

Magnetic resonance image-based brain tumour segmentation methods

Bhalodiya, JM; Lim Choi Keung , SN; Arvanitis, TN

DOI:

[10.1177/20552076221074122](https://doi.org/10.1177/20552076221074122)

License:

Creative Commons: Attribution (CC BY)

Document Version

Publisher's PDF, also known as Version of record

Citation for published version (Harvard):

Bhalodiya, JM, Lim Choi Keung , SN & Arvanitis, TN 2022, 'Magnetic resonance image-based brain tumour segmentation methods: A systematic review', *Digital Health*, vol. 8, pp. 1-19.
<https://doi.org/10.1177/20552076221074122>

[Link to publication on Research at Birmingham portal](#)

General rights

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

- Users may freely distribute the URL that is used to identify this publication.
- Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
- User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
- Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

Take down policy

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.

Magnetic resonance image-based brain tumour segmentation methods: A systematic review

Digital Health
Volume 8: 1–19
© The Author(s) 2022
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/20552076221074122
journals.sagepub.com/home/dhj



Jayendra M Bhalodiya^{1,2} , Sarah N Lim Choi Keung¹
and Theodoros N Arvanitis¹

Abstract

Background: Image segmentation is an essential step in the analysis and subsequent characterisation of brain tumours through magnetic resonance imaging. In the literature, segmentation methods are empowered by open-access magnetic resonance imaging datasets, such as the brain tumour segmentation dataset. Moreover, with the increased use of artificial intelligence methods in medical imaging, access to larger data repositories has become vital in method development.

Purpose: To determine what automated brain tumour segmentation techniques can medical imaging specialists and clinicians use to identify tumour components, compared to manual segmentation.

Methods: We conducted a systematic review of 572 brain tumour segmentation studies during 2015–2020. We reviewed segmentation techniques using T1-weighted, T2-weighted, gadolinium-enhanced T1-weighted, fluid-attenuated inversion recovery, diffusion-weighted and perfusion-weighted magnetic resonance imaging sequences. Moreover, we assessed physics or mathematics-based methods, deep learning methods, and software-based or semi-automatic methods, as applied to magnetic resonance imaging techniques. Particularly, we synthesised each method as per the utilised magnetic resonance imaging sequences, study population, technical approach (such as deep learning) and performance score measures (such as Dice score).

Statistical tests: We compared median Dice score in segmenting the whole tumour, tumour core and enhanced tumour.

Results: We found that T1-weighted, gadolinium-enhanced T1-weighted, T2-weighted and fluid-attenuated inversion recovery magnetic resonance imaging are used the most in various segmentation algorithms. However, there is limited use of perfusion-weighted and diffusion-weighted magnetic resonance imaging. Moreover, we found that the U-Net deep learning technology is cited the most, and has high accuracy (Dice score 0.9) for magnetic resonance imaging-based brain tumour segmentation.

Conclusion: U-Net is a promising deep learning technology for magnetic resonance imaging-based brain tumour segmentation. The community should be encouraged to contribute open-access datasets so training, testing and validation of deep learning algorithms can be improved, particularly for diffusion- and perfusion-weighted magnetic resonance imaging, where there are limited datasets available.

Keywords

Brain tumour, magnetic resonance imaging, segmentation, systematic review, brain, artificial intelligence

Submission date: 21 September 2021; Revision date: 20 November 2021; Acceptance date: 27 December 2021

Introduction

Brain tumours are malignancies of brain tissues. Characterising such tissues and identifying related genes can help to estimate tumour spread, and further help to identify tumour grades for the treatment planning.^{1,2} Such characterisation comprises of the different tumour components assessment. Components such as

¹Institute of Digital Healthcare, Warwick Manufacturing Group, The University of Warwick, UK

²School of Engineering and Applied Science, Ahmedabad University, Gujarat, India

Corresponding author:

Jayendra M Bhalodiya, School of Engineering and Applied Science, Ahmedabad University, Commerce Six Roads, Navrangpura, Ahmedabad, Gujarat 380009, India.

Emails: jayendra.bhalodiya@warwick.ac.uk;

jayendra.bhalodiya@ahduni.edu.in



tumour core, boundary of tumour core, peritumoral oedema, cellular proliferation (an increase of the number of cells), cellular infiltration (migration of cells or excessive growth) and vascular proliferation (leaky blood vessels) are of great clinical interest.^{1,3} Current practice involves various magnetic resonance imaging (MRI) approaches to visualise these tumour components.⁴ Particularly, the tumour core can be visible in T2-weighted MRI, and T1-weighted MRI, the enhanced boundary of tumour core can be seen in gadolinium-based T1-weighted MRI (T1-Gd), peritumoral oedema can be visible in fluid-attenuated inversion recovery (FLAIR) MRI, while cellular proliferation, cellular infiltration and vascular proliferation can be visualised in diffusion-weighted MRI and perfusion-weighted MRI.

