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Three artificial intelligence data challenges based on CT and MRI

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ABSTRACT

Purpose: The second edition of the artificial intelligence (AI) data challenge was organized by the French Society of Radiology with the aim to: (*i*), work on relevant public health issues; (*ii*), build large, multicentre, high quality databases; and (*iii*), include three-dimensional (3D) information and prognostic questions.

Abbreviations: 2D, Two-dimensional; 3D, Three-dimensional; AI, artificial intelligence; AUC, area under curve; CT, computed tomography; DICOM, digital imaging and communications in medicine; EDSS, expanded disability status scale; FLAIR, fluid-attenuated inversion recovery; GDPR, general data protection regulation; JFR, Journées Françaises de Radiologie; MS, multiple sclerosis; MSE, mean square error; ROC, receiver operating characteristic curve; SFR, Société Française de Radiologie.

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Magnetic resonance imaging (MRI)
Computed tomography (CT)

Materials and methods: Relevant clinical questions were proposed by French subspecialty colleges of radiology. Their feasibility was assessed by experts in the field of AI. A dedicated platform was set up for inclusion centers to safely upload their anonymized examinations in compliance with general data protection regulation. The quality of the database was checked by experts weekly with annotations performed by radiologists. Multidisciplinary teams competed between September 11th and October 13th 2019.
Results: Three questions were selected using different imaging and evaluation modalities, including: pulmonary nodule detection and classification from 3D computed tomography (CT), prediction of expanded disability status scale in multiple sclerosis using 3D magnetic resonance imaging (MRI) and segmentation of muscular surface for sarcopenia estimation from two-dimensional CT. A total of 4347 examinations were gathered of which only 6% were excluded. Three independent databases from 24 individual centers were created. A total of 143 participants were split into 20 multidisciplinary teams.
Conclusion: Three data challenges with over 1200 general data protection regulation compliant CT or MRI examinations each were organized. Future challenges should be made with more complex situations combining histopathological or genetic information to resemble real life situations faced by radiologists in routine practice.

1. Introduction

In recent years the number of available medical image banks has soared [1], allowing the rapid development of artificial intelligence (AI) algorithms capable of handling different tasks such as classification, detection, or segmentation in different modalities [2]. It has also fostered the emergence of many AI challenge competitions [3,4]. As AI is likely to deeply impact radiology practice [5] it will arguably be of great help to offload repetitive tasks such as organ segmentation and to grasp more useful and quantitative information from images allowing more time spent on solving complex clinical problems [6]. Liew et al. anticipated that with the rise of AI the practice of radiology will drastically transform and radiologists will have to learn how to work with many new collaborators (including AI researchers, engineers, data officers) [7].

However many pitfalls are still in the way of an efficient implementation of AI in radiologists' routine practice. Many studies have pointed out that training a deep learning model on precisely annotated databases is an essential requirement for safe deployment of such applications in a medical context [8,9]. Recent implementation in the general data protection regulation (GDPR) imposes certain restrictive but essential rules.

In this context, the first edition of the data challenge was organized during the Journées Francophones de Radiologie (JFR) in 2018; its motivations were to:

- help solving common and relevant issues of public healt,
- stimulate interactions within the AI community,
- build qualitative databases compliant with the new European Union regulations.

These objectives have been fully completed [10] and led to 6 publications with promising results in 5 challenges. They included meniscus tear detection on two-dimensional (2D) MRI [11,12], thyroid cartilage classification on 2D computed tomography (CT) [13], breast lesion characterisation on 2D MRI [14], liver lesion classification on 2D ultrasound [15] and kidney cortex segmentation using 2D CT [16].

The second edition of the data challenge took place during the JFR in 2019. The objective was to increase the level of difficulty of the challenges offered by including three-dimensional (3D) information and prognostic questions. The aim was also to increase the quality of the datasets with at least 1000 examinations for each question. Radiologists were directly involved in the labelling and the segmentation of the different datasets which allowed teaching good practices and ensuring the quality of the information provided to the teams.

2. Materials and methods

2.1. Clinical questions

The starting point for the challenge was to ask French subspecialty colleges of radiology (i.e., organ societies) of the French Society of Radiology (SFR) to suggest relevant clinical questions that could be asked to participants. This process allows being sure of putting the benefit of the patient at the core of the work carried out by the teams, sending messages to the medical community on the hot topics to deal with and spread good clinical practices. To be kept in the challenge, the questions had to meet four criteria. First, the clinical relevance was judged by organ society's experts. Second, a literature review was performed to ensure the originality of the questions (using Pubmed, Kaggle and Grand-Challenge websites). Third, the feasibility of the challenge was ensured by data-scientists (Inria Saclay, France). Finally an estimation of the number of examinations produced in France each year for each question was carried out by the organizing committee to ensure to get a sufficient number of examinations (more than 1000 per challenge). Special care was taken to define challenge questions raising different AI tasks such as classification, automatic segmentation, and regression.

