Traumatic Brain Injury Lesion Segmentation: Structured description of the challenge design

CHALLENGE ORGANIZATION

Title

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

Traumatic Brain Injury Lesion Segmentation

Challenge acronym

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

AIMS TBI - Automated Identification of Moderate-Severe Traumatic Brain Injury Lesions

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.

Moderate to Severe Traumatic Brain Injury (msTBI) is caused by external forces (eg: traffic accidents, falls, sports) causing the brain to move rapidly within the skull, resulting in complex pathophysiological changes. Primary injuries arising from the initial forces can include haematoma, hemorrhages, and contusions among others (Mckee & Daneshvar, 2015). These primary injuries subsequently induce a cascade of secondary injuries that evolve over hours to days including gliosis, encephalomalacia (Maas et al., 2008) and life threatening disorders such as raised intracranial pressure, which can require acute surgical intervention (Bullock et al., 2006). Each of these primary, secondary and surgery related processes has the potential to cause structural deformation in the brain. Each patient with msTBI has a unique accumulation of these structural changes, contributing to extremely heterogeneous lesions, considered a hallmark of msTBI (Covington & Duff, 2021). These lesions differ from other common brain pathologies (stroke, MS, brain tumor) in that they can be both focal or diffuse, varying in size, number and laterality, extending through multiple tissue types (GM/WM/CSF), and can also occur in homologous regions of both hemispheres. Lesions such as these can complicate image registration, normalization, and are known to introduce both local and global errors in brain parcellation.(Diamond et al., 2020; King et al., 2020). While multiple tools exist to compensate for lesions in neuroimaging preprocessing (HD_Bet (Isensee et al., 2019), VBG (Radwan et al., 2021), FastSurfer), many require the time consuming manual creation of lesion masks and subsequent manual quality assessment. Furthermore, in our experience, methods that have been developed for lesions of different etiologies (e.g. stroke, tumors [Henschel et al., 2020]) do not perform well in TBI.

In the absence of appropriate processing tools, current lesion compensation techniques in msTBI include ignoring the lesions (resulting in unreliable findings), excluding msTBI patients with large lesions (limiting the generalizability), or manual segmentation of lesions prior to analysis (time consuming). This last step of manual segmentation is often only feasible in smaller, single site studies which lack the statistical power to perform subgroup analyses (i.e.,divide the TBI sample according to lesion characteristics). These restrictive approaches limit the ability to investigate how factors such as type of injury (axonal injury, focal lesions, and diffuse

microlesions), severity of brain injury (mild, moderate, severe), and presence of comorbid injuries or complications (especially those that affect pulmonary and cardiovascular function, see (Crawford et al., 2019) and posttraumatic seizure [Bennett et al., 2017; Liesemer et al., 2011]) impact the relationship between lesion characteristics and patient's functional outcomes. To capture this information, msTBI researchers need access to an accurate, automatic lesion segmentation algorithm trained on large consortium analyses of multicohort MRI datasets, where MRI data is pooled/aggregated across centers. Whilst a handful of TBI specific algorithms exist, they require either multiple image types (Kamnitsas et al., 2017) (T1, T2, FLAIR, GE & PD) or can run on only CT images (Jain et al., 2019). However, the necessity for multiple image types limits the ability of large scale consortia to aggregate common MRI scans across sites and there is a larger variability in scanning sequence parameters in other MRI modalities (such as diffusion MRI). Therefore, this challenge will focus on identifying lesions in T1 weighted MRI data only as it is the most common MRI scan across our ENIGMA TBI consortium. Moreover, anatomical T1 weighted MRI scans show less parameter variation (e.g. 1 mm3 voxel size was relatively common in our previous published work, Dennis et al., 2023; Keleher et al., 2022).

