Automated Lesion Segmentation in Whole-Body FDG-PET/CT: Structured description of the challenge design

CHALLENGE ORGANIZATION

Title

Use the title to convey the essential information on the challenge mission.

Automated Lesion Segmentation in Whole-Body FDG-PET/CT

Challenge acronym

Preferable, provide a short acronym of the challenge (if any).

AutoPET

Challenge abstract

Provide a summary of the challenge purpose. This should include a general introduction in the topic from both a biomedical as well as from a technical point of view and clearly state the envisioned technical and/or biomedical impact of the challenge.

Positron Emission Tomography / Computed Tomography (PET/CT) is an integral part of the diagnostic workup for various malignant solid tumor entities. Due to its wide applicability, Fluorodeoxyglucose (FDG) is the most widely used PET tracer in an oncological setting reflecting glucose consumption of tissues, e.g. typically increased glucose consumption of tumor lesions.
As part of the clinical routine analysis, PET/CT is mostly analyzed in a qualitative way by experienced medical imaging experts. Additional quantitative evaluation of PET information would potentially allow for more precise and individualized diagnostic decisions.
A crucial initial processing step for quantitative PET/CT analysis is segmentation of tumor lesions enabling accurate feature extraction, tumor characterization, oncologic staging and image-based therapy response assessment. Manual lesion segmentation is however associated with enormous effort and cost and is thus infeasible in clinical routine. Automation of this task is thus necessary for widespread clinical implementation of comprehensive PET image analysis. Recent progress in automated PET/CT lesions segmentation using deep learning methods has demonstrated the principle feasibility of this task. However, despite these recent advances tumor lesion detection and segmentation in whole-body PET/CT is still a challenging task. The specific difficulty of lesion segmentation in FDG-PET lies in the fact that not only tumor lesions but also healthy organs (e.g. the brain) can have significant FDG uptake; avoiding false positive segmentations can thus be difficult.
One bottleneck for progress in automated PET lesion segmentation is the limited availability of training data that would allow for algorithm development and optimization.
To promote research on machine learning-based automated tumor lesion segmentation on whole-body FDG-PET/CT data we propose the autoPET challenge and provide a large, publicly available training data set.

Challenge keywords

List the primary keywords that characterize the challenge.

PET/CT, FDG, tumor, segmentation

Year

The challenge will take place in ...

2022

FURTHER INFORMATION FOR MICCAI ORGANIZERS

Workshop

If the challenge is part of a workshop, please indicate the workshop.

none

Duration

How long does the challenge take?

Half day.

Expected number of participants

Please explain the basis of your estimate (e.g. numbers from previous challenges) and/or provide a list of potential participants and indicate if they have already confirmed their willingness to contribute.

50

Publication and future plans

Please indicate if you plan to coordinate a publication of the challenge results.

We aim to summarize the design, proposed methods and results of the challenge in a manuscript to be submitted to a peer-reviewed scientific journal in the field of medical image analysis. To this end, we aim to invite the best performing participants to contribute by describing their methods and experiences. Furthermore, we aim to make the code of the best performing methods publicly available for the purpose of reproduction of results and further research.

Space and hardware requirements

Organizers of on-site challenges must provide a fair computing environment for all participants. For instance, algorithms should run on the same computing platform provided to all.

For algorithm implementation and training, the participants will use their own resources. For testing as part of the challenge we aim to use resources provided by MICCAI. As an alternative, if this is not intended by MICCAI, we would use the platform Kaggle.

TASK: PET lesion segmentation

SUMMARY

Keywords

List the primary keywords that characterize the task.

PET/CT, FDG, tumor, segmentation

ORGANIZATION

Organizers

a) Provide information on the organizing team (names and affiliations).

Sergios Gatidis (University Hospital Tübingen, MPI for Intelligent Systems Tübingen)
Thomas Küstner (University Hospital Tübingen)
Michael Ingrisch (LMU Hosputal Munich)
Matthias Fabritius (LMU Hosputal Munich)
Clemens Cyran (LMU Hosputal Munich)

b) Provide information on the primary contact person.

Sergios Gatidis
University Hospital Tübingen
72076 Tübingen, Germany
E-mail: sergios.gatidis@med.uni-tuebingen.de

Life cycle type

Define the intended submission cycle of the challenge. Include information on whether/how the challenge will be continued after the challenge has taken place.Not every challenge closes after the submission deadline (one-time event). Sometimes it is possible to submit results after the deadline (open call) or the challenge is repeated with some modifications (repeated event).

