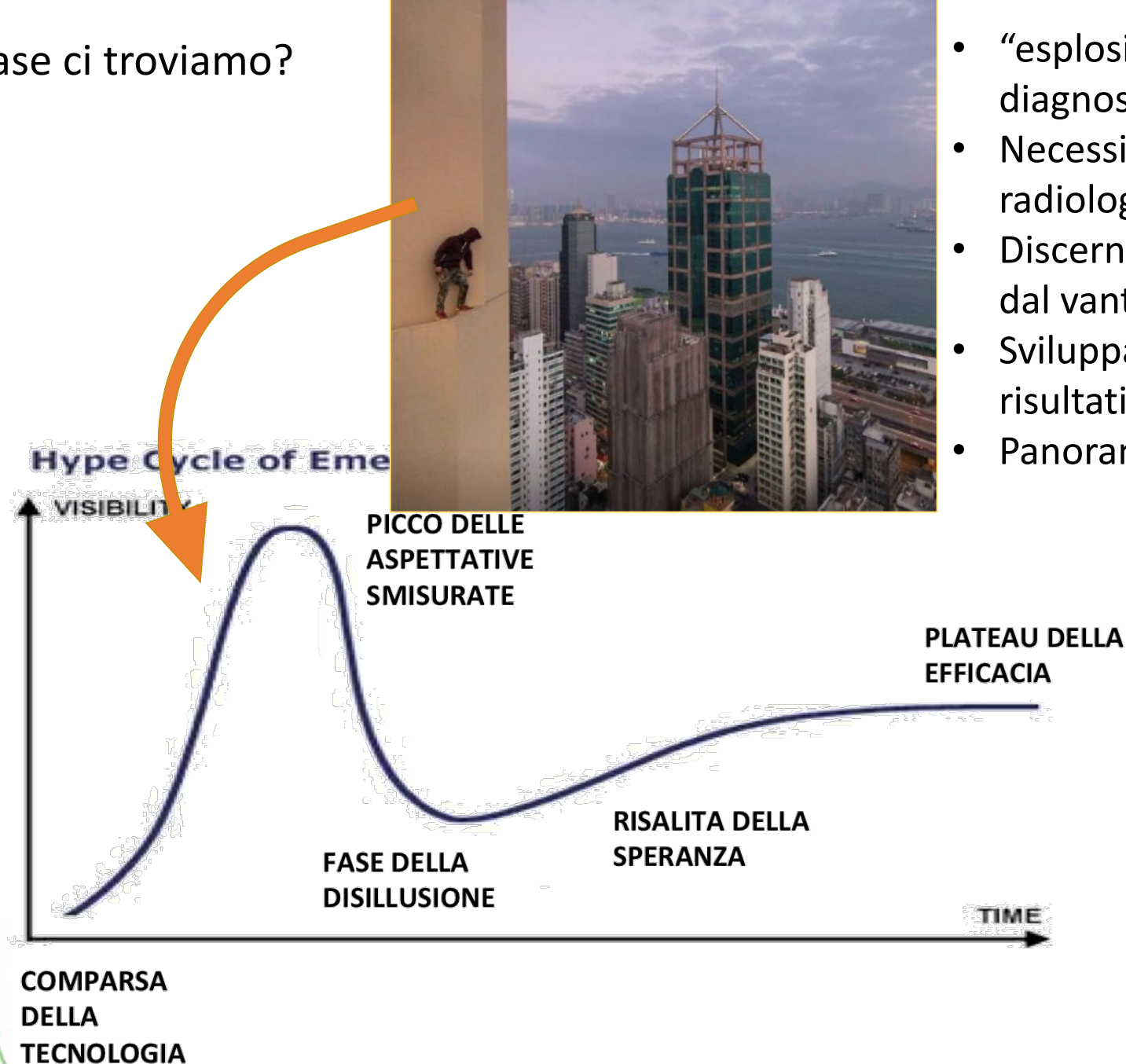
INTELLIGENZA ARTIFICIALE IN DIAGNOSTICA PER IMMAGINI

BOLOGNA 24 MAGGIO 2019
SEDE
Palazzo dell'Archiginnasio
Piazza Galvani 1 - Bologna

.. In che fase ci troviamo?



.. In che fase ci troviamo?



- “esplosione” di studi in ogni branca della diagnostica per immagini
- Necessità di integrare la cultura radiologica con la cultura informatica
- Discernere il miglioramento “tecnico” dal vantaggio clinico
- Sviluppare un senso critico di fronte a risultati “strabilianti”
- Panorama in continuo mutamento



E lo stato dell'arte?

Forse è meglio fare qualche esempio..

- Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio
- Identificare i reperti patologici
- Indicare gli esami che necessitano di refertazione in tempi brevi
- Caratterizzare le lesioni
- Semplificare l'elaborazione delle immagini e le misurazioni

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Deep Learning Enables Reduced Gadolinium Dose for Contrast-Enhanced Brain MRI

1

Enhao Gong, MS ^{1,2*} John M. Pauly, PhD,¹ Max Wintermark, MD,² and Greg Zaharchuk, PhD, MD²

Background: There are concerns over gadolinium deposition from gadolinium-based contrast agents (GBCA) administration.

Purpose: To reduce gadolinium dose in contrast-enhanced brain MRI using a deep learning method.

Study type: Retrospective, crossover.

Population: Sixty patients receiving clinically indicated contrast-enhanced brain MRI.

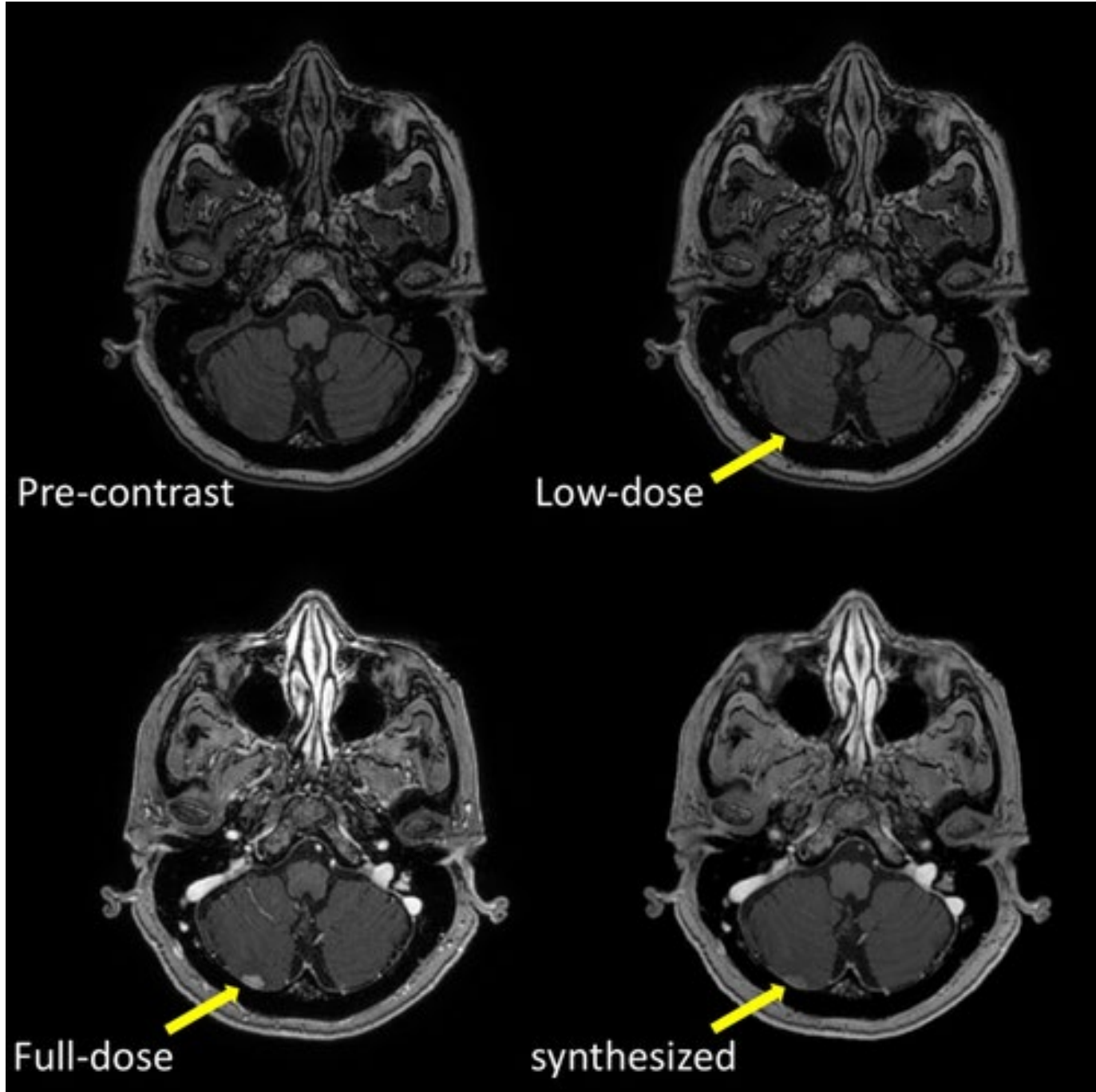
Sequence: 3D T₁-weighted inversion-recovery prepped fast-spoiled-gradient-echo (IR-FSPGR) imaging was acquired at both 1.5T and 3T. In 60 brain MRI exams, the IR-FSPGR sequence was obtained under three conditions: precontrast, postcontrast images with 10% low-dose (0.01mmol/kg) and 100% full-dose (0.1 mmol/kg) of gadobenate dimeglumine. We trained a deep learning model using the first 10 cases (with mixed indications) to approximate full-dose images from the precontrast and low-dose images. Synthesized full-dose images were created using the trained model in two test sets: 20 patients with mixed indications and 30 patients with glioma.

Assessment: For both test sets, low-dose, true full-dose, and the synthesized full-dose postcontrast image sets were compared quantitatively using peak-signal-to-noise-ratios (PSNR) and structural-similarity-index (SSIM). For the test set comprised of 20 patients with mixed indications, two neuroradiologists scored blindly and independently for the three postcontrast image sets, evaluating image quality, motion-artifact suppression, and contrast enhancement compared with precontrast images.

Statistical Analysis: Results were assessed using paired t-tests and noninferiority tests.

Results: The proposed deep learning method yielded significant ($n = 50$, $P < 0.001$) improvements over the low-dose images (>5 dB PSNR gains and $>11.0\%$ SSIM). Ratings on image quality ($n = 20$, $P = 0.003$) and contrast enhancement ($n = 20$, $P < 0.001$) were significantly increased. Compared to true full-dose images, the synthesized full-dose images have a slight but not significant reduction in image quality ($n = 20$, $P = 0.083$) and contrast enhancement ($n = 20$, $P = 0.068$). Slightly better ($n = 20$, $P = 0.039$) motion-artifact suppression was noted in the synthesized images. The non-inferiority test rejects the inferiority of the synthesized to true full-dose images for image quality (95% CI: -14 – 9%), artifacts suppression (95% CI: -5 – 20%), and contrast enhancement (95% CI: -13 – 6%).

Data Conclusion: With the proposed deep learning method, gadolinium dose can be reduced 10-fold while preserving contrast information and avoiding significant image quality degradation.