In the literature, MRI-based image processing methods addressed the outlining of tumour components.⁵ These methods can distinguish between healthy and tumour tissues. Moreover, they can distinguish among different tumour components within the tumour. Such methods are commonly known as segmentation methods,⁵ which can be manual, semi-automatic or automatic. With the increase of segmentation methods, the medical image analysis community has reviewed them using publicly available benchmark datasets (e.g. the brain tumour segmentation – BraTS dataset) to assess their performance.^{5,6} Additionally, individual reviews addressing only deep learning methods,⁷ only automated methods,⁸ classical reviews,⁹ and practical implications¹⁰ are reported. However, a systematic review to identify promising, and widely adapted brain tumor segmentation methods is not reported in the literature. Moreover, in the literature, individual methods, and their validation show technical advancements in most MR image-based approaches, but they are not fully explored in all MRI sequences in the imaging of brain tumours. For example, diffusion-weighted, and perfusion-weighted MRI are often overlooked or limited in brain tumor segmentation method development, and validation. In addition, a recent trend of deep learning methods has extensively contributed to the development of automatic segmentation methods, in order to avoid the subjective, and time-consuming nature of manual techniques. However, the performance of these deep learning methods relies on the data types used, single or multi-centre data collection, the number of available data samples for training, validation and testing of the approach. Therefore, it is crucial to explore the various studies in deep learning methods. Such a study can help understanding and justifying the need for further large open-access data repositories and alternative artificial intelligence (AI)-based techniques, such as transfer learning.

In this systematic review, we addressed the following PICO (P: population, I: intervention, C: comparison, O: outcome) format research question:

What automated brain tumour segmentation techniques can medical imaging specialists, and clinicians use to identify tumour components, compared to manual segmentation?

To answer the above question, we reviewed brain tumour segmentation methods which are based on physics or mathematics models, deep learning models, and software or semi-automatic methods. The methods, which use at least four types of MRI sequences (T1-weighted, T1-Gd, T2-weighted and FLAIR MRI), are included in the synthesis as they are common in clinical practice. Articles based on images from other MRI sequences are discussed, individually. The accuracy measures and study population of the various segmentation methods are also reviewed. Moreover, deep learning architectures are reviewed for their underlying network architecture (for example, U-Net, VGG etc.) with a list of articles that adapted such architectures in their studies. Technical specifications of such architectures are listed in the discussion.

Materials and methods

Study protocol

A protocol for this study is prepared internally but not registered elsewhere. However, the PROSPERO database is checked to ensure the originality of the study.

Article search

For source articles' systematic identification, we have searched the following online databases: PubMed, Embase Ovid and Engineering Village. The different combinations of the keywords 'glioma', 'medulloblastoma', 'brain tumour' and 'segmentation' were used. After discussion among the authors, the combination, 'glioma', and 'segmentation', and 'brain tumour', was used for the article search. The search duration was defined to include articles published in the period from 2015 until 2020. In PubMed, the specific search filters were full-text, humans, English and segmentation keyword must be in the article title or abstract. In Engineering Village, the specific search filters were that the segmentation keyword must be in the abstract, and glioma, and brain tumour keywords must be in the subject or title or abstract. All the articles were stored using Zotero¹¹ software. After removing the duplicates, study inclusion/exclusion criteria were applied.

Study inclusion/exclusion criteria

Articles are screened at two levels for inclusion/exclusion. First, the articles are screened at the abstract, and title level. At this level, the studies, which are not segmentation studies, are excluded. The excluded studies are grouped into the following categories: clinical analysis studies, case

studies, image pre-processing studies, general overall surveys, tumour classification studies, tumour detection and identification studies, information learning for model training studies, surgical planning studies, datasets and not accessible studies.

Second, the segmentation studies are screened by reading the full text. At this level, the articles, which are eligible for synthesis, are identified by reviewing the imaging modalities, and associated data types used in their segmentation method. The studies, which are not MRI-based, are excluded. As a result, among the MRI-based studies, articles that utilised T1-weighted, T2-weighted, T1-Gd and FLAIR MRI are included for the final synthesis. All the inclusion/exclusion criteria are mentioned in the PRISMA¹² diagram of Figure 1.

Data extraction

After removing duplicates, all the articles are organised, as a table, in Microsoft Excel (Please refer to S1 Appendix). For each article, data is extracted according to the following parameters: publication id, publication type, publication year, author, article title, publisher, DOI, issue number, volume number, type of study, type of technical methodology, type of imaging modality, type of MRI, type of tumour, single or multi-centre data collection, the number of data samples and performance score.