The Enhancing NeuroImaging Genetics through MetaAnalysis (ENIGMA) Consortium is a global collaborative framework for neuroimaging researchers with >50 working groups examining various neurological, psychiatric, and developmental disorders (Thompson et al., 2022). The ENIGMA TBI working group formed in 2016, and has since grown to over 200 researchers (Dennis et al., 2020). Within the ENIGMA TBI WG, there are subgroups based on the TBI patient population, two of which focus on msTBI: Pediatric msTBI and Adult msTBI. This challenge will leverage the data shared with these subgroups. There are nearly 1,300 T1 weighted MRI datasets from msTBI patients across these groups (age range=5 to 85 years), and based on preliminary rates of manual lesion identification in the dataset, we expect that approximately 1,000 datasets will include lesions that are visible on T1w MRI. 800 of these will be made available for the purposes of this challenge. Advances in lesion segmentation and the implementation of an accurate lesion mask resulting from the lesion segmentation into the next image processing and analyses (such as parcellation, functional connectivity analyses, connectomics, fixel based analysis) will allow for a more accurate prognostication and may improve long term outcomes for patients.

Challenge keywords

List the primary keywords that characterize the challenge.challenge_

traumatic brain injury, lesion, MRI, segmentation, TBI

Year

The challenge will take place in 2024

FURTHER INFORMATION FOR CONFERENCE 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.

Based on the number of teams who have participated in related challenges (BraTS - 30, ATLAS - 14, ISLES - 110), we estimate that at least 10 teams will participate.

Publication and future plans

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

Yes, in addition to the publications submitted as part of the challenge, we will coordinate a publication after the conclusion of the challenge with members from the 3 top-performing teams.

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.

Our challenge will be hosted on the Grand Challenge platform. All data will be available through the Challenge platform, and we will use the platform for validation and testing. Projectors will be needed during the half day challenge, and possibly microphones/speakers depending on the size of the room

TASK 1: Automated MRI lesion segmentation using T1-weighted MRI scans in moderate-severe traumatic brain injury

SUMMARY

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.

Segment lesions in T1-weighted MRI data from moderate-severe traumatic brain injury.

Keywords

List the primary keywords that characterize the task.

T1-weighted MRI, TBI, traumatic brain injury, lesion, segmentation

ORGANIZATION

Organizers

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

Emily Dennis - University of Utah
Nick Tustison - University of Virginia
Evelyn Deutscher - Deakin University
Elisabeth Wilde - University of Utah
Karen Caeyenberghs - Deakin University

b) Provide information on the primary contact person.

Emily Dennis - emily.dennis@hsc.utah.edu

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, although it may become a repeated event based on the results of this year. There may be additional opportunities for follow-up challenges including lesion inpainting.

Challenge venue and platform

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

This challenge will coordinate with the BrainLesion Workshop and will take place during that scheduled workshop.

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

grand-challenge.org (Type 2)

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

N/A

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.

Publicly available data is 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.

Members of the organizers institutes that are not associated with the challenge may participate and are eligible for awards.

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

The top 3 performing teams will receive a cash prize - $1000USD for first place, $650 for second place, $350 for third place.

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.

Algorithm performance will be shared privately with each team on the challenge website during the validation phase and updated with each submission. Final performance will be announced at the MICCAI in-person challenge event and the top 3 teams will be listed on the challenge website at this time.

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).

Participating teams will be asked to submit a 4-6 page paper on their algorithms and results after the validation phase, due Aug 1 2024, as part of the challenge. The top three teams will be invited to work with the challenge organizers on a challenge paper to be submitted to a medical imaging journal after the conclusion of the

challenge.
Teams may publish any additional papers after the challenge after an embargo period of 6 months.

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.

Algorithm container submission (type 2) on Grand Challenge.

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.

We plan to release a validation subset 6 weeks after the release of the training data. The ground truth data for the validation set will not be released, but multiple submissions will be allowed for groups to fine tune their algorithms prior to the final test. Results from the validation phase will only be shared with individuals.

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

- March 4: Teams interested in participating may start to coordinate data use agreements (DUA) with the University of Utah
- April 1: Training data will be released when the challenge website opens
- May 15: Validation data will be released
- June 30: Validation phase closes
- July 1: Final model submission opens
- August 1: Deadline for challenge papers
- Oct 6/10: Final results announced during the MICCAI 2024 meeting

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).