Pre-contrast

Low-dose

Full-dose

synthesized

Pre-contrast

Full-dose

synthesized

- **Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio**
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- Semplificare l'elaborazione delle immagini e le misurazioni



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ARTICLE OPEN

Advanced machine learning in action: identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration

Mohammad R. Arbabshirani¹, Brandon K. Fornwalt^{1,2}, Gino J. Mongelluzzo¹, Jonathan D. Suever^{1,2}, Brandon D. Geise¹, Aalpen A. Patel^{1,2} and Gregory J. Moore¹

Intracranial hemorrhage (ICH) requires prompt diagnosis to optimize patient outcomes. We hypothesized that machine learning algorithms could automatically analyze computed tomography (CT) of the head, prioritize radiology worklists and reduce time to diagnosis of ICH. 46,583 head CTs (~2 million images) acquired from 2007–2017 were collected from several facilities across Geisinger. A deep convolutional neural network was trained on 37,074 studies and subsequently evaluated on 9499 unseen studies. The predictive model was implemented prospectively for 3 months to re-prioritize “routine” head CT studies as “stat” on realtime radiology worklists if an ICH was detected. Time to diagnosis was compared between the re-prioritized “stat” and “routine” studies. A neuroradiologist blinded to the study reviewed false positive studies to determine whether the dictating radiologist overlooked ICH. The model achieved an area under the ROC curve of 0.846 (0.837–0.856). During implementation, 94 of 347 “routine” studies were re-prioritized to “stat”, and 60/94 had ICH identified by the radiologist. Five new cases of ICH were identified, and median time to diagnosis was significantly reduced ($p < 0.0001$) from 512 to 19 min. In particular, one outpatient with vague symptoms on anti-coagulation was found to have an ICH which was treated promptly with reversal of anticoagulation, resulting in a good clinical outcome. Of the 34 false positives, the blinded over-reader identified four probable ICH cases overlooked in original interpretation. In conclusion, an artificial intelligence algorithm can prioritize radiology worklists to reduce time to diagnosis of new outpatient ICH by 96% and may also identify subtle ICH overlooked by radiologists. This demonstrates the positive impact of advanced machine learning in radiology workflow optimization.

npj Digital Medicine (2018)1:9; doi:10.1038/s41746-017-0015-z

Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study

Sasank Chilamkurthy, Rohit Ghosh, Swetha Tanamala, Mustafa Biviji, Norbert G Campeau, Vasantha Kumar Venugopal, Vidur Mahajan, Pooja Rao, Prashant Warier

Summary

Lancet 2018; 392: 2388–96

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See Comment page 2331

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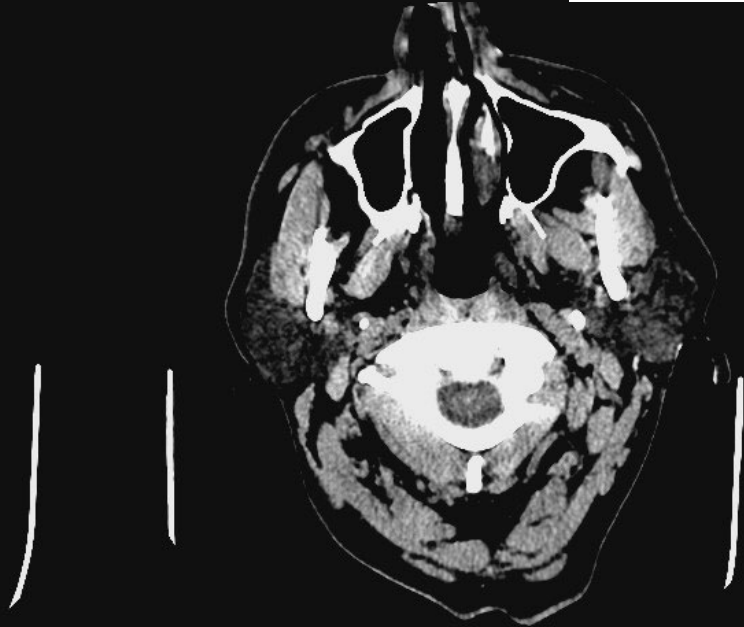
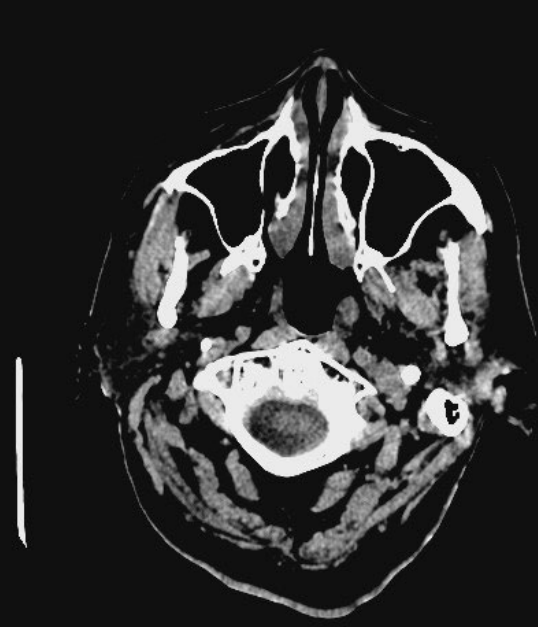
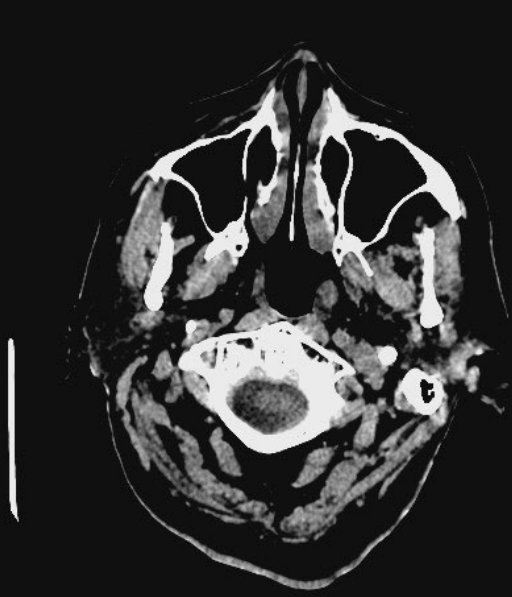
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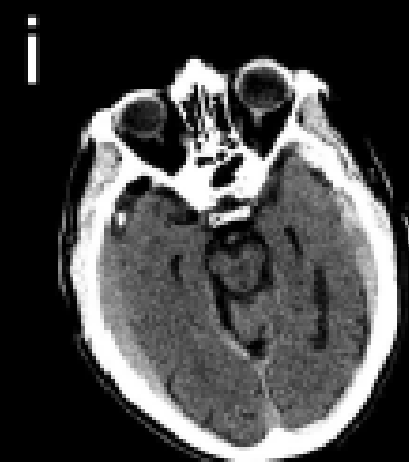
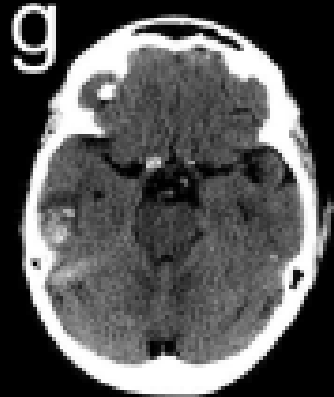
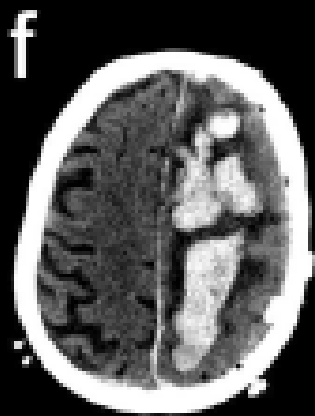
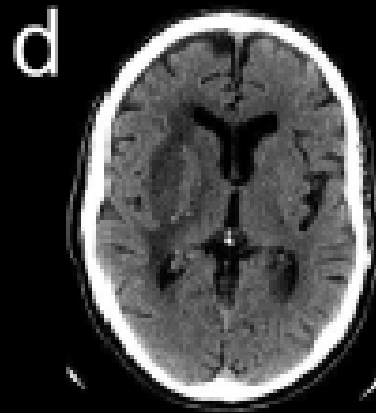
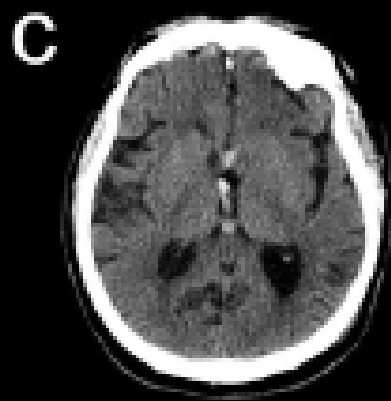
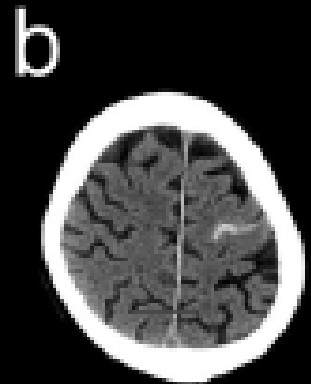
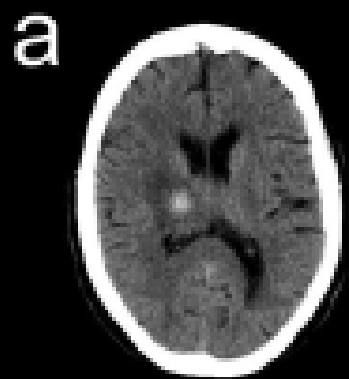
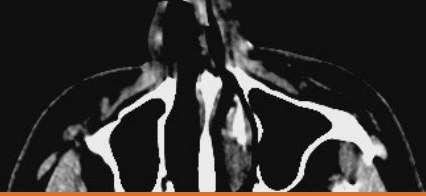
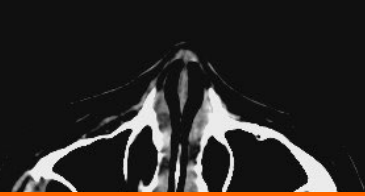
Background Non-contrast head CT scan is the current standard for initial imaging of patients with head trauma or stroke symptoms. We aimed to develop and validate a set of deep learning algorithms for automated detection of the following key findings from these scans: intracranial haemorrhage and its types (ie, intraparenchymal, intraventricular, subdural, extradural, and subarachnoid); calvarial fractures; midline shift; and mass effect.