Among the aforementioned parameters, the ‘data samples’ parameter is sub-categorised into study population, training data, validation data and test data. The types of technical methods in image-based tumour segmentation are organised into three categories: physics or mathematics-based methods, deep learning-based methods and software or semi-automatic methods. The performance score of each segmentation method is retrieved from the respective article and included in our table. In articles, authors have used various performance score measures, which include match, accuracy, Jaccard similarity coefficient, Tanimoto similarity, Hausdorff distance, dice score, positive predictive value, specificity, sensitivity, negative predictive value, precision, recall, misclassification error, intersection over union, Lin’s concordance correlation coefficient, quality measure, balanced error rate, kappa, correlation, mean square error, false-positive rate per patient, the extent of resection, mutual information, residual tumour volume, root mean square error, the ratio of overlap, coefficient of variation, agreement index, interoperator variance, F1 score, volume difference, peak signal-to-noise ratio, qualitative evaluation, difference ratio of pixels, similarity, overlap index, absolute error, percent error, the difference with the gold standard, paired *t*-test mean difference, linear regression and area under the curve. The details of each performance score matrix can be found in their respective articles as mentioned in the data extraction matrix (S1 Appendix). We synthesised the performance of

each method in segmenting whole tumour (WT), non-enhancing tumour core (TC) and enhanced tumour (ET). The values are stored as a tuple of ‘whole tumour, tumour core, enhanced tumour’. Each missing value in a performance score tuple is recorded as *null*. As shown in the PRISMA diagram of Figure 1, the imaging modalities, and MRI sequences are identified at the eligibility level. Broadly, four imaging modalities have been identified: magnetic resonance imaging (MRI), computed tomography, positron emission tomography, and ultrasound. Specifically in MRI, the identified imaging sequences include T1-weighted MRI, gadolinium-enhanced T1-weighted MRI (T1-Gd), T2-weighted MRI, FLAIR MRI, diffusion-weighted MRI, fMRI, perfusion-weighted MRI, magnetic resonance spectroscopy, apparent diffusion constant, fractional anisotropy, diffusion tensor, dynamic susceptibility contrast, dynamic contrast enhancement, diffusion kurtosis, magnetisation prepared rapid gradient echo, T1-MPRAGE and T1-weighted with turbo field echo.

Risk of bias assessment

All reviewers assessed studies or validated data extraction matrix independently. JMB assessed each study and populated data extraction matrix records. SLCK validated the data extraction matrix. TNA verified, and confirmed the data extraction matrix. The whole process was performed manually, and without using any automation tools.

Synthesis methods

Studies are synthesised according to the publication year, technical methods used in method development (type of study), MRI sequences used in the segmentation method development, deep learning methods (technical architectures used in deep learning studies), performance score to evaluate accuracy in segmenting three tumour components – whole tumour, and tumour core, and enhanced tumour, study population, and specific studies with additional MRI sequences. The studies having at least T1-weighted, T2-weighted, T1-Gd and FLAIR MRI sequences used are included for the synthesis. The synthesis of a number of articles is visualised as a bar plot, and pie charts showing the total number of articles in each year, and category. The synthesis of the study population in terms of data samples used, and performance score measure in terms of median Dice score are visualised as results. The outcome is depicted as Matlab box plots as commonly found in the synthesised articles. Deep learning studies are tabulated to identify the most widely adapted deep learning technology.

Benchmark review articles and particular imaging sequences studies are mentioned in the specific imaging studies’ section. Studies of segmentation methods using diffusion-weighted, and perfusion-weighted MRI, are reported individually.