Examples:

- One-time event with fixed conference submission deadline
- Open call (challenge opens for new submissions after conference deadline)
- Repeated event with annual fixed conference submission deadline

One-time event with fixed conference submission deadline. The challenge submission system and dataset will remain available also after the first evaluation in the context of MICCAI 2022.
Additional data and/or annotations may be added in the future leading to a repeated event.

Challenge venue and platform

a) Report the event (e.g. conference) that is associated with the challenge (if any).

MICCAI.

b) Report the platform (e.g. grand-challenge.org) used to run the challenge.

grand-challenge.org

c) Provide the URL for the challenge website (if any).

not yet established

Participation policies

a) Define the allowed user interaction of the algorithms assessed (e.g. only (semi-) automatic methods allowed).

Fully automatic.

b) Define the policy on the usage of training data. The data used to train algorithms may, for example, be restricted to the data provided by the challenge or to publicly available data including (open) pre-trained nets.

No additional data allowed.

c) Define the participation policy for members of the organizers' institutes. For example, members of the organizers' institutes may participate in the challenge but are not eligible for awards.

May participate but not eligible for awards and not listed in leaderboard.

d) Define the award policy. In particular, provide details with respect to challenge prizes.

We foresee the following awards for the best submission:

First prize: 6,000 €
Second prize: 3,000 €
Third prize: 2,000
4rd-7th: 1,000 €

At the moment, we are in the process of coordinating support for this challenge by the European Society of Radiology and by potential sponsors. Depending on the outcome of this process this award policy may be adapted.

e) Define the policy for result announcement.

Examples:

- Top 3 performing methods will be announced publicly.
- Participating teams can choose whether the performance results will be made public.

All submissions will be reported in the leaderboad.
Participating teams can opt out of publication of their results in the leaderboard.
Top 7 performing methods will be announced publicly as part of a scientific session at the MICCAI annual meeting.

f) Define the publication policy. In particular, provide details on ...

- ... who of the participating teams/the participating teams' members qualifies as author
- ... whether the participating teams may publish their own results separately, and (if so)
- ... whether an embargo time is defined (so that challenge organizers can publish a challenge paper first).

The top 7 performing teams will be invited to contribute to draft and submit a manuscript describing the methods and results of the challenge in a peer-reviewed journal.
The first and last author of the top 7 submissions will be also listed as authors of this planned manuscript.
The participating teams may publish their own results separately after coordination to avoid siginficant overlap

with the challenge paper.

Submission method

a) Describe the method used for result submission. Preferably, provide a link to the submission instructions.

Examples:

- Docker container on the Synapse platform. Link to submission instructions: <URL>
- Algorithm output was sent to organizers via e-mail. Submission instructions were sent by e-mail.

Algorithms will be accepted as Docker containers. Submission details will be published at the time point of challenge announcement.

b) Provide information on the possibility for participating teams to evaluate their algorithms before submitting final results. For example, many challenges allow submission of multiple results, and only the last run is officially counted to compute challenge results.

In order to enable participants to assess the technical compatibility of their to be submitted algorithm, we will provide information on successful algorithm deployment upon submission.
To this end, the submited algorithms will be applied to a small number of test data ensuring technical compatibility.
This will allow participants to resubmit their algorithms in case of technical failure.

Challenge schedule

Provide a timetable for the challenge. Preferably, this should include

- the release date(s) of the training cases (if any)
- the registration date/period
- the release date(s) of the test cases and validation cases (if any)
- the submission date(s)
- associated workshop days (if any)
- the release date(s) of the results

Challenge announcement and release of training cases: 02/2022
Registration: starting 02/2022
Submission deadline: 09/2022

Ethics approval

Indicate whether ethics approval is necessary for the data. If yes, provide details on the ethics approval, preferably institutional review board, location, date and number of the ethics approval (if applicable). Add the URL or a reference to the document of the ethics approval (if available).

The ethics committee of the University Hospital Tübingen was consulted regarding anonymized publication of training data. Due to the anonymized nature of the training data, necessity for ethical approval was waived.

Data usage agreement

Clarify how the data can be used and distributed by the teams that participate in the challenge and by others during and after the challenge. This should include the explicit listing of the license applied.