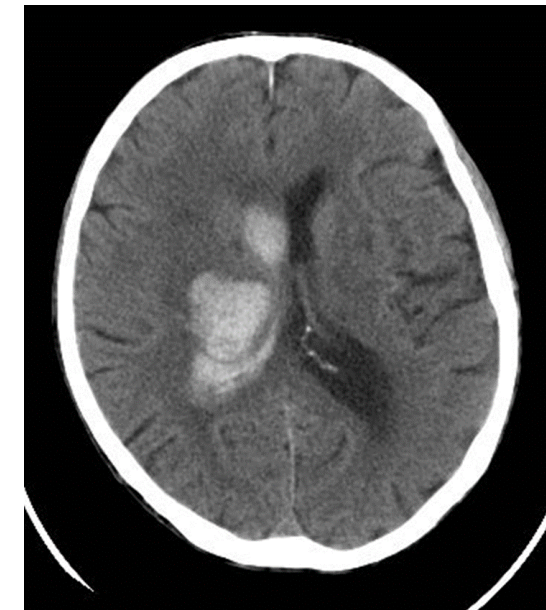
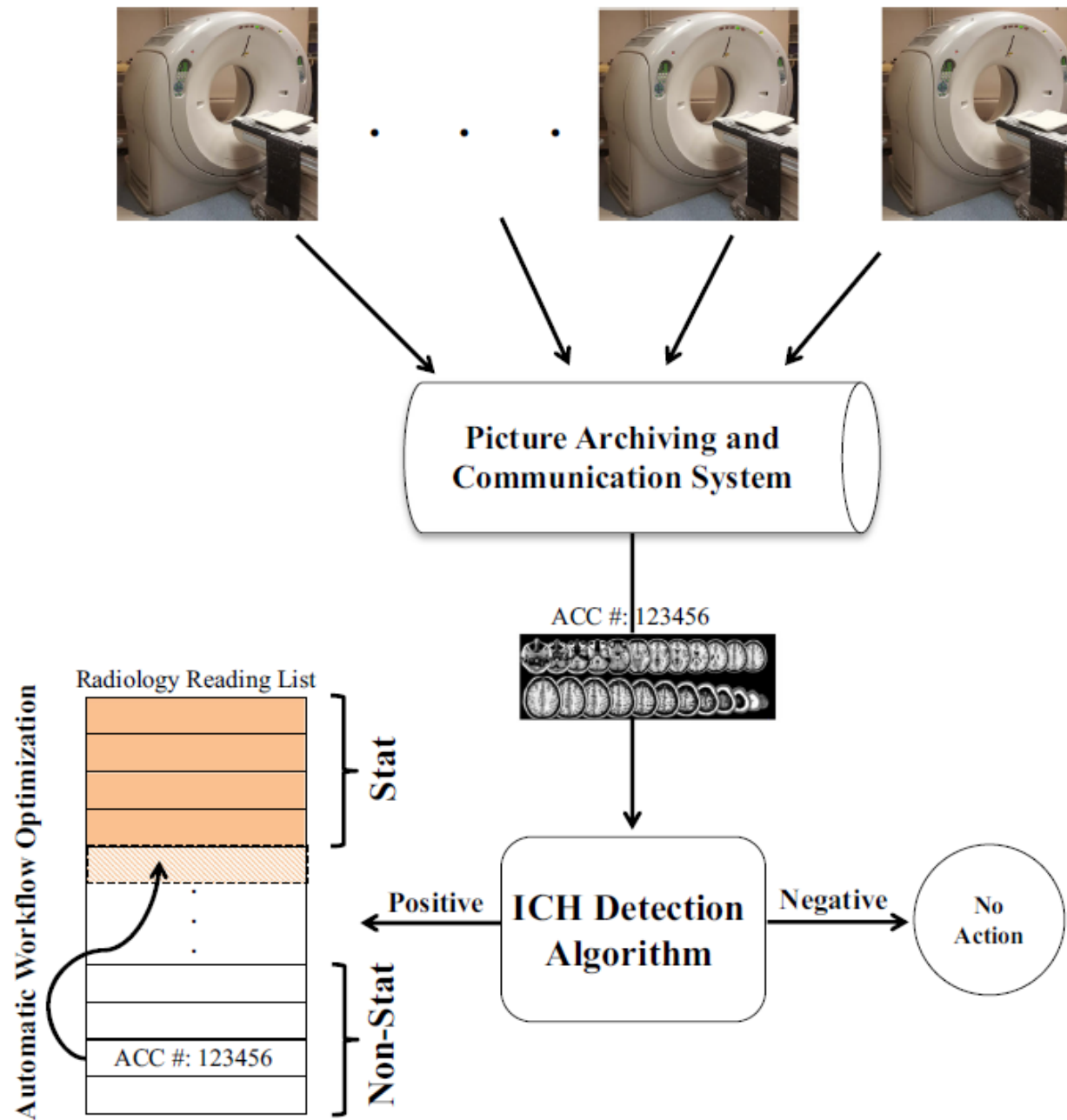
Methods We retrospectively collected a dataset containing 313 318 head CT scans together with their clinical reports from around 20 centres in India between Jan 1, 2011, and June 1, 2017. A randomly selected part of this dataset (Qure25k dataset) was used for validation and the rest was used to develop algorithms. An additional validation dataset (CQ500 dataset) was collected in two batches from centres that were different from those used for the development and Qure25k datasets. We excluded postoperative scans and scans of patients younger than 7 years. The original clinical radiology report and consensus of three independent radiologists were considered as gold standard for the Qure25k and CQ500 datasets, respectively. Areas under the receiver operating characteristic curves (AUCs) were primarily used to assess the algorithms.

Findings The Qure25k dataset contained 21 095 scans (mean age 43 years; 9030 [43%] female patients), and the CQ500 dataset consisted of 214 scans in the first batch (mean age 43 years; 94 [44%] female patients) and 277 scans in the second batch (mean age 52 years; 84 [30%] female patients). On the Qure25k dataset, the algorithms achieved an AUC of 0.92 (95% CI 0.91–0.93) for detecting intracranial haemorrhage (0.90 [0.89–0.91] for intraparenchymal, 0.96 [0.94–0.97] for intraventricular, 0.92 [0.90–0.93] for subdural, 0.93 [0.91–0.95] for extradural, and 0.90 [0.89–0.92] for subarachnoid). On the CQ500 dataset, AUC was 0.94 (0.92–0.97) for intracranial haemorrhage (0.95 [0.93–0.98], 0.93 [0.87–1.00], 0.95 [0.91–0.99], 0.97 [0.91–1.00], and 0.96 [0.92–0.99], respectively). AUCs on the Qure25k dataset were 0.92 (0.91–0.94) for calvarial fractures, 0.93 (0.91–0.94) for midline shift, and 0.86 (0.85–0.87) for mass effect, while AUCs on the CQ500 dataset were 0.96 (0.92–1.00), 0.97 (0.94–1.00), and 0.92 (0.89–0.95), respectively.

Interpretation Our results show that deep learning algorithms can accurately identify head CT scan abnormalities requiring urgent attention, opening up the possibility to use these algorithms to automate the triage process.









Picture Archiving and

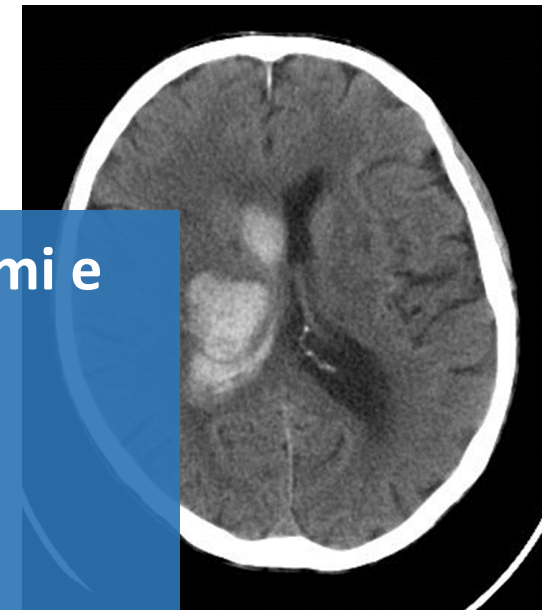
- Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio

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- Caratterizzare le lesioni

- Semplificare l'elaborazione delle immagini e le misurazioni



Automatic Workflow Optimization



Radiology Reading Room

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Development and Validation of Deep Learning–based Automatic Detection Algorithm for Malignant Pulmonary Nodules on Chest Radiographs

Ju Gang Nam, MD • Sunggyun Park, PhD* • Eui Jin Hwang, MD • Jong Hyuk Lee, MD • Kwang-Nam Jin, MD, PhD • Kun Young Lim, MD, PhD • Thienkai Huy Vu, MD, PhD • Jae Ho Sohn, MD • Sangheum Hwang, PhD • Jin Mo Goo, MD, PhD • Chang Min Park, MD, PhD*

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Development and Validation of a Deep Learning–Based Automated Detection Algorithm for Major Thoracic Diseases on Chest Radiographs

Eui Jin Hwang, MD; Sunggyun Park, MS; Kwang-Nam Jin, MD; Jung Im Kim, MD; So Young Choi, MD; Jong Hyuk Lee, MD; Jin Mo Goo, MD, PhD; Jaehong Aum, PhD; Jae-Joon Yim, MD; Julien G. Cohen, MD; Gilbert R. Ferretti, MD; Chang Min Park, MD, PhD; for the DLAD Development and Evaluation Group

Purpose: To develop and validate a deep learning–based automatic detection algorithm (DLAD) for malignant pulmonary nodules on chest radiographs and to compare its performance with physicians including thoracic radiologists.

Materials and Methods: For this retrospective study, DLAD was developed by using 43 292 chest radiographs (normal radiograph–to–nodule radiograph ratio, 34 067:9225) in 34 676 patients (healthy-to-nodule ratio, 30 784:3892; 19 230 men [mean age, 52.8 years; age range, 18–99 years]; 15 446 women [mean age, 52.3 years; age range, 18–98 years]) obtained between 2010 and 2015, which were labeled and partially annotated by 13 board-certified radiologists, in a convolutional neural network. Radiograph classification and nodule detection performances of DLAD were validated by using one internal and four external data sets from three South Korean hospitals and one U.S. hospital. For internal and external validation, radiograph classification and nodule detection performances of DLAD were evaluated by using the area under the receiver operating characteristic curve (AUROC) and jackknife alternative free-response receiver-operating characteristic (JAFROC) figure of merit (FOM), respectively. An observer performance test involving 18 physicians, including nine board-certified radiologists, was conducted by using one of the four external validation data sets. Performances of DLAD, physicians, and physicians assisted with DLAD were evaluated and compared.

Results: According to one internal and four external validation data sets, radiograph classification and nodule detection performances of DLAD were a range of 0.92–0.99 (AUROC) and 0.831–0.924 (JAFROC FOM), respectively. DLAD showed a higher AUROC and JAFROC FOM at the observer performance test than 17 of 18 and 15 of 18 physicians, respectively ($P < .05$), and all physicians showed improved nodule detection performances with DLAD (mean JAFROC FOM improvement, 0.043; range, 0.006–0.190; $P < .05$).

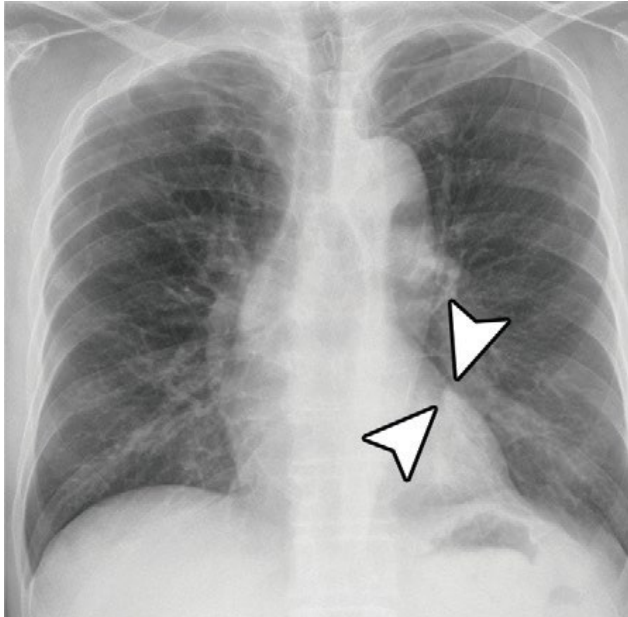
Conclusion: This deep learning–based automatic detection algorithm outperformed physicians in radiograph classification and nodule detection performance for malignant pulmonary nodules on chest radiographs, and it enhanced physicians' performances when used as a second reader.

DESIGN, SETTING, AND PARTICIPANTS This diagnostic study developed a deep learning-based algorithm using single-center data collected between November 1, 2016, and January 31, 2017. The algorithm was externally validated with multicenter data collected between May 1 and July 31, 2018. A total of 54 221 chest radiographs with normal findings from 47 917 individuals (21 556 men and 26 361 women; mean [SD] age, 51 [16] years) and 35 613 chest radiographs with abnormal findings from 14 102 individuals (8373 men and 5729 women; mean [SD] age, 62 [15] years) were used to develop the algorithm. A total of 486 chest radiographs with normal results and 529 with abnormal results (1 from each participant; 628 men and 387 women; mean [SD] age, 53 [18] years) from 5 institutions were used for external validation. Fifteen physicians, including nonradiology physicians board-certified radiologists, and thoracic radiologists, participated in observer performance testing. Data were analyzed in August 2018.