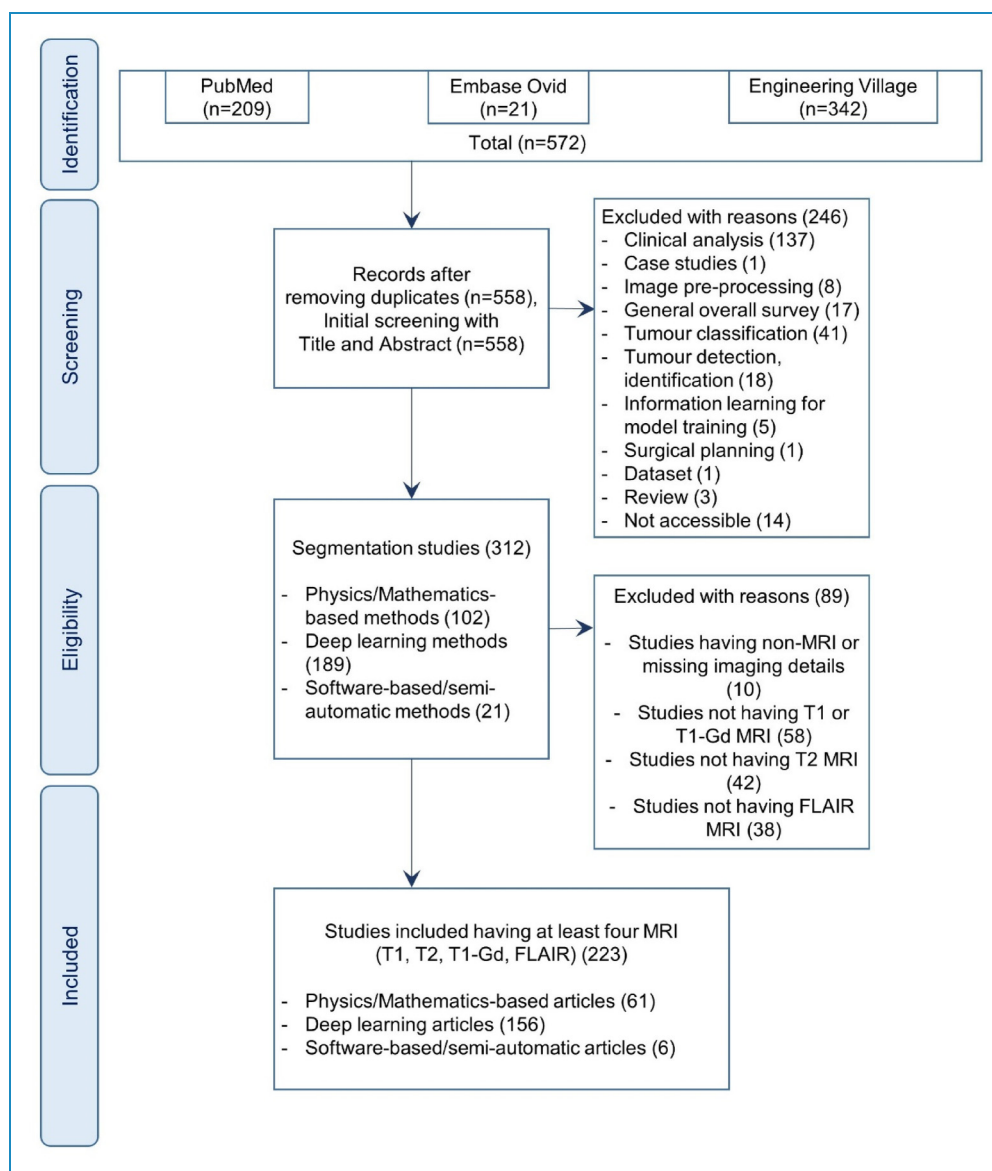


Figure 1. PRISMA diagram. PRISMA diagram of the systematic review of brain tumour segmentation methods.

During the synthesis, the unavailable values of performance score measures and data samples are considered as *null* values.

Results

Article identification

In this systematic review, 572 articles are identified from online publication repositories. Out of these, 14 duplicates are removed and the remaining 558 articles are screened for the eligibility criteria. After screening titles and abstracts, 246 articles are excluded, and the remaining 312 articles are screened by reading the full text. After the full-text screening, 89 articles are excluded

with reasons, and 223 articles are included for synthesis. The summary of exclusion reasons and the number of excluded articles are shown in the PRISMA diagram (Figure 1).

Publications over the time

As shown in the PRISMA diagram, after screening at the abstract and title level, we selected 312 articles. Following that we applied the eligibility criteria, which provided us with 223 articles for the synthesis. These articles are categorised over the publication year, as shown in Figure 2 bar plot. Further, the articles are categorised as per the technical method category, as shown in Figure 2 pie charts.

Type of study

After the screening at the title and abstract level, 312 studies are included. Among them, 102 are physics or mathematics-based, 189 are deep learning-based and 21 are software-based or semi-automatic methods articles. After the full-text screening, 223 studies are included for synthesis. Among them, 61 are physics or mathematics-based,¹³⁻⁷⁴ 156 are deep learning-based and six are software-based or semi-automatic⁷⁵⁻⁸⁰ methods articles.

Imaging sequences in synthesised studies

A total of 223 studies have used at least four MRI sequences (T1-weighted, T2-weighted, T1-Gd and FLAIR MRI) which are included in the final synthesis.

Technical architectures in studies

We synthesised 156 deep learning articles to identify the commonly reported deep learning architecture in automatic brain tumour segmentation. We reported deep learning architectures such as convolutional neural network (CNN),⁸¹⁻⁸³ visual geometry group (VGG) network,⁸⁴⁻⁸⁶ DeepMedic,^{84,87-92} U-Net,^{84,91,93-114} autoencoder,¹¹⁵⁻¹¹⁷ generative adversarial network (GAN),¹¹⁸⁻¹²⁰ W-net,¹¹³ a cascade of W-Net E-Net, and T-Net,¹¹³ squeeze, and excitation network (SENet),¹²¹ multiresolution neural network,¹²² holistically-nested edge detection (HED) network,¹²³ multi-level upsampling network,¹²⁴ V-net,¹²⁵ residual network (ResNet),^{125,126} hourglass network,¹²⁷ multi-view network (MvNet),¹²⁸ DeepSCAN,^{129,130} densely connected,⁸⁵ inception,^{85,99} ensemble net,¹³¹ PixelNet,^{132,133} ContextNet,¹³⁴ dense neural network,¹³⁵ MC-Net,¹³⁶ OM-Net,¹³⁶ ConvNet,¹³⁷

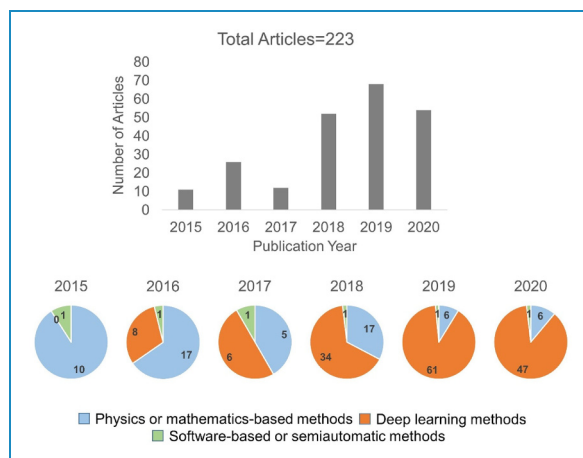


Figure 2. A number of articles (2015–2020). The bar plot represents the number of articles published over the review period (2015–2020), and pie charts depict published articles in each category of technical method in each corresponding year. Total articles = 223 refers to the articles included for the synthesis.