Examples:

- CC BY (Attribution)
- CC BY-SA (Attribution-ShareAlike)
- CC BY-ND (Attribution-NoDerivs)
- CC BY-NC (Attribution-NonCommercial)
- CC BY-NC-SA (Attribution-NonCommercial-ShareAlike)
- CC BY-NC-ND (Attribution-NonCommercial-NoDerivs)

CC BY NC ND.

Code availability

a) Provide information on the accessibility of the organizers' evaluation software (e.g. code to produce rankings). Preferably, provide a link to the code and add information on the supported platforms.

Code for algorithm evaluation will be available at the time point of challenge submission on github.com

b) In an analogous manner, provide information on the accessibility of the participating teams' code.

Publication of algorithm code will be a prerequisite for award eligibility. To this end code will need to be published on a publicly accessible repository of the teams‘ choice after within a week after submission deadline.

Conflicts of interest

Provide information related to conflicts of interest. In particular provide information related to sponsoring/funding of the challenge. Also, state explicitly who had/will have access to the test case labels and when.

This challenge is an initiative of the Radiology Departments of the University Hospitals of Tübingen and LMU together with the European Society of Radiology (ESR) and the European Society for Hybrid, Molecular and Translational Imaging (ESHI-MT).
We aim to seek funding for this challenge from major companies in the field of medical imaging and data analysis. So far, no concrete sponsoring has been agreed on.
Test cases and labels will only be available to a limited number of colleagues involved in organizing this challenge at the University Hospitals of Tübingen and the LMU.

MISSION OF THE CHALLENGE

Field(s) of application

State the main field(s) of application that the participating algorithms target.

Examples:

- Diagnosis
- Education
- Intervention assistance
- Intervention follow-up
- Intervention planning
- Prognosis
- Research
- Screening
- Training
- Cross-phase

Research, CAD, Decision support, Treatment planning, Diagnosis, Prognosis.

Task category(ies)

State the task category(ies).

Examples:

- Classification
- Detection
- Localization
- Modeling
- Prediction
- Reconstruction
- Registration
- Retrieval
- Segmentation
- Tracking

Segmentation.

Cohorts

We distinguish between the target cohort and the challenge cohort. For example, a challenge could be designed around the task of medical instrument tracking in robotic kidney surgery. While the challenge could be based on ex vivo data obtained from a laparoscopic training environment with porcine organs (challenge cohort), the final biomedical application (i.e. robotic kidney surgery) would be targeted on real patients with certain characteristics defined by inclusion criteria such as restrictions regarding sex or age (target cohort).

a) Describe the target cohort, i.e. the subjects/objects from whom/which the data would be acquired in the final biomedical application.

The target cohort consists of patients undergoing FDG-PET/CT examinations in an oncologic context for diagnosis, staging or therapy response assessment.

b) Describe the challenge cohort, i.e. the subject(s)/object(s) from whom/which the challenge data was acquired.

The challenge cohort consists of patients with histologically proven malignant melanoma, lymphoma or lung cancer as well as negative control patients who were examined by FDG-PET/CT in two large medical centers.
Of the 1,200 data sets overall, 500 are negative controls. These negative datasets were regarded negative based on the clinical PET/CT report stating no evidence for malignant lesions in CT or PET.

Imaging modality(ies)

Specify the imaging technique(s) applied in the challenge.

All PET/CT data within this challenge have been acquired on state-of-the-art PET/CT scanners (Siemens Biograph mCT) using standardized protocols following international guidelines. CT as well as PET data are provided as 3D volumes consisting of stacks of axial slices.

Context information

Provide additional information given along with the images. The information may correspond ...

a) ... directly to the image data (e.g. tumor volume).

No additional information will be provided regarding the image data.

b) ... to the patient in general (e.g. sex, medical history).

age, sex, diagnosis

Target entity(ies)

a) Describe the data origin, i.e. the region(s)/part(s) of subject(s)/object(s) from whom/which the image data would be acquired in the final biomedical application (e.g. brain shown in computed tomography (CT) data, abdomen shown in laparoscopic video data, operating room shown in video data, thorax shown in fluoroscopy video). If necessary, differentiate between target and challenge cohort.