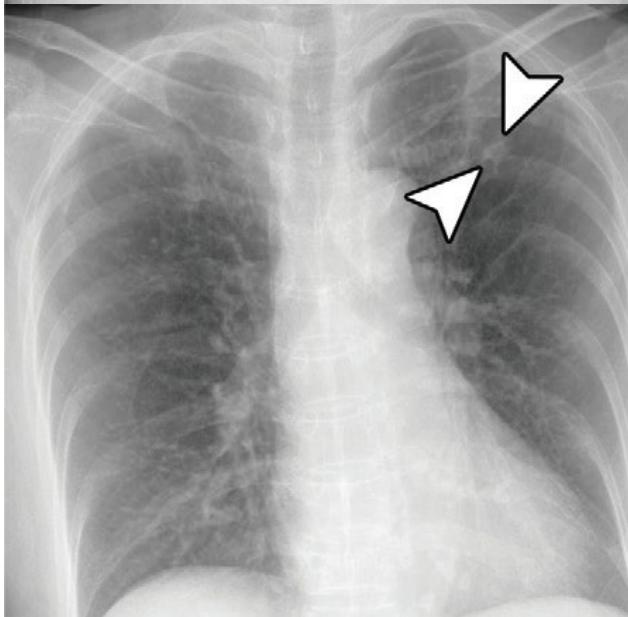
RESULTS The algorithm demonstrated a median (range) area under the curve of 0.979 (0.973-1.000) for image-wise classification and 0.972 (0.923-0.985) for lesion-wise localization; the algorithm demonstrated significantly higher performance than all 3 physician groups in both image-wise classification (0.983 vs 0.814-0.932; all $P < .005$) and lesion-wise localization (0.985 vs 0.781-0.907; all $P < .001$). Significant improvements in both image-wise classification (0.814-0.932 to 0.904-0.958; all $P < .005$) and lesion-wise localization (0.781-0.907 to 0.873-0.938; all $P < .001$) were observed in all 3 physician groups with assistance of the algorithm.

CONCLUSIONS AND RELEVANCE The algorithm consistently outperformed physicians, including thoracic radiologists, in the discrimination of chest radiographs with major thoracic diseases,

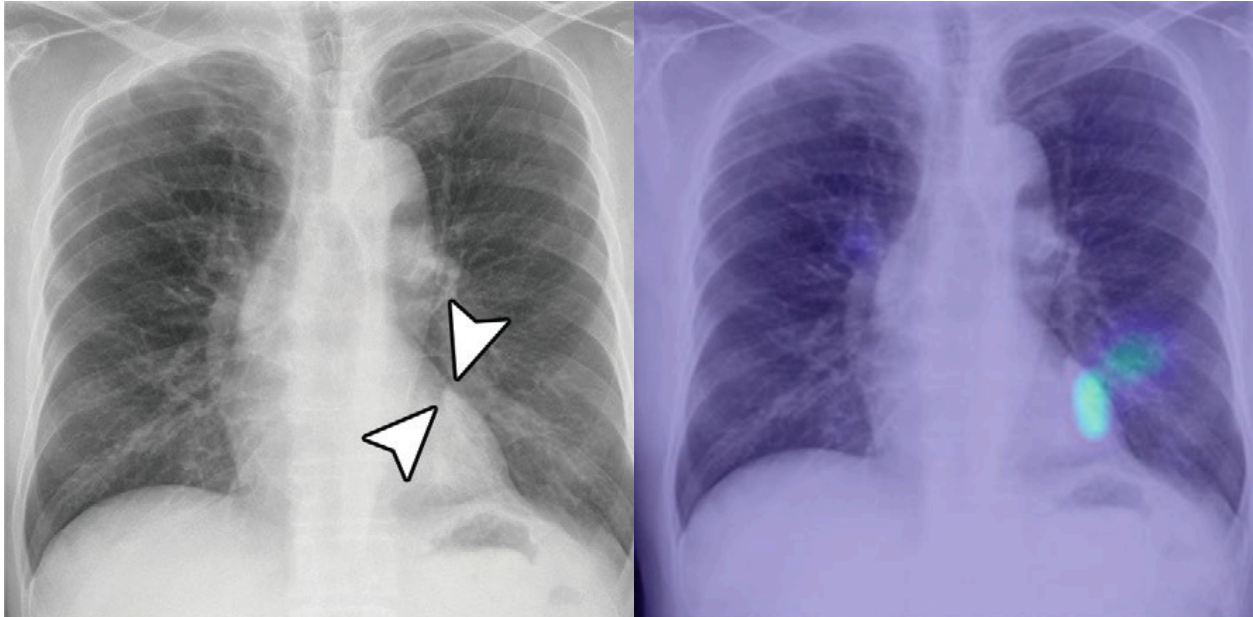
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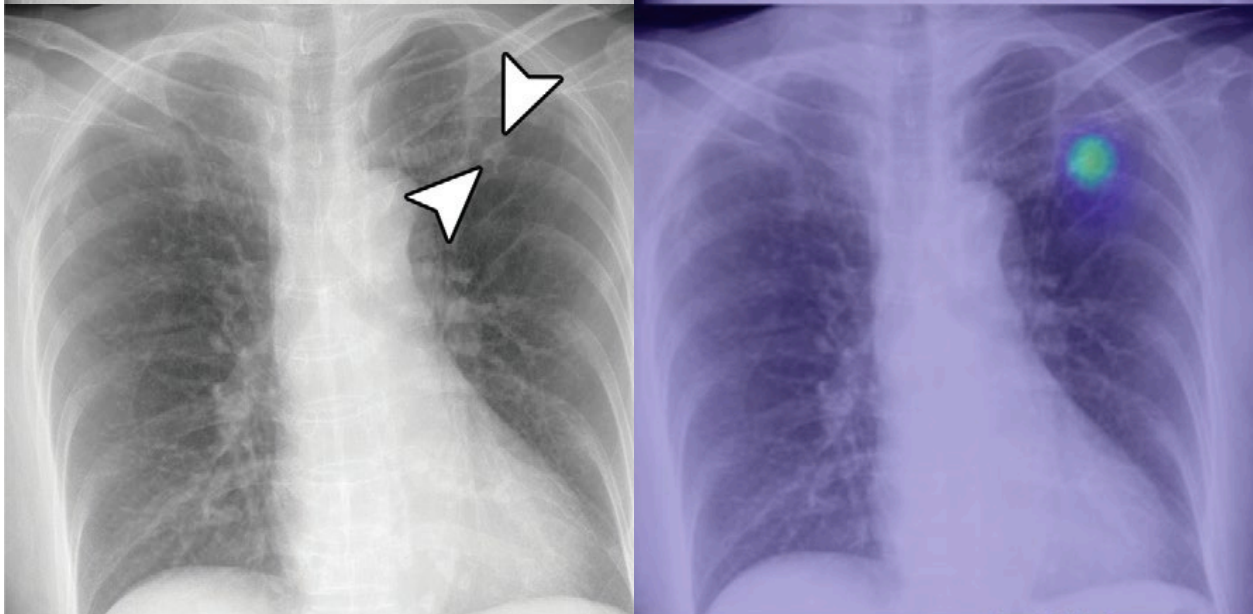
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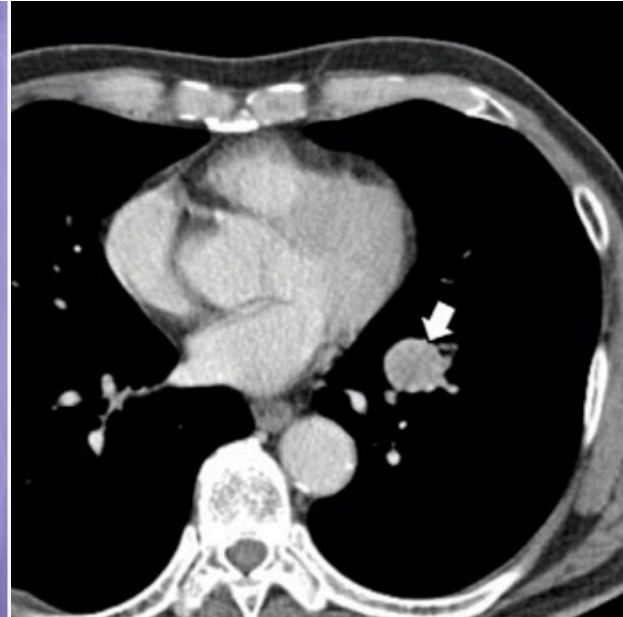
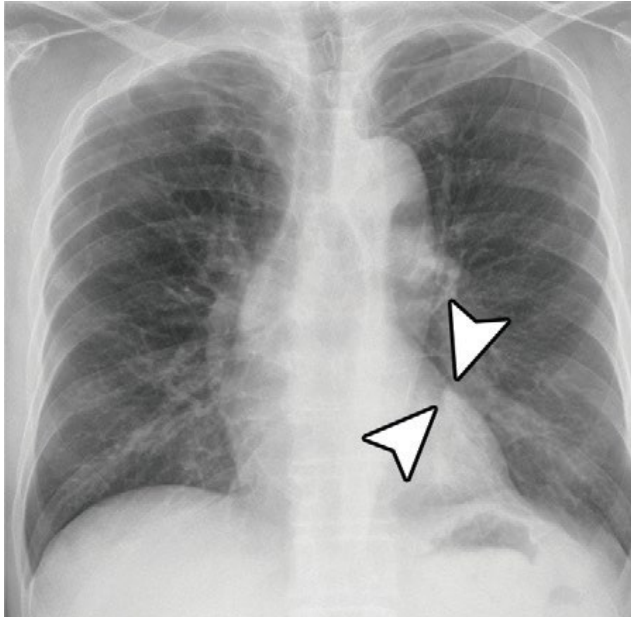
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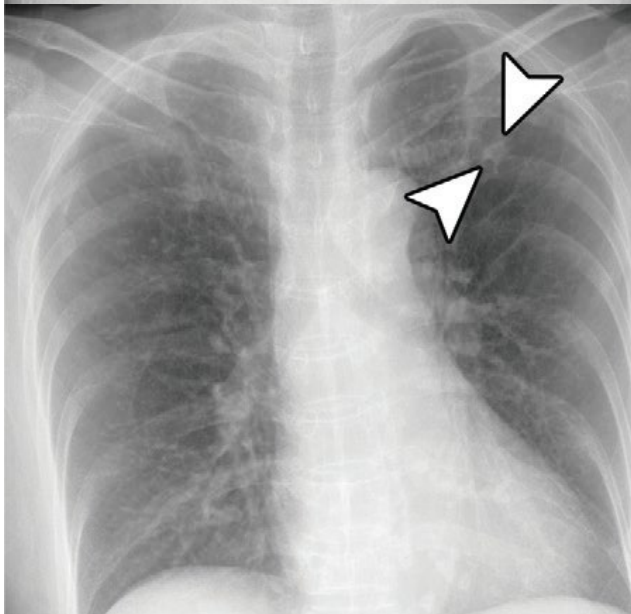
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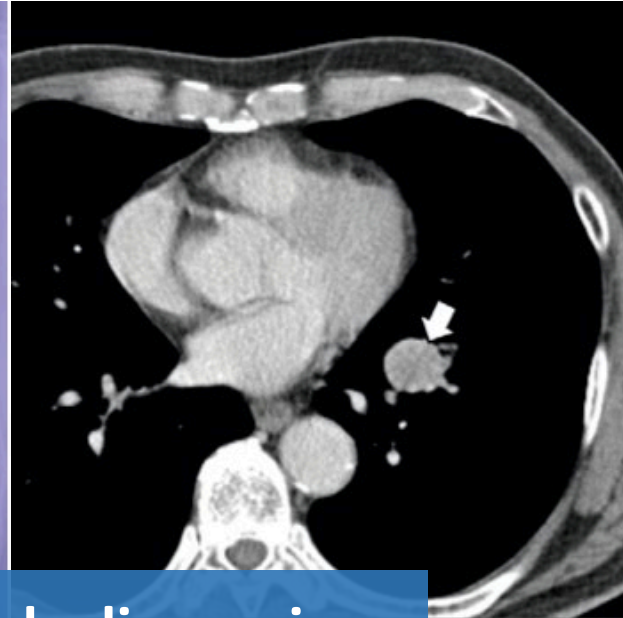
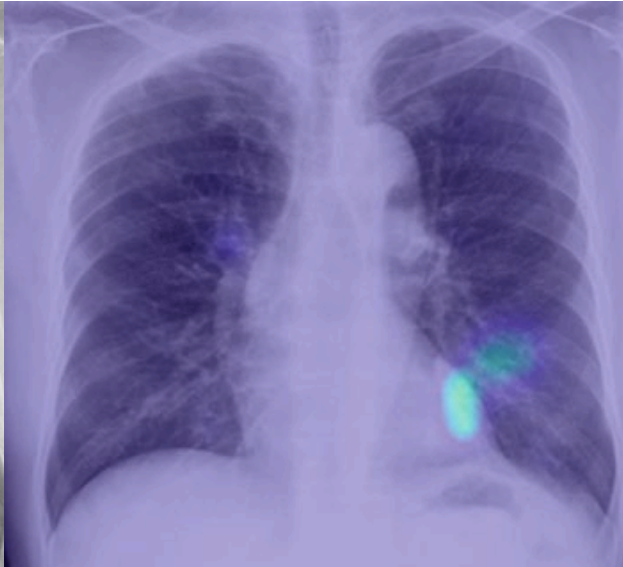
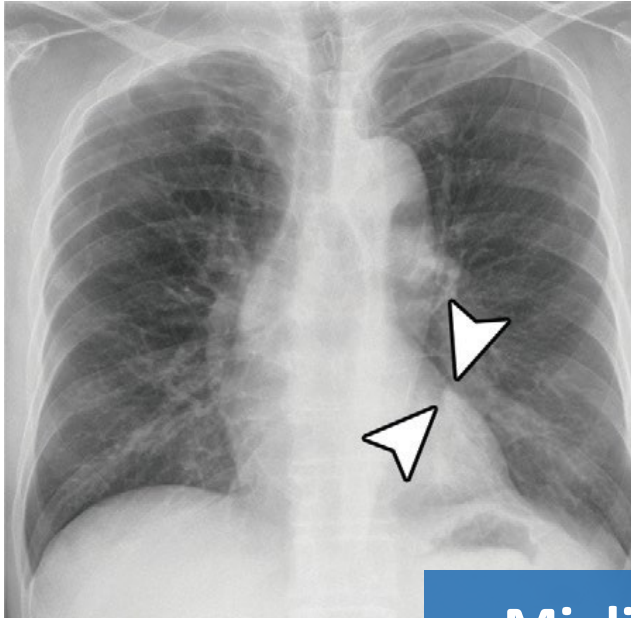
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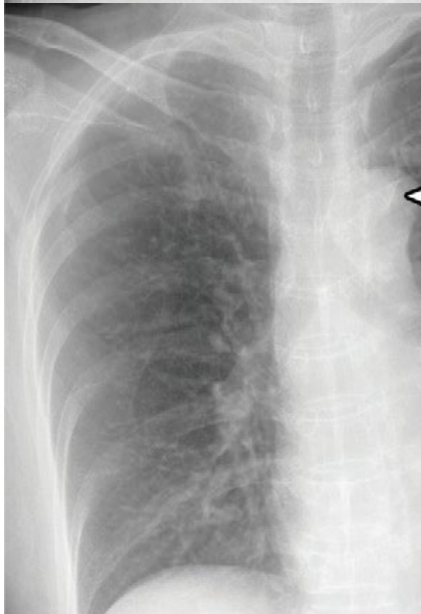
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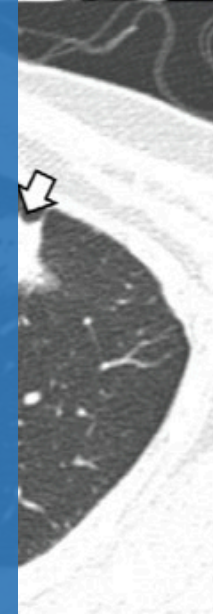
Caso 1