wide residual network, and pyramid pool network (WRN-PPNet),¹³⁸ deep convolutional network,^{139,140} neuro-morphic neural network,¹⁴¹ DeepLabv3+,¹⁴² recurrent neural network¹⁴³ and German cancer research centre (DFKZ) network.¹⁰⁷ Moreover, we mentioned the extensions of these architectures in the discussion section. Deep architectures, and their extensions, with associated publications, are summarised in Table 1.

Performance score evaluation matrices of studies

From our data extraction matrix, it was apparent that the most common accuracy measure used is the Dice score. Therefore, in Figure 3, we have shown the median Dice score values in segmenting the WT, TC and ET areas of brain tumours, considering all the 223 articles. We have compared Dice score among physics or mathematics-based methods, deep learning methods and software-based or semi-automatic methods.

Study population

The study population is summarised as the total number of data samples used in the study. The median data sample used in segmentation studies is 351 (median \pm stdev = 351 \pm 232.67). Moreover, deep learning segmentation methods are noted to have data samples divided into three categories: training data, validation data and test data. As shown in Figure 4, the median \pm stdev of each training, validation and test data sample in deep learning methods are also reported, which is 285 \pm 154.41, 54 \pm 41.60 and 110 \pm 85.29, respectively.

Specific imaging studies

A rigorous review, using an open-access dataset, is published as the gliomas segmentation benchmark article,⁵ which encouraged a tumour segmentation method development using T1-weighted, T2-weighted, T1-Gd and FLAIR MRI sequences. Among the 223 synthesised articles, five studies have used additional imaging sequences. Three studies^{71,117,236} have used diffusion imaging sequences, and one study²¹² has used perfusion imaging and multiple CT imaging sequences. These three studies are noted to have deep learning, or physics or mathematics-based methods. Moreover, we noted that a few studies have used perfusion imaging sequences, and diffusion imaging sequences but did not use the aforementioned all four MRI sequences. These studies are perfusion imaging studies^{212,238-241} and diffusion imaging studies.^{117,169,236,239-247} Also, two studies are noted to have used ultrasound imaging.^{248,249}

Discussion

In this systematic review, we addressed a PICO style question to put the brain tumour segmentation methods in the

Table 1. Deep architectures, and their extensions used in tumour segmentation.

Deep architecture	Associated publications
CNN	81–83,87,107,144–165
VGG	84–86,166,167
DeepMedic	84,87–92,168,169
U-Net	84,91,93,94,95,96,97,98–100,101–110,111–114,155,157,162,163,170,171,172–181,182–191,192–201,202–210
Autoencoder	115–117,211
GAN	118–120,212–214
W-net and cascade of W-net E-net and T-net	113,215–218
SENet	121
Multiresolution neural network	122
HED	123
Multi-level upsampling network	124
V-net	125,219
ResNet	125,126,197,220,221
Hourglass network	127
MvNet	128
DeepSCAN	129,130
Densely connected	85
Inception	85,99
Ensemble net	131
PixelNet	132,133
ContextNet	134
Dense neural network	135,222
MC-Net	136
OM-Net	136
ConvNet	137,223
WRN-PPNet	138,224
Deep convolutional network	139,140,159,225
Neuromorphic neural network	141

(continued)

Table 1. Continued.

Deep architecture	Associated publications
DeepLabv3 +	142
Recurrent neural network	143
DFKZ	107
EMMA	91
SegNet	226
ResNeXt	227
DenseAFPNet	228
DMFNet	229-231
P-Net	197
MFNet	232
HNF-Net	233
Deep neural network	234,235
D2C2N	236
DeepSeg	237

CNN: convolutional neural network; VGG: visual geometry group; GAN: generative adversarial network; SENet: squeeze, and excitation network; HED: holistically-nested edge detection; ResNet: residual network; MvNet: multi-view network, WRN-PPNet: wide residual network, and pyramid pool network, DFKZ: German cancer research centre; EMMA: ensembles of multiple models, and architecture; DenseAFPNet: Dense atrous feature pyramid network; DMFNet: dilated multi-fibre network; MFNet: multi-direction fusion network; HNF-Net: high-resolution, and non-local feature network; D2C2N: dilated densely connected convolutional network.