2.2. Security and data protection

This challenge has been entirely designed following the GDPR, as ensured by the French regulation office called Commission Nationale Informatique et Libertés. This year, the SFR has taken on the role of data protection officer for these three challenges. In each inclusion center, patients were provided a letter with complete description of the use of their examinations during and after the challenge. An ethical charter has been signed by members of the AI groups of the SFR and radiologists who uploaded the images. All images sent by the different centers had to be anonymized. Still, a second check was done to remove all potentially identifying digital imaging and communications in medicine (DICOM) fields with a dedicated Python script. Participating teams during the challenges only worked with anonymized, pseudonymized and processed images.

2.3. Inclusion and communication

Inclusions for the three challenges started on April 1st and ended August 30th 2019. Newsletters have been sent to radiology departments of French hospitals. A dedicated website was built used as a platform to upload images/annotations and check their quality for all challenges. It allowed sharing information such as inclusion criteria, challenge timeline and files such as tutorials for the segmentation software, "3D slicer".

The infrastructure has been provided by the department of digital transformation and information services of Institut Gustave Roussy, which includes a platform to exchange examinations, a server for hosting the event's website, and the storage of all the datasets.

To maintain a sufficient inclusion rate to reach the 1000 examinations included per challenges, information newsletters were sent two times a week to participants by email. Also, a margin of 10% of additional examinations was requested to deal with poor quality examinations and damaged files.

Once received from the inclusion centers, data were reviewed by an expert engineer from an external partner (EASYS) to ensure anonymization and formatting. The quality was then checked by radiology experts from the organ societies. This year the data control and quality check was done in real time allowing giving rapid feedbacks.

2.4. Team gathering and challenge

The challenge's website was also used as a platform for teams to register and get information. The teams were asked to be multidisciplinary, including at least one radiologist, one engineering/data-scientist student, and a research lab and/or company. Different networks were used to gather such team (JFR and SFR for radiologists, French graduate schools, Universities, and life imaging networks for students and research laboratories).

The first batch of data was sent to the teams on September 11th, 2019, the second batch was sent a month later, on October 11th. Finally, the validation set was sent on Sunday, October 13th. The different teams had limited time (two hours for the pulmonary nodule and one hour for the other two challenges) to generate results on the validation set. After scores calculation and jury deliberations, the winning team of each challenge was announced on October 14th, 2019.

3. Results

Three subjects were selected to constitute the 2019 data challenge: classification of pulmonary nodule on 3D CT, prediction of expanded disability status scale (EDSS) score in multiple sclerosis (MS) on 3D MRI, and estimation of abdominal sarcopenia on 2D CT.

3.1. Pulmonary nodule (CT)

The risk of malignancy of a pulmonary nodule rises with the increase in its diameter. Screening studies using semi-automated volume measurements have shown higher accuracy and reproducibility compared to diameter measurements, and it has been shown that small nodules (those with a volume < 100 mm^3 or diameter < 5 mm) are not predictive for lung cancer [17]. For this question, teams had different tasks: to recognize pulmonary nodule on 3D CT chest scanners, to segment them, to estimate their volume and to classify them into probable benign (volume < 100 mm^3) or probably malignant nodules (volume $\geq$ 100 mm^3).

3.2. Neurological impairment in multiple sclerosis (MRI)

The EDSS is used in the clinical evaluation of MS to rate neurological impairment. MRI has become essential in the diagnosis and disease monitoring of patients with MS. Significant associations have been shown between T2 lesion measures and EDSS measures [18], and that automated lesion volume quantification can be applied reliably on 3D fluid-attenuated inversion recovery (FLAIR) data sets [19]. For this question, candidates had to develop a two-year predictive EDSS-score algorithm based on brain MRI of known multiples sclerosis patients. The training set included 3D FLAIR or axial T2 FLAIR brain MRI and the corresponding clinical data (patients' age, sex, EDSS-score at two years from the images).