Caso 2



- Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio
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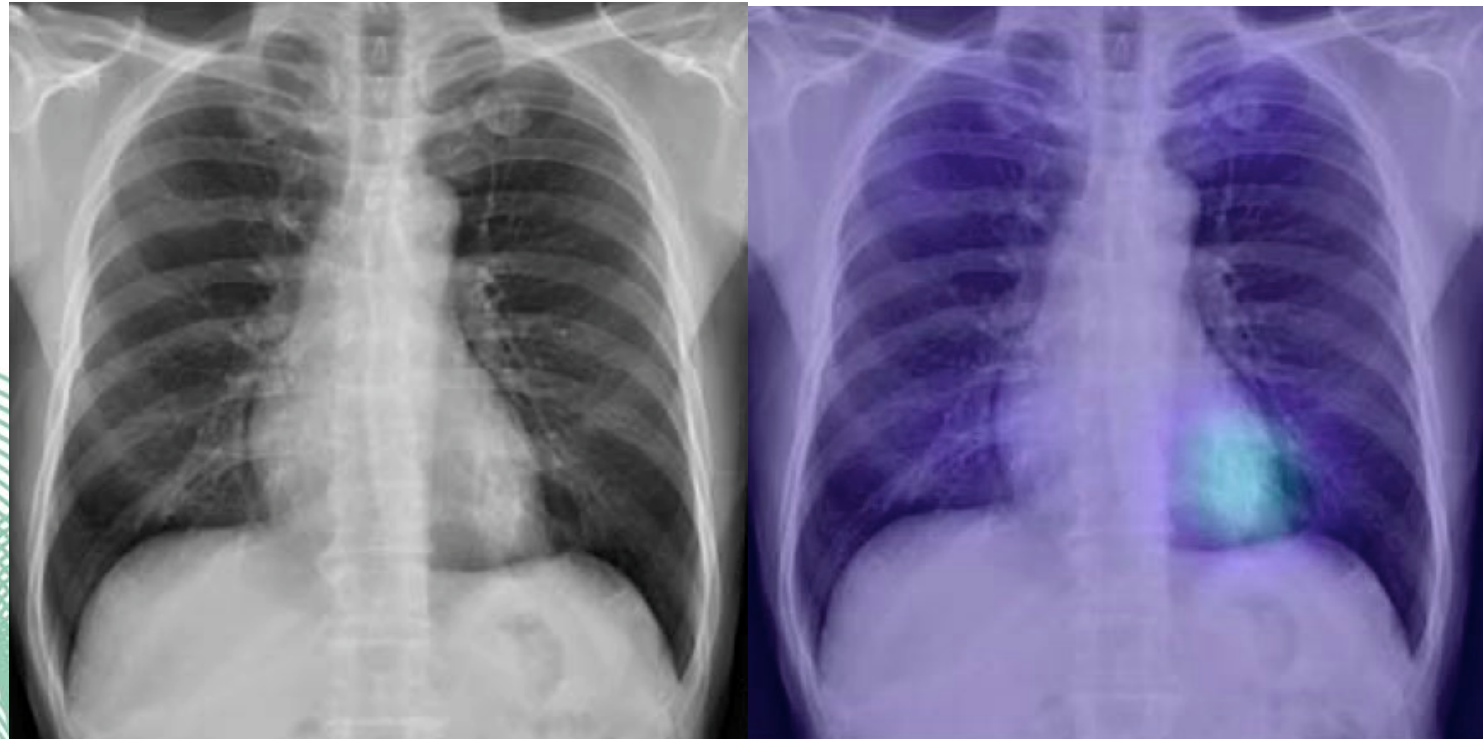
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DLAD had limitations. DLAD did not accurately detect small (< 1 cm; detection rate, 11% [two of 18]) and less conspicuous nodules. Because DLAD was trained under the supervision of labeling and annotation information provided by radiologists, the limitations of human perception are reflected in the DLAD performance. In the future, establishing an algorithm supervised by annotations on chest radiographs containing radiologically undetectable nodules by using CT as the reference standard is warranted. DLAD also did not detect any retrophrenic nodules, whereas thoracic radiologists detected 31% (11 of 36) retrophrenic nodules. Because DLAD was trained to focus on the lung area to prevent false-positive findings detected outside the lungs, DLAD was undertrained for the retrophrenic area.



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Deep learning for liver tumor diagnosis part I: development of a convolutional neural network classifier for multi-phasic MRI

Objectives To develop and validate a proof-of-concept convolutional neural network (CNN)–based deep learning system (DLS) that classifies common hepatic lesions on multi-phasic MRI.

Methods A custom CNN was engineered by iteratively optimizing the network architecture and training cases, finally consisting of three convolutional layers with associated rectified linear units, two maximum pooling layers, and two fully connected layers. Four hundred ninety-four hepatic lesions with typical imaging features from six categories were utilized, divided into training ($n=434$) and test ($n=60$) sets. Established augmentation techniques were used to generate 43,400 training samples. An Adam optimizer was used for training. Monte Carlo cross-validation was performed. After model engineering was finalized, classification accuracy for the final CNN was compared with two board-certified radiologists on an identical unseen test set.

Results The DLS demonstrated a 92% accuracy, a 92% sensitivity (Sn), and a 98% specificity (Sp). Test set performance in a single run of random unseen cases showed an average 90% Sn and 98% Sp. The average Sn/Sp on these same cases for radiologists was 82.5%/96.5%. Results showed a 90% Sn for classifying hepatocellular carcinoma (HCC) compared to 60%/70% for radiologists. For HCC classification, the true positive and false positive rates were 93.5% and 1.6%, respectively, with a receiver operating characteristic area under the curve of 0.992. Computation time per lesion was 5.6 ms.

Conclusion This preliminary deep learning study demonstrated feasibility for classifying lesions with typical imaging features from six common hepatic lesion types, motivating future studies with larger multi-institutional datasets and more complex imaging appearances.

Key Points

- Deep learning demonstrates high performance in the classification of liver lesions on volumetric multi-phasic MRI, showing potential as an eventual decision-support tool for radiologists.
- Demonstrating a classification runtime of a few milliseconds per lesion, a deep learning system could be incorporated into the clinical workflow in a time-efficient manner.