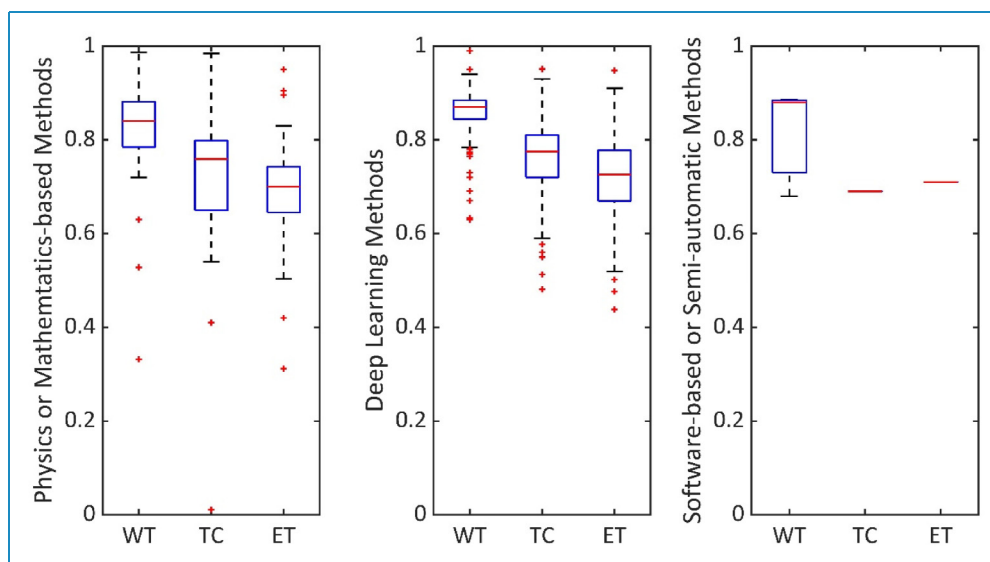


Figure 3. Comparison of segmentation results. Performance score evaluation, in segmenting WT, TC and ET, by considering all 223 articles. WT: whole tumour, TC: tumour core, ET: enhanced tumour.

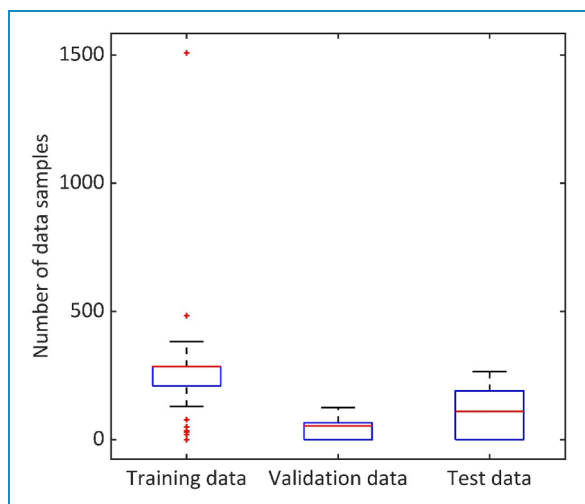


Figure 4. Data samples in deep learning studies. Summary of training, validation and test data samples reported in deep learning methods. Median of training, validation and test data samples are 285, 54 and 110, respectively.

context of clinical utility. Our population (P) is brain tumour patients, intervention (I) is segmentation methods, comparison (C) with manual segmentation evaluated as Dice score and outcome (O) is automated segmentation methods. Accordingly, we systematically found a promising technology, U-Net, which performs automated brain tumour segmentation using multiple MRI sequences. Its validation with manually segmented ground truth has achieved a Dice score of 0.9. Moreover, U-Net is majorly cited compared to other automated methods. Such merits show that U-Net has the potential to be considered for the

Research in context

Evidence before this study: In the literature, individual studies of brain tumour segmentation methods, a benchmark framework (BraTS) to assess these methods using an open-access dataset of T1-weighted, T2-weighted, T1-Gd and FLAIR MRI are reported. A few studies used diffusion-weighted and perfusion-weighted MRI to validate their methods.

Added value of this study: U-Net is systematically identified as a promising technology (Dice score 0.9 and cited the most) for brain tumour segmentation. Moreover, it is noted that the contribution of open-access datasets, including diffusion-weighted, and perfusion-weighted MRI, should be encouraged for training, validation and testing of brain tumour segmentation algorithms.

Implications of all the available evidence: The identified technologies can help medical imaging specialists, and clinicians to semi-automatically or automatically segment brain tumours, compared to manually.

clinical efficacy studies of automated brain tumour segmentation.

As shown in Figure 2 orange sections, deep learning articles in segmenting brain tumours are increasingly dominating the literature compared to software-based or semi-automatic methods, and considerably increased compared to physics or mathematics-based methods during the 2015–2020 period. The potential reasons could be the subjective nature of a software-based approach, limiting its efficiency, and limited transfer learning in physics-based models. Deep learning methods are attractive for efficient automatic segmentation, and the learned weights using one dataset can be further utilised with another dataset.

From a clinical point of view, the articles, which have reported segmentation of all three regions (whole tumour-WT, non-enhancing tumour core-TC, and enhanced tumour-ET), are synthesised. The whole tumour, including peritumoral oedema, is visible in FLAIR MRI, non-enhancing solid tumour core is visible in T2-weighted MRI, and necrotic/cystic core and enhanced core are visible in T1-weighted, and T1-Gd MRI.^{5,250} Specific details, such as cellular proliferation and cellular infiltration, can be visualised with diffusion-weighted imaging.^{251,252} Moreover, vascular proliferation can be visualised with perfusion-weighted imaging.²⁵¹ The inclusion of tumour components, such as cellular proliferation, infiltration and vascular proliferation, are addressed in very few articles. The potential reason could be the limited availability of open-access diffusion and perfusion-weighted imaging datasets.