Data provided as part of this challenge consists of whole-body examinations. Usually, the scan range of these examinations extends from the skull base to the mid-thigh level. If clinically relevant, scans can be extended to cover the entire body including the entire head and legs/feet.

b) Describe the algorithm target, i.e. the structure(s)/subject(s)/object(s)/component(s) that the participating algorithms have been designed to focus on (e.g. tumor in the brain, tip of a medical instrument, nurse in an operating theater, catheter in a fluoroscopy scan). If necessary, differentiate between target and challenge cohort.

The target structures of the to be developed algorithms are FDG-avid malignant tumors (i.e. primary tumors and metastases).

Assessment aim(s)

Identify the property(ies) of the algorithms to be optimized to perform well in the challenge. If multiple properties are assessed, prioritize them (if appropriate). The properties should then be reflected in the metrics applied (see below, parameter metric(s)), and the priorities should be reflected in the ranking when combining multiple metrics that assess different properties.

- Example 1: Find highly accurate liver segmentation algorithm for CT images.
- Example 2: Find lung tumor detection algorithm with high sensitivity and specificity for mammography images.

Corresponding metrics are listed below (parameter metric(s)).

Accuracy, Specificity.

Additional points: Aim I.) Accurate detection and segmentation of FDG-avid tumor lesions in whole body FDG-PET/CT. The specific challenge in automated segmentation of FDG-avid lesions in PET is to avoid false-positive segmentation of anatomical structures that have physiologically high FDG-uptake (e.g. brain, kidney, heart, etc...) while capturing all tumor lesions.
Aim II.) Robust behavior of the algorihtms in term of moderate changes in acquisition protocol or acquisition site. This will be reflected by the test data which will be drawn partly from the same distribution as the training data and partly from a different hospital with a similar, but slightly different acquisition setup.

DATA SETS

Data source(s)

a) Specify the device(s) used to acquire the challenge data. This includes details on the device(s) used to acquire the imaging data (e.g. manufacturer) as well as information on additional devices used for performance assessment (e.g. tracking system used in a surgical setting).

All PET/CT data were acquired on state-of-the-art PET/CT scanners (Siemens Biograph mCT, mCT Flow and Biograph 64, GE Discovery 690).

b) Describe relevant details on the imaging process/data acquisition for each acquisition device (e.g. image acquisition protocol(s)).

PET/CT acquisition protocols:

Tübingen: Patients fasted at least 6 h prior to the injection of approximately 350 MBq 18F-FDG. Whole-body PET/CT images were acquired using a Biograph mCT PET/CT scanner (Siemens, Healthcare GmbH, Erlangen, Germany) and were initiated approximately 60 min after intravenous tracer administration. Diagnostic CT scans of the neck, thorax, abdomen and pelvis (200 reference mAs; 120 kV) were acquired 90 sec after intravenous injection of a contrast agent (90–120 ml Ultravist 370, Bayer AG). PET Images were reconstructed iteratively (three iterations, 21 subsets) with Gaussian post-reconstruction smoothing (2 mm full width at half-maximum). Slice thickness on contrast-enhanced CT was 2 or 3 mm.

LMU: Patients fasted at least 6 h prior to the injection of approximately 250 MBq 18F-FDG. Whole-body PET/CT images were acquired using a Biograph 64 TruePoint or Biograph mCT Flow PET/CT scanner (Siemens, Healthcare GmbH, Erlangen, Germany) or a GE Discovery 690 (GE Healthcare, US), and were initiated approximately 60 min after intravenous tracer administration. Diagnostic CT scans of the neck, thorax, abdomen and pelvis (100–190 mAs; 120 kV) were acquired 90 sec after weight-adapted intravenous injection of a contrast agent (Ultravist 300, Bayer AG or Imeron 350, Bracco Imaging Deutschland GmbH). PET Images were reconstructed iteratively (three iterations, 21 subsets) with Gaussian post-reconstruction smoothing (2 mm full width at half-maximum). Slice thickness on contrast-enhanced CT was 3 mm.

c) Specify the center(s)/institute(s) in which the data was acquired and/or the data providing platform/source (e.g. previous challenge). If this information is not provided (e.g. for anonymization reasons), specify why.

Data were acquired on two large university hospitals (University Hospital Tübingen and University Hospital of the LMU in Munich).

d) Describe relevant characteristics (e.g. level of expertise) of the subjects (e.g. surgeon)/objects (e.g. robot) involved in the data acquisition process (if any).

Data were acquired by specialized teams consisting of Radiologists, Nuclear Medicine Physicians and Technologists.
Manual segmentation of tumor lesions was performed by two Radiologists with experience in Hybrid Imaging.