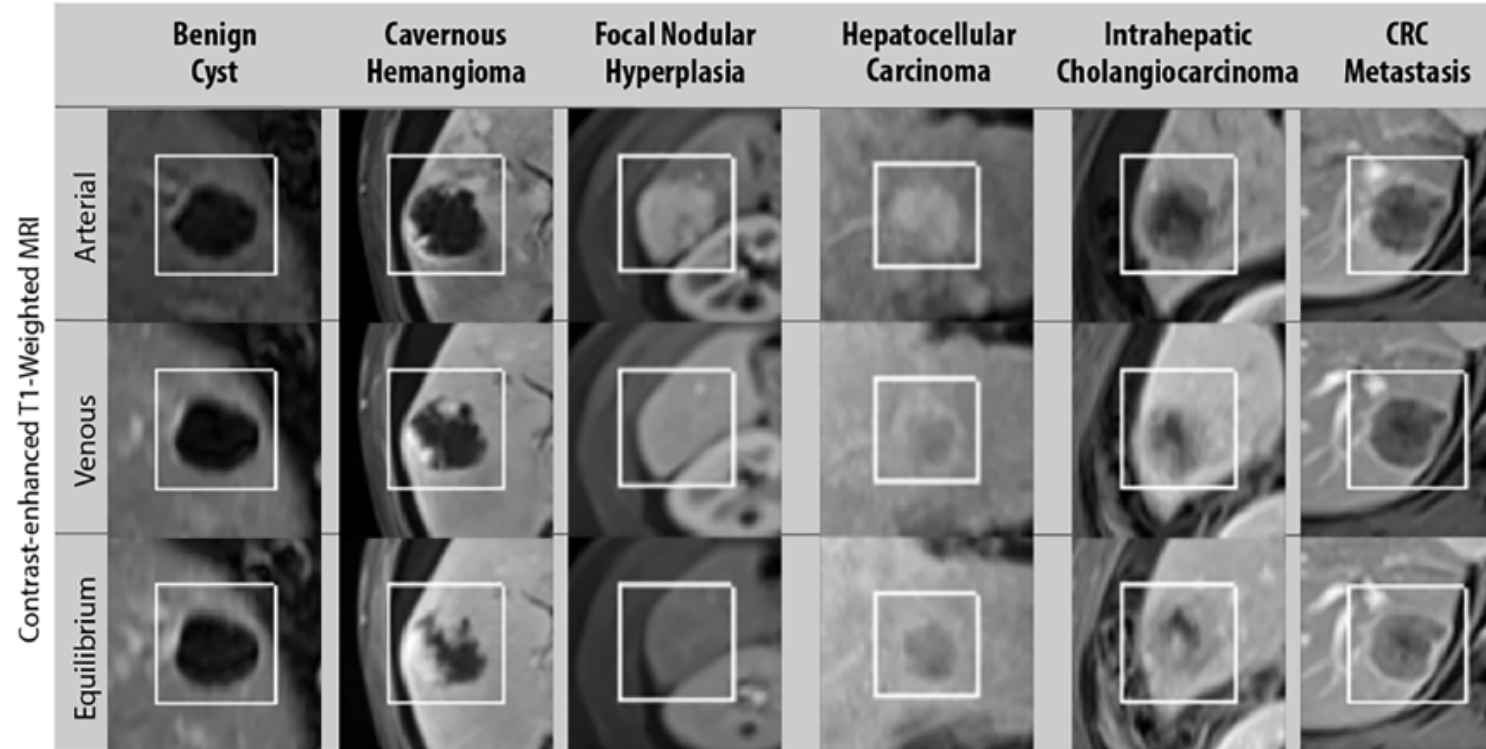


Table 4 Model and radiologist performance metrics for individual lesion types and LI-RADS classes

	Accuracy of lesion classification (mean $\pm$ SD %)	Accuracy of derived LI-RADS classification (mean $\pm$ SD %)	Runtime (mean $\pm$ SD)
Average of 20 iterations			
Model training set	98.7 $\pm$ 1.0	99.1 $\pm$ 0.7	29 min $\pm$ 4
Model test set	91.9 $\pm$ 2.9	94.3 $\pm$ 2.9	5.6 ms $\pm$ 4.6
Reader study ($n = 60$)			
Model	90.0	91.7	1.0 ms $\pm$ 0.4
Radiologist 1	80.0	88.3	14 $\pm$ 10 s
Radiologist 2	85.0	88.3	17 $\pm$ 24 s

Lesion type	Average of 20 iterations		Reader study					
	Model test set		Model		Radiologist 1		Radiologist 2	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
Cyst	99%	100%	100%	100%	90%	96%	100%	98%
Hemangioma	91%	99%	100%	100%	100%	96%	100%	94%
FNH	91%	98%	90%	96%	90%	98%	90%	94%
HCC	94%	98%	90%	98%	70%	100%	60%	100%
ICC	90%	97%	60%	100%	80%	94%	90%	100%
CRC metastasis	89%	98%	100%	94%	50%	92%	70%	96%
Overall	92%	98%	90%	98%	80%	96%	85%	97%



- Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio
- Identificare i reperti patologici
- Indicare gli esami che necessitano di refertazione in tempi brevi
- Caratterizzare le lesioni
- Semplificare l'elaborazione delle immagini e le misurazioni

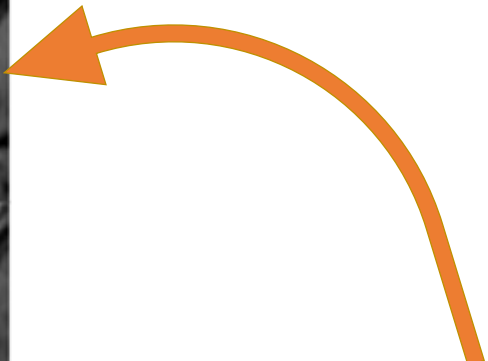
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Radiologist 2	85.0	88.3					

Lesion type	Radiologist 1		Radiologist 2	
	Sensitivity	Specificity	Sensitivity	Specificity
Cyst	90%	96%	100%	98%
CH	100%	96%	100%	94%
FNH	90%	98%	90%	94%
ICC	70%	100%	60%	100%
ICC metastasis	50%	92%	70%	96%
Overall	80%	96%	85%	97%

Contrast-enhanced T1-Weighted MRI

	Benign Cyst	Cavernous Hemangioma	Focal Nodular Hyperplasia	Hepatocellular Carcinoma	Intrahepatic Cholangiocarcinoma	CRC Metastasis
Arterial						
Venous						
Equilibrium						



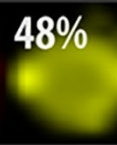
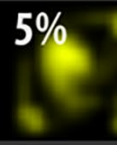
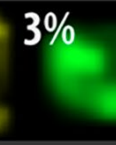
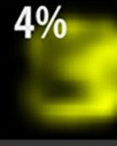
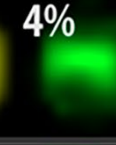
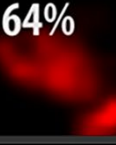
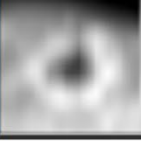
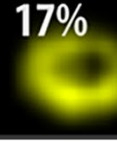
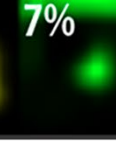
Contrast-enhanced T1-w MRI			Labeled radiological feature	Contrast-enhanced T1-w MRI			Labeled radiological feature
Arterial	Venous	Delayed	Hepatic lesion classes that typically exhibit the feature	Arterial	Venous	Delayed	Hepatic lesion classes that typically exhibit the feature
			Arterial phase hyperenhancement FNH, HCC				Infiltrative appearance ICC
			Central scar FNH				Isointensity in venous and delayed phase FNH
			Enhancing rim CRC metastasis				Nodularity ICC
			Capsule/pseudocapsule HCC				Nodular/discontinuous peripheral enhancement Cavernous hemangioma
			Heterogeneous lesion ICC, HCC (OPTN5B/X)				Progressive centripetal filling Cavernous hemangioma
			Hyperenhancing mass in delayed phase Cavernous hemangioma				Progressive hyperenhancement CRC metastasis, ICC
			Hypoenhancing core CRC metastasis				Thin-walled mass Cyst
			Hypoenhancing mass Cyst				Washout HCC

Grouped into a single feature

Grouped into a single feature



Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features

Lesion Class	Contrast-Enhanced T1-w MRI			Feature Maps and Relevance Scores			Radiological Features Identified
	Arterial Phase	Venous Phase	Delayed Phase	Feature 1	Feature 2	Feature 3	
Benign Cyst				52% 	48% 		Thin-walled mass Hypoenhancing mass
Cavernous Hemangioma				92% 	5% 	3% 	Hyperenhancing mass in delayed phase Nodular peripheral enhancement Progressive centripetal filling
Focal Nodular Hyperplasia				96% 	4% 		Arterial phase hyperenhancement Isointensity in venous/delayed phase
Hepatocellular Carcinoma				54% 	42% 	4% 	Capsule/pseudocapsule Arterial phase hyperenhancement Washout
Intrahepatic Cholangio-carcinoma				64% 	29% 	7% 	Progressive hyperenhancement Nodularity Heterogeneous lesion
Colorectal Carcinoma Metastasis				76% 	17% 	7% 	Hypoenhancing core Enhancing rim Progressive hyperenhancement

Results The interpretable deep learning system achieved 76.5% positive predictive value and 82.9% sensitivity in identifying the correct radiological features present in each test lesion. The model misclassified 12% of lesions. Incorrect features were found more often in misclassified lesions than correctly identified lesions (60.4% vs. 85.6%). Feature maps were consistent with original image voxels contributing to each imaging feature. Feature relevance scores tended to reflect the most prominent imaging criteria for each class.

Deep Learning–based Method for Fully Automatic Quantification of Left Ventricle Function from Cine MR Images: A Multivendor, Multicenter Study