University of Utah IRB has acknowledged the ENIGMA projects as not human subjects due to data de-identification. The University of Utah has DUAs/MTAs/CRADAs/SCCs in place with each site that has contributed data. Data will be further anonymized with the following steps:
- MRI data will be defaced with any subject or site data stripped from the metadata
- Subject IDs will be recoded with the key securely held at the University of Utah
- Data will be pooled across sites with no way to re-identify site
- The only demographic data provided along with the MRI data will be age (rounded to the nearest year) and time since injury (in weeks)
With these steps, we are confident that subject/site re-identification will be impossible. Participating challenge teams will need to complete a DUA with the University of Utah prior to receiving access to the data.

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.

A script for evaluating results will be made available on the challenge website when the training data is released.

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

Participating teams will be required to submit their code as a container (preferably Singularity) through the challenge website. These will be kept private until the final test, when the top-performing algorithm will be published

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.

The National Institutes of Health funds this work.

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

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 would be patients who have sustained a moderate-severe TBI who have T1-weighted MRI data

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

The challenge cohort includes subjects from the ENIGMA Pediatric msTBI and ENIGMA Adult msTBI working groups who have T1-weighted MRI data that has been shared with the University of Utah.

Imaging modality(ies)

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

T1-weighted MRI

Context information

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

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

None

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

Patient age and time since injury.

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.

Brain MRI scan

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.

3D lesions in the brain

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)).

Find highly accurate TBI lesion segmentation algorithm for T1-weighted MRI images.

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).

T1-weighted MRI data from multiple MRI scanner manufacturers (GE, Siemens, Philips)

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

Data acquisition includes T1-weighted MRI data acquired on 1.5T and 3T scanners. The vast majority will have 1 mm isotropic voxel sizes, but some sites will vary within standard parameter ranges.

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.

Baylor College of Medicine, University of California Los Angeles, Pennsylvania State University, Kennedy Krieger Institute, Loma Linda University, Nationwide Children's Hospital, Murdoch Children's Research Institute, Deakin University, University of Texas Houston, Kessler Foundation, VA Palo Alto, Icahn School of Medicine at Mt. Sinai, and the University of Oslo.

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).

Image acquisition was performed by trained health professionals/radiologists at each respective institution.

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 refers to one T1w MRI scan from a particular patient. Some patients will have longitudinal data but "case" refers to individual MRI datasets.The ground-truth (binary lesion masks) will be provided for the training cases only.

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

A total of 800 T1-weighted MRI datasets are split into 400 training (50%), 100 validation (12.5%), and 300 test cases (37.5%). Data will come from 12 different cohorts, with approximately the same distribution of training, validation, and test data randomly selected across sites.

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

400 training datasets - a relatively large number of datasets to train a reliable model
100 validation datasets - a relatively small number of datasets to fine tune models and ensure fairness
300 test datasets - a relatively large number of datasets for an accurate, fair, final assessment of model performance

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.

None

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.

Manual annotation by 7 primary and 5 expert annotators. Primary annotators were staff at the University of Utah. Expert raters were Emily Dennis, Evelyn Deutscher, Karen Caeyenberghs, Hannah Lindsey, and Elisabeth Wilde.

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.

Training materials and instructions are summarized here:
https://drive.google.com/drive/folders/1LPoeCDBzCP_VfVOUoIPciCpHP8QdM1Gy

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.