Segmentation methods are commonly validated in terms of Dice scores ranging from 0 to 1.0. 1.0 shows the best matching between segmentation ground truth and method output. As shown in Figure 3, physics or mathematics-based methods, deep learning methods and software-based or semi-automatic methods have median Dice score, as (WT, TC, ET) tuple, (0.84, 0.76, 0.7), (0.87, 0.78, 0.73) and (0.88, 0.69, 0.71), respectively. Particularly, physics or mathematics-based methods, and deep learning methods studies are enabled to explore accuracy in segmenting WT, TC and ET due to the availability of ground truth in datasets such as BraTS.⁵ As the whole tumour covers a larger area, the value of WT is higher compared to TC or ET in each category.

As shown in the PRISMA diagram Figure 1, we have synthesised articles with physics or mathematics-based methods, deep learning-based methods and software or semi-automatic methods. The technical architectures are specifically reviewed for deep learning-based methods, as they have the potential to transfer learning from one dataset to another dataset.¹¹⁷ Modifications of CNN are fully CNN,^{81–83} hyper-dense CNN,¹⁶¹ cascaded CNN,^{162,163} cascaded fully CNN,¹⁶⁴ multi-path CNN,^{87,165} ensembled CNN,¹⁴⁴ holistic CNN,¹⁴⁵ full-resolution residual CNN,¹⁴⁶ two-phase patch-based

Table 2. Articles of widely used deep architectures and their technical details.

Deep architecture	Article	Technical details
U-Net	84	3D U-Net, which synthesises information at each scale by combining local and contextual information
	103	Modified 3D U-Net with better gradient flow
	108	Modified U-Net with an upsampled component, which is based on the nearest neighbour algorithm and elastic transformation
	109	2D U-Net network using a biophysics-based domain adaptation method with a generative adversarial model, which synthesises known ground truth data
	110	Modified U-Net with up skip connection, inception module and efficient cascade training
	111	3D U-Net with DenseNet, which was pre-trained on ImageNet
	112	U-Net network
	113	3D U-Net with test time augmentation
	114	U-Net with dice loss function to tackle class imbalance problem, and extensive data augmentation to prevent over-fitting
	93	Ensemble of 3D U-Nets with different hyperparameters
	94	U-Net training, which is followed by Bit-plane method output
	95	U-Net with double convolutional layers, inception modules and dense modules
	96	Modified U-Net, which is addressing class imbalance problem, with weighted cross-entropy and generalised dice loss function
	97	Deep learning radiomics algorithm model with 3D patch-based U-Net
	98	U-net with encoder adaption block and densely connected fusion blocks in the decoder
	91	An ensemble of two 3D U-Nets in which skip connections are used as a summation of signals in the up-sampling part of one network, and the other network uses concatenated skip connections and stridden convolutions
	99	Inception modules with U-Net
	100	Multi-scale images as input to the 3D U-Net and including 3D atrous spatial pyramid pooling layer to boost the performance of the network
	101	U-Net training improvement using large patch sizes, region-based training, additional data and a combination of loss functions
	102	U-Net with separable 3D convolution by dividing each 3D convolution block into three parallel branches
104	Two 3D U-Nets in which the first detect the tumour, and the second one segments multiple regions of the tumour	
105	U-Net	

(continued)

Table 2. Continued.

Deep architecture	Article	Technical details
	106	The tree structure of 3D U-Nets such that the first node of the tree predicts oedema, and then feed the output to the subsequent nodes to detect tumorous subregions of oedema
	107	U-Net in an ensemble of networks
VGG	84	3D fully connected network which is based on VGG with skip connections that combine coarse high scale information with fine low scale information
	85	3D convolutions, except max pool layers, VGG-based, an ensemble of multiple architectures
	86	CNN, which is based on VGG-16 and initially trained on ImageNet weights, and then fine-tuned with MICCAI data, relies on a pseudo-3D method which enables 3D segmentation from 2D colour-like images, and ultimately gives faster segmentation
DeepMedic	84	Two path network based on DeepMedic network which allows gathering low, and high resolution features together
	87	Multi-path CNN, which is inspired by DeepMedic which includes large, and small patches
	88	DeepMedic network
	89	A computer-aided diagnosis that combined DeepMedic, and radiomics features such as first-order features, shape features and texture features
	90	DeepMedic with additional residual connections
	91	An ensemble of two DeepMedic architectures
	92	A DeepMedic-based network is followed by a fully connected network to remove false positives
Autoencoder	115	Encoder, and decoder based 3D architecture that includes a variational auto-encoder branch to reconstruct the input image, which could be used as a regulariser for the shared decoder
	116	Stacked denoising auto-encoder
	117	Stacked denoising auto-encoder
GAN	118	Discriminator and generator based conditional generative adversarial network
	119	Adversarial network, discriminator is trained along with a generator to produce synthetic results, synthetic labels and ground truth are discriminated by discriminator, discriminator output is fed back to generator for improved segmentation accuracy
	120	Generative adversarial network with a coarse-to-fine generator to generate generic augmented data

VGG: visual geometry group; GAN: generative adversarial network; CNN: convolutional neural network; MICCAI: Medical Image Computing, and Computer-Assisted Interventions.