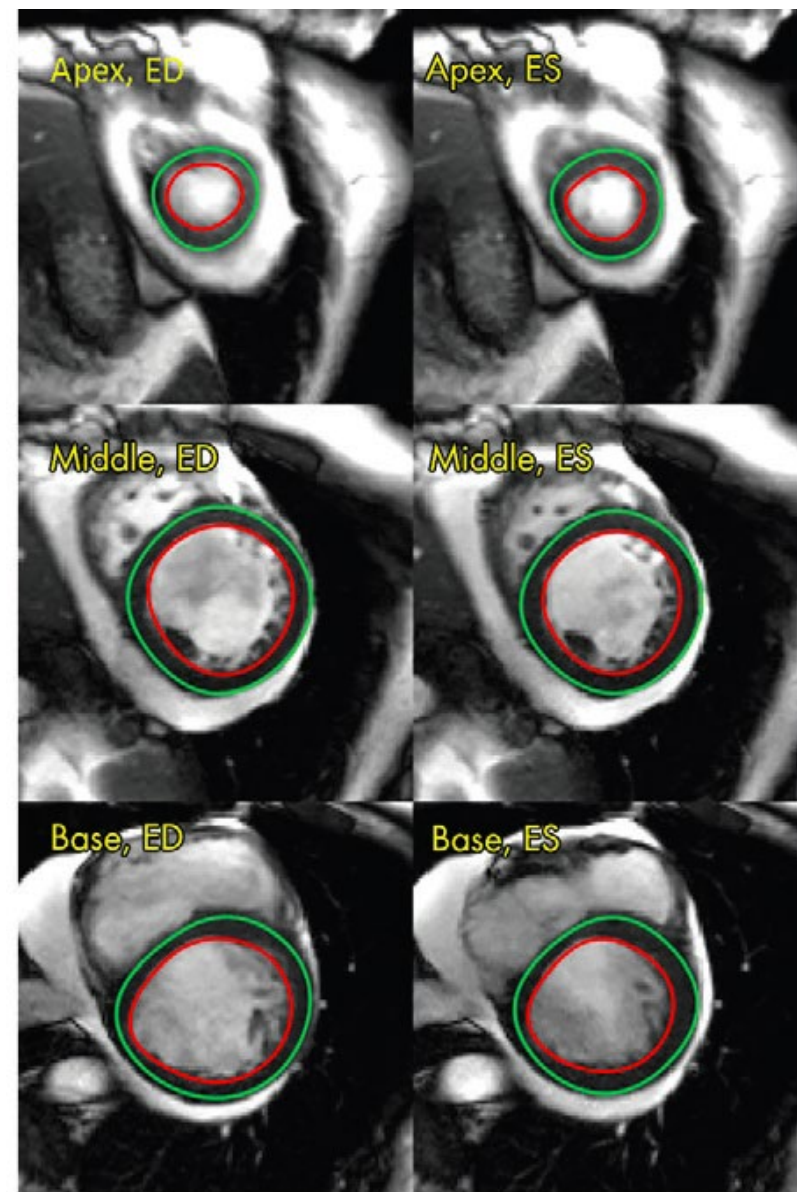
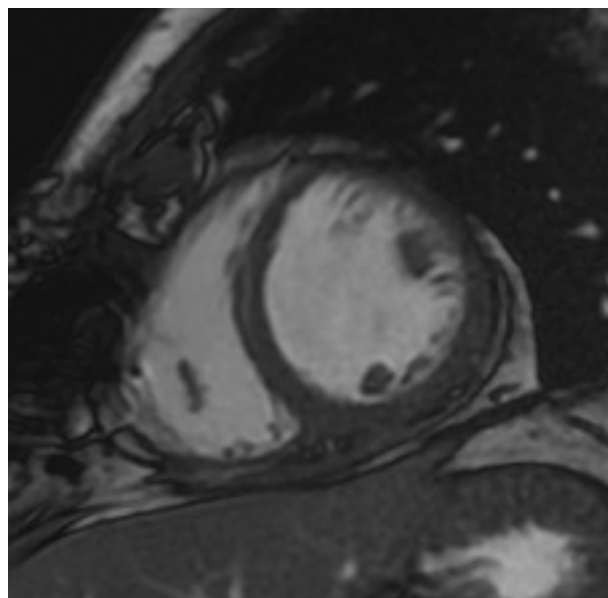
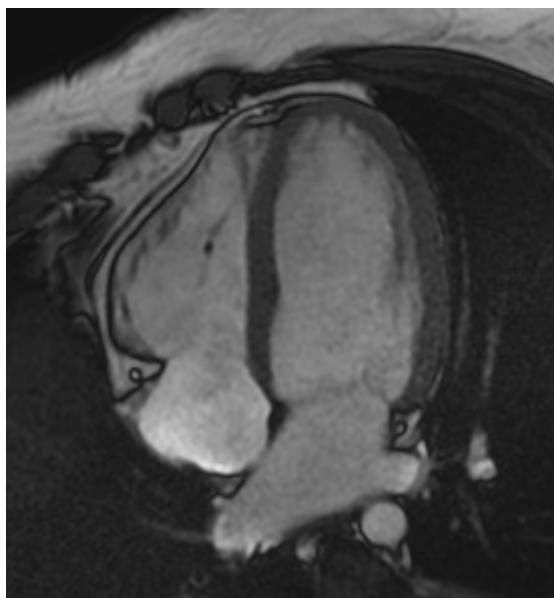
Materials and Methods: This retrospective study included cine MRI data sets obtained from three major MRI vendors in four medical centers from 2008 to 2016. Three convolutional neural networks (CNNs) with the U-NET architecture were trained on data sets of increasing variability: (a) a single-vendor, single-center, homogeneous cohort of 100 patients (CNN1); (b) a single-vendor, multicenter, heterogeneous cohort of 200 patients (CNN2); and (c) a multivendor, multicenter, heterogeneous cohort of 400 patients (CNN3). All CNNs were tested on an independent multivendor, multicenter data set of 196 patients. CNN performance was evaluated with respect to the manual annotations from three experienced observers in terms of (a) LV detection accuracy, (b) LV segmentation accuracy, and (c) LV functional parameter accuracy. Automatic and manual results were compared with the paired

Results: CNN3 achieved the highest performance on the independent testing data set. The average perpendicular distance compared with manual analysis was $1.1 \text{ mm} \pm 0.3$ for CNN3, compared with $1.5 \text{ mm} \pm 1.0$ for CNN1 ($P < .05$) and $1.3 \text{ mm} \pm 0.6$ for CNN2 ($P < .05$). The LV function parameters derived from CNN3 showed a high correlation ($r^2 \geq 0.98$) and agreement with those obtained by experts for data sets from different vendors and centers.

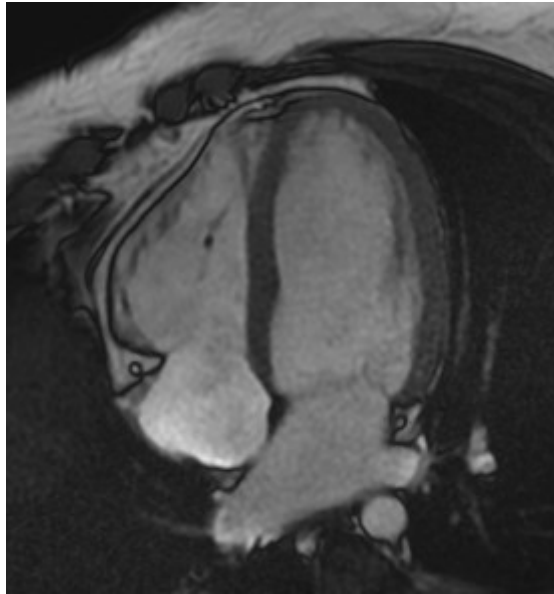
Implications for Patient Care

- Deep learning–based image segmentation enables fast and accurate left ventricle function assessment from short-axis cine MR images without requiring any user interaction.
- Integration of the developed deep learning method as a fully automated in-line processing module would allow faster reporting of cardiac MRI studies, without the delay caused by time-consuming manual image analysis.

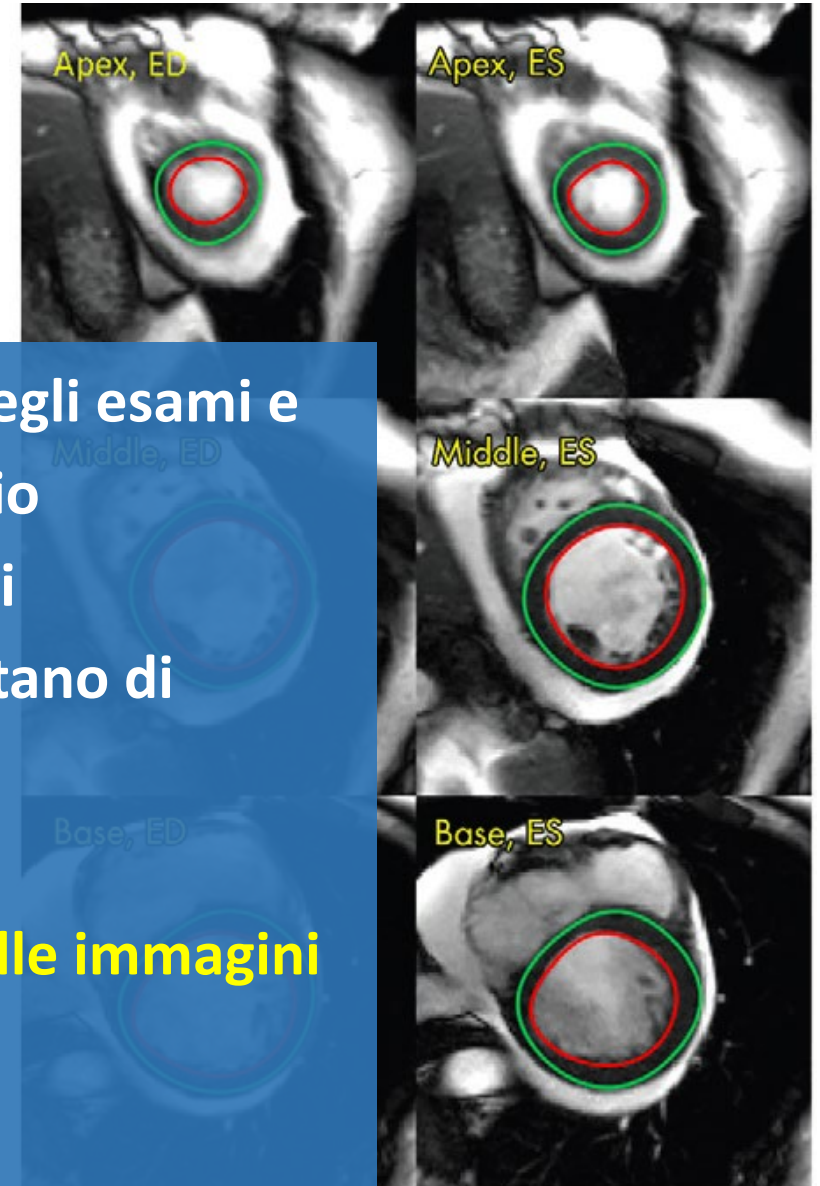
Deep Learning–based Method for Fully Automatic Quantification of Left Ventricle Function from Cine MR Images: A Multivendor, Multicenter Study



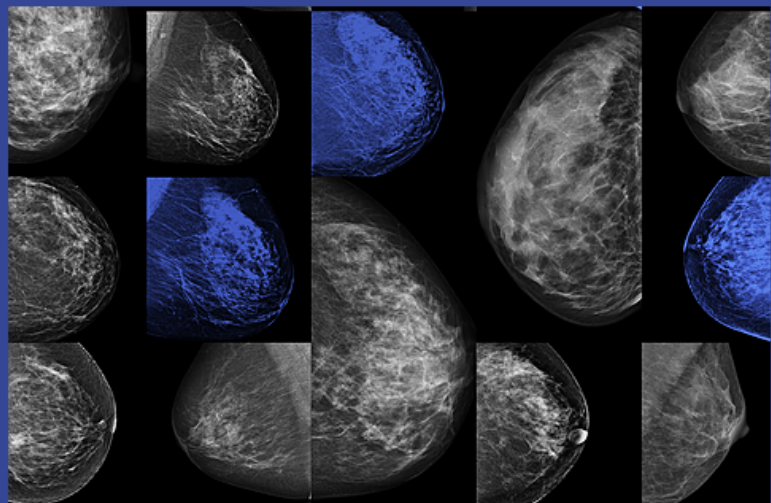
Deep Learning–based Method for Fully Automatic Quantification of Left Ventricle Function from Cine MR Images: A Multivendor, Multicenter Study



- Migliorare la qualità tecnica degli esami e ottimizzare i protocolli di studio
- Identificare i reperti patologici
- Indicare gli esami che necessitano di refertazione in tempi brevi
- Caratterizzare le lesioni
- **Semplificare l'elaborazione delle immagini e le misurazioni**



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Transpara Perception Aid
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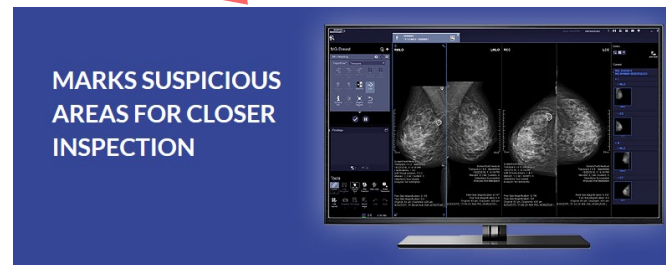
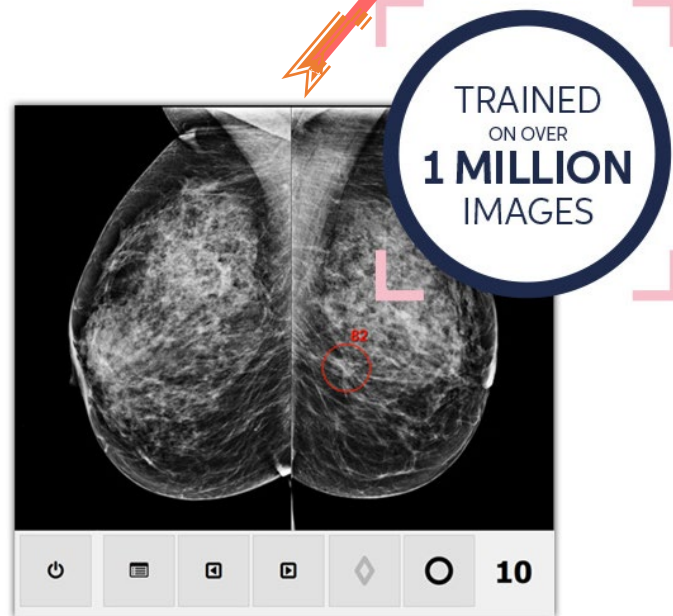
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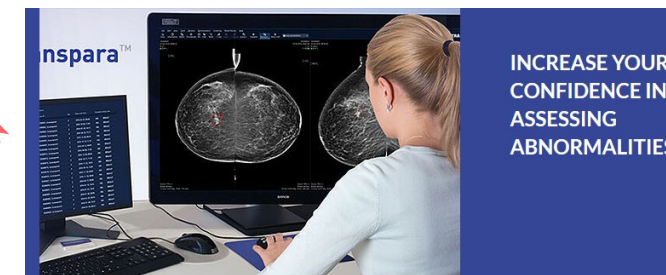
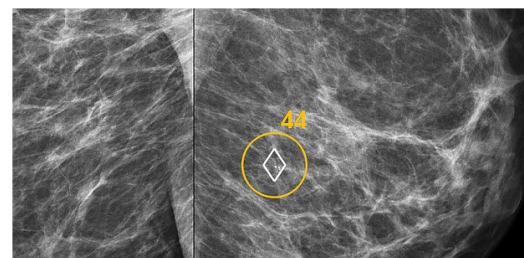
Combined, they employ the latest developments in Big Data, deep learning and artificial intelligence with functionality that's already familiar to you, so that you can work more effectively every day. Even better, you can query any finding as you're screening - without slowing down your process.