Staff at the University of Utah served as primary raters and were trained under the same protocol and completed segmentations on the same training data. Training data were reviewed by experts (ED and ED) and staff were approved to proceed to real data once they achieved a DSC of 0.6.
Lesion identification was performed in a 3 step manual process
- one primary rater reviewed the scan and manually segmented any lesions in ITK-SNAP
- a different primary rater reviewed the lesion segmented by the first rater and provided additional edits if necessary
- a third rater (expert rater) reviewed the lesion segmentation, provided minor edits if necessary, and approved the segmentations (any minor edits were communicated back to the primary raters to improve their following segmentations)

Some publicly available resources might be of interest to the participant:
Datasets:

Aphasia Recovery Cohort (ARC) (https://openneuro.org/datasets/ds004884/versions/1.0.1)
ATLAS v2.0 (https://www.nature.com/articles/s41597-022-01401-7)
A vanilla u-net was trained on the ATLAS v2.0 dataset using the ANTsPy/ANTsPyNet packages. Training scripts are available (https://github.com/ntustison/ANTsXNetTraining/blob/main/Lesions/). Note that this is not a participating algorithm but contains illustrations of certain approaches/tools that might be useful to the participants including:
Preprocessing (e.g., bias field correction, denoising, normalization to a template, brain extraction).
Data augmentation (e.g., simulated bias field, added noise, histogram intensity warping, random spatial transformations).
All these Python-based and R-based tools, including the lesion segmentation algorithm, are listed and demonstrated, complete with data, at http://www.tinyurl.com/antsxtutorial.

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.

Two raters reviewed each segmentation, with the second rater either approving or providing additional edits

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.

The only pre-processing will be defacing to protect subject privacy. The goal is for the resulting algorithms to be able to handle data from various sources, so no other preprocessing has been done.

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.

N/A

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

N/A

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)

- Dice similarity coefficient - DSC (voxelwise) = 2TP/ (2TP + FN + FP)
- Absolute volume difference - AVD (voxelwise) = volume annotated - volume rater
- Absolute lesion count difference - Count (lesion-wise) = Total predicted - total rater

- Detection rate - Detection (lesion-wise) = 2TP/ (2TP + FN + FP)

TP=true positive, FN=false negative, FP=false positive

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

The metrics chosen were selected to assess both detection accuracy and segmentation accuracy, with Dice widely used in medical segmentation challenges and tasks.
Lesion size varies considerably across the dataset as is characteristic of TBI. For an algorithm to be broadly useful, it needs to identify lesions of all sizes. For this reason, we are using the additional metrics of lesion count difference and detection rate, as DSC will be biased towards larger lesions. DSC will be calculated both by subject and by lesion cluster. Combining this with the number of lesions and lesion volume, we will have metrics concerning the performance of the algorithms in identifying and segmenting lesions of all sizes.

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.

The goal is to identify the algorithm that generates the most accurate lesion segmentation and the metrics selected will assess detection performance and segmentation accuracy. Similar ranking schemes have been used in previous medical imaging segmentation challenges.

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

Up to 10% missing data will be accepted with scores calculated across remaining data. Beyond 10% missing data, the scores for missing cases will be incorporated into calculations.

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

We will compute average DSC, AVD, Count, and Detection across cases. The groups will receive a rank of 1 through N (number of teams participating) for each of the four metrics with rank 1 for DSC and detection given to the team with the highest values and rank 1 for AVD and count given to the team with the lowest values. These four ranks will be summed and the team with the smallest sum will rank first and on down.

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.

None

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

None

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.

None

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.

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Covington, N. V., & Duff, M. C. (2021). Heterogeneity Is a Hallmark of Traumatic Brain Injury, Not a Limitation: A New Perspective on Study Design in Rehabilitation Research. American Journal of Speech Language Pathology / American Speech Language Hearing Association, 30(2S), 974 to 985.

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Isensee, F., Schell, M., Pflueger, I., Brugnara, G., Bonekamp, D., Neuberger, U., Wick, A., Schlemmer, H.P., Heiland, S., Wick, W., Bendszus, M., MaierHein, K. H., & Kickingereder, P. (2019). Automated brain extraction of multisequence MRI using artificial neural networks. Human Brain Mapping, 40(17), 4952 to 4964.

Jain, S., Vyvere, T. V., Terzopoulos, V., Sima, D. M., Roura, E., Maas, A., Wilms, G., & Verheyden, J. (2019). Automatic

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Further comments

Further comments from the organizers.

N/A