3.3. Sarcopenia (CT)

It has been shown that assessing muscular body surface on a single axial CT slice at the height of the third lumbar vertebra was highly correlated with clinically valuable parameters of body composition [20]. For this question, teams had two tasks: to segment muscular body mass and to estimate its surface. The dataset was composed of single axial 2D slices from CT abdominal scanners. The images and segmentation received from the different centers were checked by an expert radiologists and divided into 4 classes from A to D based on the quality of the segmentation, A being the best. Only classes from A to C were kept in the dataset communicated to the teams. The training set included the 2D slices in DICOM format, its segmentation masks and its surface in mm^2. For the test set on which teams were evaluated only the images were provided. Participants should return a binary predicted mask with the same size and format and the estimation of the surface of interest in mm^2. For each question, inclusion criteria were different (Table 1).

Table 1
Image inclusion criteria for each challenge.

Challenge	Sarcopenia	Pulmonary nodules	Multiple sclerosis
Modality	CT	CT	MRI
Image type	2D	3D	3D
Images specifications	Soft filter Slice thickness 1.25 to 7 mm With or without contrast agent injection	Hard filter (mostly) Slice thickness < 1.25 mm With or without contrast agent injection Containing between 1 and 5 nodules (density: mainly solid, but also mixed or ground glass). Malignant nodules defined by a volume > 100 mm^3, or diameter > 6 mm	3D FLAIR or axial 2D FLAIR

2D = two-dimensional; 3D = three-dimensional; CT = Computed tomography; MRI = magnetic resonance imaging; FLAIR = fluid-attenuated inversion recovery

Table 2
Inclusion centers for three data challenges.

Sarcopenia	Pulmonary nodules	Multiple sclerosis
1557 2D CT examinations	1237 3D CT examinations	1468 3D MRI examinations
Multicentric	Multicentric	Multicentric
CHU Pitié-Salpêtrière (518)	CHU Bichat (267)	OFSEP* (1468)
Gustave Roussy (328)	CHU de Nîmes (143)	
CHU de Nîmes (252)	CHU Rennes (137)	
CHU Henri-Mondor (177)	CHU Bordeaux (105)	
CHU Lille (101)	CHU Cochin (102)	
Hospices Civils Lyon (68)	CHU Grenoble (100)	
CHU Bicêtre (58)	CHU Nice (99)	
GHPSJ (30)	CHU Avicenne (98)	
Centre Léon Bérard (16)	CHU Clermont-Ferrand (50)	
RPO (9)	Gustave Roussy (45)	
	CHU Montpellier (42)	
	CH Douai (25)	
	CHU Strasbourg (17)	
	CHRU Besançon (6)	
	Institut A. Tzanck (1)	

OFSEP = Observatoire Français de la Sclérose en Plaque; CT = computed tomography; MRI = magnetic resonance imaging. Numbers in parentheses are the numbers of examination provided by each individual center.

Table 3
Examinations received and included for each challenge.

Challenge	Number of examinations received	Number of examinations kept in the dataset
Sarcopenia	1557	1515 (1515/1557; 97%)
Pulmonary nodules	1237	1031 (1031/1237; 83%)
Multiple sclerosis	1468	1461 (1461/1468; 99%)
Total	4262	4007 (4262/4007; 94%)

A total of 4262 examinations were uploaded from 24 different inclusion centers (Table 2). The 3 challenges gathered nearly the same number of examinations. Of the 4262 examinations uploaded from the inclusion centers, 4007 (94%) met the predefined inclusion criteria (Table 3). For each medical question, data was split into three datasets: training set, validation set, and test set (Table 4).

3.4. Score computation

3.4.1. Muscle area calculation (sarcopenia challenge)

For the Sarcopenia Challenge, the score was calculated using a combination of Dice coefficient (measure of similarity between predicted and ground truth segmentation) and mean square error (MSE) between predicted and ground-truth surfaces (Table 5). The final score of each team was calculated using the following equation

$$\text{Final score} = \text{minimum score}(rank_{Dice} + rank_{MSE})$$

Segmentation of abdominal muscles was made using an attenuation value threshold ranging from −29 to 150 Hounsfield units (HU). The teams were evaluated based on the Dice coefficient between the predicted segmentation and the ground-truth segmentation and the MSE between the predicted surface and the ground-truth surface. The overall score is the sum of the team's ranks in the two metrics. The winning team was, therefore, the one with the lowest score. In case of equality, the winning team was the one with the best Dice score. Many teams got very close results in terms of Dice score (Table 6).