Training and test case characteristics

a) State what is meant by one case in this challenge. A case encompasses all data that is processed to produce one result that is compared to the corresponding reference result (i.e. the desired algorithm output).

Examples:

- Training and test cases both represent a CT image of a human brain. Training cases have a weak annotation (tumor present or not and tumor volume (if any)) while the test cases are annotated with the tumor contour (if any).
- A case refers to all information that is available for one particular patient in a specific study. This information always includes the image information as specified in data source(s) (see above) and may include context information (see above). Both training and test cases are annotated with survival (binary) 5 years after (first) image was taken.

A case (training or test case) consists of one 3D whole body FDG-PET volume, one corresponding 3D whole body CT volume and one 3D binary mask of manually segmented tumor lesions on FDG-PET of the size of the PET volume. CT and PET were acquired simultaneously on a single PET/CT scanner in one session; thus PET and CT are anatomically aligned up to minor shifts due to physiological motion. A pre-processing script for resampling the PET and CT to the same matrix size will be provided.

b) State the total number of training, validation and test cases.

Training cases: 1,000
Test cases: 250

c) Explain why a total number of cases and the specific proportion of training, validation and test cases was chosen.

The number of training cases is a trade-off between effort of manual lesions segmentation and necessity for sufficient training data. To our knowledge this is the largest publicly available labeled whole body PET/CT data set.

d) Mention further important characteristics of the training, validation and test cases (e.g. class distribution in classification tasks chosen according to real-world distribution vs. equal class distribution) and justify the choice.

All training cases are drawn from one Hospital (University Hospital Tübingen).
Test cases are split in two subgroups: 100 are drawn from the same hospital as the training cases (University Hospital Tübingen, Siemens Scanner) and 150 are drawn from a different hospital (University Hospital of LMU in Munich, Siemens and GE Scanners) with similar acquisition protocols.
The rationale behind this selection of test cases is to assess the performance of submitted algorithms on data with slightly different characteristics and thus estimate algorithm robustness and generalizability.

Annotation characteristics

a) Describe the method for determining the reference annotation, i.e. the desired algorithm output. Provide the information separately for the training, validation and test cases if necessary. Possible methods include manual image annotation, in silico ground truth generation and annotation by automatic methods.

If human annotation was involved, state the number of annotators.

All training and test data were manually annotated by Radiologists with experience in Hybrid Imaging. To this end, FDG-avid tumor lesions were manually segmented on the PET image data using dedicated software.

b) Provide the instructions given to the annotators (if any) prior to the annotation. This may include description of a training phase with the software. Provide the information separately for the training, validation and test cases if necessary. Preferably, provide a link to the annotation protocol.

The following annotation protocol was defined:
Step 1: Identification of FDG-avid tumor lesions by visual assessment of PET and CT information together with the

clinical examination reports.
Step 2: Manual free-hand segmentation of identified lesions in axial slices

c) Provide details on the subject(s)/algorithm(s) that annotated the cases (e.g. information on level of expertise such as number of years of professional experience, medically-trained or not). Provide the information separately for the training, validation and test cases if necessary.

Two experts annotated training and test data:
At the University of Tübingen, a Radiologist with 10 years of experience in Hybrid Imaging and experience in machine learning research annotated all data.
At LMU, a Radiologist with 5 years of of experience in Hybrid Imaging and experience in machine learning research annotated all data.

d) Describe the method(s) used to merge multiple annotations for one case (if any). Provide the information separately for the training, validation and test cases if necessary.

N/A

Data pre-processing method(s)

Describe the method(s) used for pre-processing the raw training data before it is provided to the participating teams. Provide the information separately for the training, validation and test cases if necessary.

For training and test data, original DICOM files will be anonymized and converted to the NIfTI format. In addition, the PET data will be standardized by converting image units from activity counts to standardized uptake values. A pre-processing script for resampling the PET and CT to the same matrix size will be provided.

Sources of error

a) Describe the most relevant possible error sources related to the image annotation. If possible, estimate the magnitude (range) of these errors, using inter-and intra-annotator variability, for example. Provide the information separately for the training, validation and test cases, if necessary.

One relevant possible error source for image annotation is the uncertainty for whether an FDG-avid lesions is actually malignant as this cannot always be determined by PET/CT alone. For experienced readers and regarding the tumor entities chose in this challenge, a rough estimate of false classification of lesions in this sense is about 5-10%.