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Transpara Perception Aid
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Findings that Transpara detects can be marked for review using traditional mammography CAD functionality, to reduce the risk of overlooking significant abnormalities. For soft-tissue lesions, Transpara produces very few false positives - fewer than one in ten cases - to prevent distraction and unnecessary call-backs.

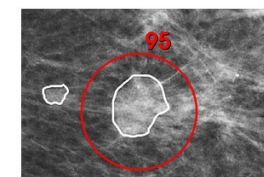


**INCREASE YOUR
CONFIDENCE IN
ASSESSING
ABNORMALITIES**

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- Increase your confidence for both normal and suspicious cases.
- Automatically link corresponding areas in CC and MLO views.
- Integrate decision support into your workflow - without slowing you down.

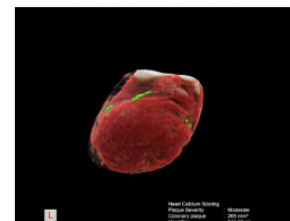


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Home > Digital Health Solutions > Digital Portfolio Overview > Clinical decision support > AI-Rad Companion Chest CT

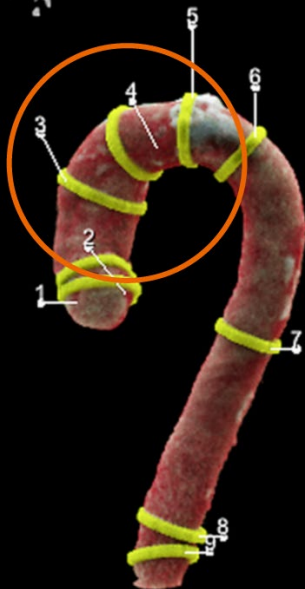
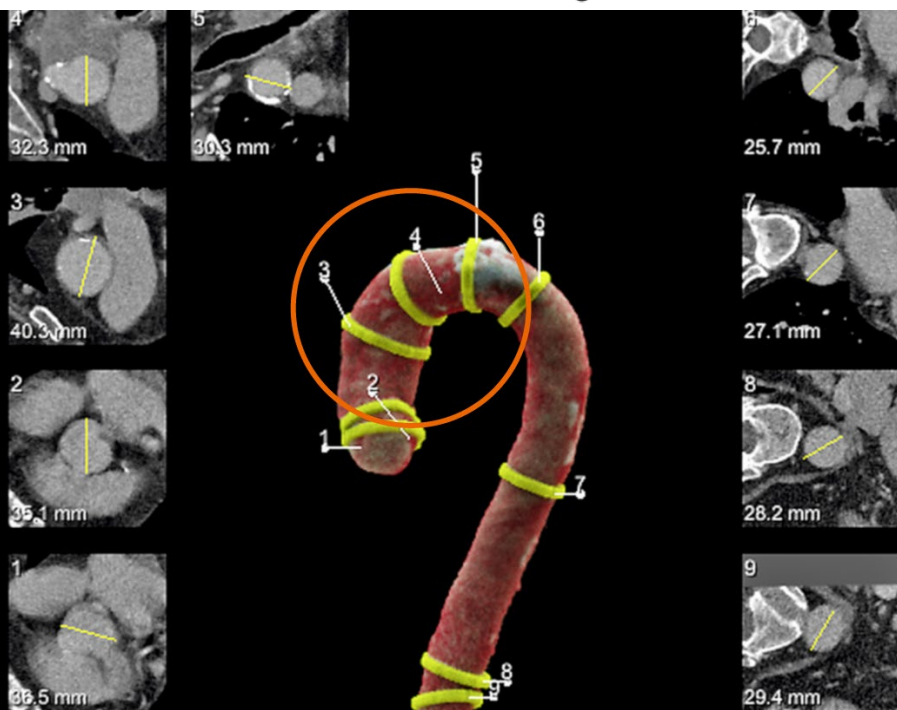
AI-Rad Companion Chest CT

More accurate and faster image interpretation through AI-assisted medical diagnosis



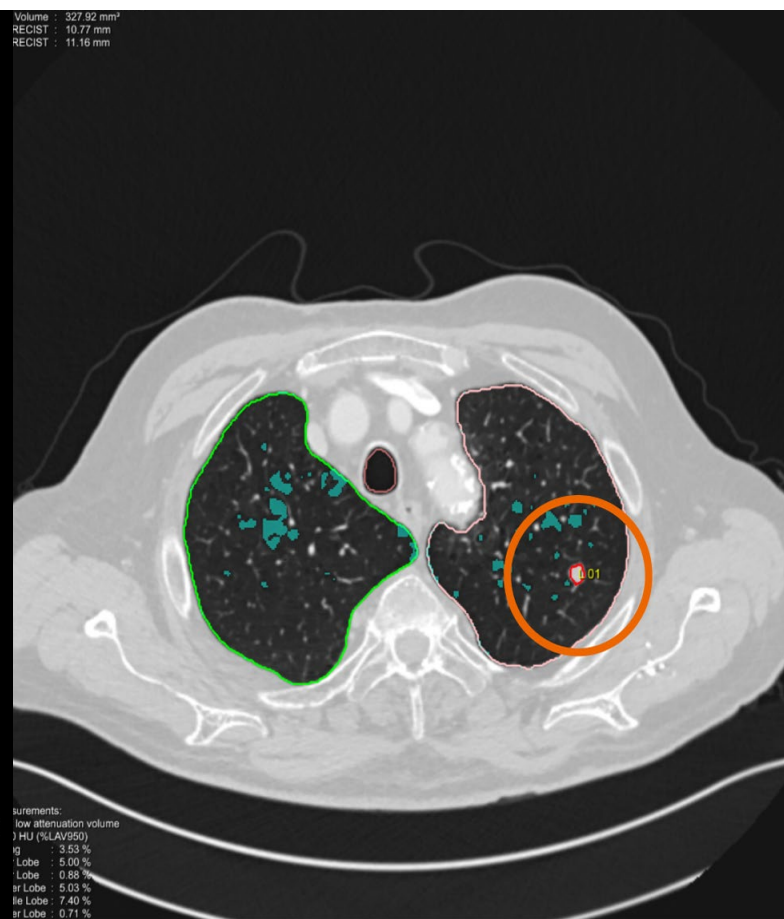
AI-Rad Companion Chest CT

Color-coded anatomical indicators allow easy, precise, and quick recognition of abnormalities.

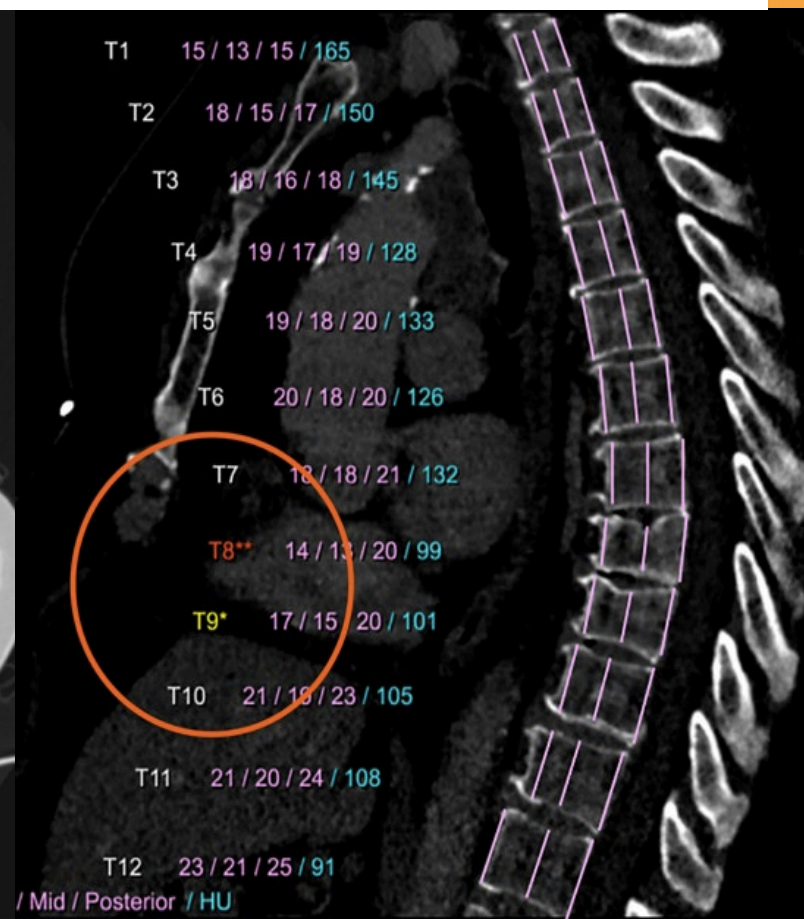


- 1 : Sin. of Valsalva (36.5 mm)
- 2 : Sinotub. junction (35.1 mm)
- 3 : Mid ascending (40.3 mm)
- 4 : Proximal arch (32.3 mm)
- 5 : Mid arch (30.3 mm)

- 6 : Prox. descending (25.7 mm)
- 7 : Mid descending (27.1 mm)
- 8 : Diaphragm (28.2 mm)
- 9 : Abdominal (29.4 mm)



Parameters:
low attenuation volume
> HU (%LAV/950)
lg : 3.53 %
Lobe : 5.00 %
Lobe : 0.88 %
R Lobe : 5.03 %
R Lobe : 7.40 %
R Lobe : 0.71 %



T1 15 / 13 / 15 / 165
T2 18 / 15 / 17 / 150
T3 18 / 16 / 18 / 145
T4 19 / 17 / 19 / 128
T5 19 / 18 / 20 / 133
T6 20 / 18 / 20 / 126
T7 18 / 18 / 21 / 132
T8** 14 / 13 / 20 / 99
T9* 17 / 15 / 20 / 101
T10 21 / 19 / 23 / 105
T11 21 / 20 / 24 / 108
T12 23 / 21 / 25 / 91
/ Mid / Posterior / HU

*Tutte le verità sono facili da capire una volta
che sono state rivelate. Il difficile è scoprirle.*

Galileo Galilei



Grazie per l'attenzione! cberzovini@cittadellasalute.to.it