3.4.2. Pulmonary nodule classification (pulmonary nodule challenge)

For the Pulmonary Nodule Challenge, the score was the area under the curve (AUC) between probability of abnormal examination and ground-truth. Examinations were annotated by expert radiologist for each abnormal nodule (up to 5 nodules). The location of each nodule was also annotated. No images resampling was done on these images. Pixel size was giving using DICOM field PixelSpacing. Teams were asked to provide an Excel file containing the name of the examination and the probability of normal/abnormal. The winning team was the one with the best AUC score between the probability of abnormality established by their method and ground-truth. Because of time restrictions, 6 out of 13 teams that joined the pulmonary nodule challenge did not submit their results on time (Table 6).

3.4.3. Neurological impairment prediction (MS challenge)

For the Multiple Sclerosis Challenge, the score was the MSE for EDSS score assessment. The inclusion criteria for the EDSS prediction in patients with MS from MRI was an available 3D FLAIR or axial T2 FLAIR MRI examination. Patient data included also age, sex, examination date, and EDSS score at 2 years. The results expected by the team was a comma-separated value file containing the examination identifier and the associated EDSS score. The score was then calculated using the MSE between the EDSS score evaluated by the team and the reference score evaluated by a neurologist.

For this 2019 year's edition, 20 teams were participating with 143 members including: 61 engineers working in start-ups or in big companies, 25 students, 31 radiologists and 26 researchers or Ph. D. students. The teams were ranging from 3 to 15 members. Of the 20 teams, 16 were able to submit results. Six prizes were announced on October 15th three for the best teams, and three for the best inclusion center. For sarcopenia estimation the winning team was Owkin with members from Assistance Publique des Hôpitaux de Paris and École Polytechnique, the best inclusion center was Pitié-Salpêtrière hospital. The Pixyl team won the pulmonary nodules challenge with members from Groupement des Hôpitaux de l'Institut Catholique de Lille, University Hospital of Grenoble and Grenoble University. University Hospital of Bichat was the center with largest numbers of included patients. IBM-France Cognitive team with members from Centre Jean Perrin, Quantacell, Ecole National de l'Aviation Civile and DataValoris won the EDSS prediction challenge with data from the Observatoire Français de la Sclérose en Plaques. For each challenge, the winning team members were invited on stage to present their method and to receive 3000 € provided by the SFR. Because of time restriction more than half of teams which joined multiple sclerosis challenge did not submit their results on time (Table 6).

Table 4
Training, validation, and testing dataset for each challenge.

Challenge	Sarcopenia	Pulmonary nodules	Multiple sclerosis
Training set	513	343	480
Validation set	512	344	498
Test set	500	344	483
Total (# examinations)	1525	1031	1461

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Table 5
Details of the score used to rank the teams.

Score	Equation
Dice score	$D = 2\,\lvert X \cap Xc \rvert \,/\, \lvert X \rvert + \lvert Xc \rvert$, *with X ground truth segmentation and Xc, segmentation from teams*
Mean squared error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}n - Yn\right)^2$, *with Y = team's value estimation, and Y = ground truth value*

Dice score is the similarity index (*i.e.*, Sørensen–Dice index, "similarity coefficient" or "index", Dice similarity coefficient).

Table 6
Results calculated for each team by challenge.

Teams	Sarcopenia (Dice & Mean square error)	Pulmonary nodules (AUC)	Multiple sclerosis (Mean square error)
Aidence		0.878	
ALICEMEDICAL			5.47
Autonomous Radio	11	*N.S*	*N.S*
Axone	16		*N.S*
Azmed			4.61
biSEPs	*N.S*		
Dapsi-AI	*N.S*		
EASYPICKY	*N.S*		
GAMC	7	0.793	*N.S*
Ghicl-Pixyl			**3.04**
IBM-France-Cognitive		0.899	
icometrix			3.80
ILLUIN TECHNOLOGY	*N.S*		
LEVIATAN	10	*N.S*	*N.S*
LyPhTe	7	0.838	3.92
Milvue	6		
NAIS		0.681	*N.S*
ONCONEURAL		0.644	*N.S*
Owkin	**4**	0.768	*N.S*
Tripode-Rouen	11		

Bold indicates the winner for each question . N.S. indicates that the team left the challenge. Empty cell indicates not competing team.

4. Discussion

The second edition of the JFR data challenge took in consideration the results of the previous edition [10] and increased the difficulty as requested by the competitors. Three questions were selected for their medical interest and technical feasibility: pulmonary nodule detection and classification from 3D CT, prediction of EDSS in MS using 3D MRI and segmentation of muscular surface for sarcopenia estimation from 2D slices of CT at L3 level. The medical questions went from diagnostic (in last year edition) to prognostic (this year edition). Participants had to handle 3D information from CT and MRI and were asked to perform various tasks.