The second relevant possible error source is the uncertainty of defining lesion boundaries especially on PET data that have low intrinsic resolution. The difference in segmentation volumes can range from 5-30 %.

b) In an analogous manner, describe and quantify other relevant sources of error.

A further potential error source are image artifacts in PET and/or CT that may result in altered image properties.

ASSESSMENT METHODS

Metric(s)

a) Define the metric(s) to assess a property of an algorithm. These metrics should reflect the desired algorithm properties described in assessment aim(s) (see above). State which metric(s) were used to compute the ranking(s) (if any).

- Example 1: Dice Similarity Coefficient (DSC)
- Example 2: Area under curve (AUC)

We will use a combination of 3 metrics reflecting the aims and specific challenges for the task of PET lesion segmentation:
1) Foreground Dice score of segmented lesions.
2) Volume of false positive connected components that do not overlap with positives.
3) Volume of positive connected components (in the ground truth) that have no overlap with the predicted segmentation.

In case of test data that do not contain positives (no FDG-avid lesions), only metric 2 will be used.

b) Justify why the metric(s) was/were chosen, preferably with reference to the biomedical application.

Ad 1) The Dice score will be used as a measure of overall segmentation performance.
Ad 2) The volume of false positive connected components that do not overlap with positives is chosen as a measure of false positive segmentations of physiological FDG uptake (not within tumor lesions).
Ad 3) The volume of positive connected components (in the ground truth) that have no overlap with the predicted segmentation is chosen as a measure for completely missed (potentially small) lesions.

Ranking method(s)

a) Describe the method used to compute a performance rank for all submitted algorithms based on the generated metric results on the test cases. Typically the text will describe how results obtained per case and metric are aggregated to arrive at a final score/ranking.

Step 1: Seperate rankings will be computed based on each metric (for metric 1: higher Dice score = better, for metrics 2 and 3: lower volumes = better)
Step 2: From the three ranking tables, the mean ranking of each participant will be computed as the numerical mean of the single rankings (metric 1: 50 % weight, metrics 2 and 3: 25 % weight each)
Step 3: In case of equal ranking, the achieved Dice metric will be used as a tie break.

b) Describe the method(s) used to manage submissions with missing results on test cases.

Submission with missing results on test cases will not be considered for the leader board.

c) Justify why the described ranking scheme(s) was/were used.

The described ranking system was used to reflect the specific challenges of the underlying task. One the one hand, it is important to accurately segment tumor lesions; on the other hand, the specific challenge of this task is to avoid false positive segmentations of physiological FDG uptake while not completely missing small lesions.

Statistical analyses

a) Provide details for the statistical methods used in the scope of the challenge analysis. This may include

- description of the missing data handling,
- details about the assessment of variability of rankings,
- description of any method used to assess whether the data met the assumptions, required for the particular statistical approach, or
- indication of any software product that was used for all data analysis methods.

For each submission, mean, standard deviation over the test cohort and range of the defined metrics will be

computed.
In addition, these statistics will be calculated separately for the two parts of the test data set (data from the two Hospitals)

b) Justify why the described statistical method(s) was/were used.

These statistical will be used in order to provide an overview of algorithm performance and reliability as well as generalizability across institutions.

Further analyses

Present further analyses to be performed (if applicable), e.g. related to

- combining algorithms via ensembling,
- inter-algorithm variability,
- common problems/biases of the submitted methods, or
- ranking variability.

ADDITIONAL POINTS

References

Please include any reference important for the challenge design, for example publications on the data, the annotation process or the chosen metrics as well as DOIs referring to data or code.

Pfannenberg C, Gueckel B, Wang L, Gatidis S, Olthof SC, Vach W, Reimold M, la Fougere C, Nikolaou K, Martus P. Practice-based evidence for the clinical benefit of PET/CT-results of the first oncologic PET/CT registry in Germany. Eur J Nucl Med Mol Imaging. 2019 Jan;46(1):54-64. doi: 10.1007/s00259-018-4156-3. Epub 2018 Sep 29. PMID: 30269155.

Further comments

Further comments from the organizers.

This challenge is an initiative of the University Hospitals of Tübingen and the LMU in Munich togethter witht the European Society of Radiology (ESR) and the European Society of Hybrid, Molecular and Translational Imaging (ESHI-MT).