Larger databases were collected in 2019 edition compared to the previous edition, more than 1000 examinations by challenge versus less than 500 for the previous edition from 24 different centers. Improvements have been made during the inclusion phase regarding the quality of the data since only 6% of examinations did not match the inclusion criteria against 19% last year. This was made possible by giving continuous feedback to the different medical centers during the inclusion phase. The challenge successfully achieved to gather radiologists from many French hospitals, large companies and start-ups, academics and engineering students from French top engineering schools. This emphasizes the great interest and dynamism shown by the community with regards to the development of AI. While numerous data challenges have been organized these past years, many of which can be found in the Grand Challenge website, a special effort has been made here to tackle original questions that were not addressed yet.

Sarcopenia is defined by a loss of muscular mass, frequently observed on oncologic patients. Assessment of muscular body mass has been revealed to be a strong prognostic indicator because sarcopenia has been associated with cancer outcomes including treatment toxicity, worse overall survival and disease-free survival in multiple stages and cancer types [21]. Barnard et al. have developed an algorithm capable of segmenting truncal musculature at multiple lumbar levels on 102 patients achieving a dice score of 0.94% [22]. Participants of our challenge were working at only one lumbar level but reached a slightly better Dice score on a much larger set of patients (1025 patients for training and 500 for testing). It is also probable that the bottleneck for this question lies in the quality of the ground truth segmentation than in the deep learning analysis as many teams got very close results in terms of Dice score. Higher quality ground truth segmentation may have been achieved by keeping only segmentation of class 3 and 4 or asking 3 expert radiologists to decide by consensus of the segmentation as it is done in [23].

MS is the most common immune-mediated disorder affecting the central nervous system and the most common cause of chronic neurological disability in young people. In this disease, the myelin sheath of neurons is damaged, which disrupts the ability of parts of the nervous system to communicate, resulting in a range of signs and symptoms, including physical, mental, and sometimes psychiatric problems. To our knowledge, no studies have been published concerning the prediction of the EDSS from 3D FLAIR images using deep learning. Attempts have been made to extract biomarkers from MRI examinations correlated with disability progression [24,25] but these studies only focus on a limited number of patients with no use of AI techniques. The winning team was the fruit of a successful cooperation and collaboration between seven specialized radiologists from two hospitals, one start-up, and one academic laboratory. They manage to predict EDSS with a significant 3.04 mean square error.

Lung cancer is still the leading cause of cancer-related deaths in Europe. Screening with CT is effective in reducing mortality from lung cancer [26]. Size is the most important morphologic criteria used to distinguish between malignant and benign pulmonary nodule. Many studies have been published for automatic detection and classification of pulmonary nodules [27–29]. Ather et al. believe that thanks to the availability of such large databases, the automation of nodule classification is expected to be one of the first application of AI [30]. They nevertheless emphasize the work that has to be done by radiologists to ensure the safe implementation of those tools. Many studies are using the public Lung Imaging Database Consortium [31]. However, most studies perform classification over 2D crops of pulmonary nodules. Nasrullah et al. have described a model capable of detecting and classifying pulmonary nodule from 3D CT that was trained and tested on two large datasets [32]. The originality of the question asked to the participants of our data challenge was to work on a completely new multicentric dataset.

In conclusion, three data challenges with data from over 1200 GDPR compliant examinations each were organized. Future challenges should be made with more complex situations combining different modalities such as histopathological or genetic information to resemble real life situations faced by radiologists in routine practice.

Ethical statement

Human rights

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World Medical Association revised in 2013 for experiments involving humans.

Informed consent and patient details

The authors declare that they obtained a written informed consent from the patients and/or volunteers included in the article. The authors also confirm that the personal details of the patients and/or volunteers have been removed.

Security and data protection

Participating teams during the challenges only worked with anonymized, pseudonymized and processed images.

This challenge has been entirely designed following the General Data Protection Regulations (GDPR), as ensured by the French regulation office called Commission Nationale Informatique et Libertés (CNIL). This year, the SFR has taken on the role of Data Protection Officer for these three challenges. In each inclusion center, patients were provided a letter with complete description of the use of their examinations during and after the challenge. An ethical charter has been signed by members of the AI groups of the SFR and radiologists who uploaded the images. All images sent by the different centers had to be anonymized. Still, a second verification was done to remove all potentially identifying DICOM fields with a dedicated Python script.

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Contribution of authors

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

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