CNN¹⁴⁷ and cascaded anisotropic CNN.¹⁰⁷ U-Net is modified as cascaded U-Net,^{162,163} residual U-Net,^{170,171} domain adapted U-Net¹⁷² and efficient spatial pyramid (ESP) network.¹⁷³ A modification of W-net is reported as the cascade of W-net, E-net and T-net,¹¹³ and a modification of V-net is reported as the cascaded V-net.²¹⁹ Modifications of ResNet are dilated ResNet²²⁰ and fully convolutional residual neural network.²²¹ An ensemble of

multiple deep architectures is also reported as ensembles of multiple models, and architecture (EMMA).⁹¹ A modification of GAN is reported as conditional GAN.²¹² Modifications of ConvNet are reported as classification ConvNet²²³ and detection ConvNet.²²³

As summarised in Table 1, among all these deep architectures, U-Net based architectures are reported the most among the U-Net based articles, the maximum accuracy

of segmenting a tuple of (WT, TC, ET) is reported as (0.92, 0.95, 0.94) in terms of Dice score. Several other architectures such as VGG, DeepMedic, autoencoder and GAN are also frequently reported, and extended. A summary of the technical specifications of U-Net, VGG, DeepMedic, autoencoder and GAN-based architectures is reported in Table 2. In physics or mathematics-based studies, and software-based or semi-automatic studies, the maximum reported Dice score in segmenting a tuple of (WT, TC, ET) is (0.97, 0.86, 0.95) and (0.88, 0.69, 0.71), respectively.

In this study, we have synthesised the study population and performance measures from the articles. Among the 223 synthesised articles, 217 studies have used multi-centre datasets, five studies have used single-centre datasets, and one study has used only a synthetic dataset. Note that, data variety could be limiting in the generalisation of Dice score performance comparison reported in our study. A potential solution is to develop an open-access data repository and review the studies with the same data samples. Moreover, some of the studies have missing values, which could limit our synthesis results. A benchmark framework to report the evaluation measures could be useful to mitigate such limitations in the future. In this study, we identified brain tumour segmentation techniques and synthesised results as found from their respective articles, which could be a limitation. In order to apply these methods at clinics, a separate efficacy study should be performed by clinical staff members utilising data at respective clinics.

Conclusion

In conclusion, we systematically addressed a review question that can help medical imaging specialists, and clinicians to identify automatic brain tumour segmentation techniques, compared to manual segmentation. Our specific inclusion criteria emphasised having multiple MRI sequences in the method development. We noted that four MR-based sequences, i.e. T1-weighted, T2-weighted, T1-Gd and FLAIR MRI, are used the most. Diffusion weighted, and perfusion-weighted MRIs are rarely used. Among the segmentation methods, deep learning methods have contributed the most compared to other methods during the 2015–2020 period. Within the deep learning methods, U-Net-based methods are adapted the most and have an accuracy of approximately 0.9 Dice score in segmenting a brain tumour. We also noticed that the benchmark BraTS dataset does not have perfusion-weighted and diffusion-weighted MRI data, motivating the development of an open-access data repository with such MRI sequences.

In the future, a novel dataset can be developed with additional imaging data such as diffusion-weighted, and perfusion-weighted MRI, similar to the frequently reported open-access dataset^{5,6} which contains the data samples of

T1-weighted, T2-weighted, T1-Gd and FLAIR MRI of gliomas patients. Creating such an open-access dataset can help to include cellular proliferation, infiltration and vascular proliferation in brain tumour segmentation techniques (cellular proliferation: increase of the number of cells; cellular infiltration: migration of cells or excessive growth; vascular proliferation: leaky blood vessels). Moreover, medulloblastoma cases are rare (European annual rate: 6.8/million, age: 0–14 years, duration: 2000–2007).^{253,254} Therefore, a comprehensive adult dataset may be useful to address childhood tumours with transfer learning methods.

Acknowledgements: The authors thank HDR UK for receiving funding for this work. HDR UK is funded by the UK Medical Research Council, Engineering and Physical Sciences Research Council, Economic and Social Research Council, Department of Health and Social Care (England), Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Health and Social Care Research and Development Division (Welsh Government), Public Health Agency (Northern Ireland), British Heart Foundation and Wellcome Trust Funder: HDR UK – Medical Research Council – Award Reference HDR-3001.

Conflict of interest: The authors declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: Professor Theodoros N. Arvanitis (TNA) is joint Editor-in-Chief of Digital Health.



Contributorship: All the authors reviewed this manuscript. JMB prepared data extraction matrix, analyse data, wrote, and edited manuscript. SLCK validated the data extraction matrix and reviewed the manuscript. TNA verified the data extraction matrix, reviewed the manuscript, and acquired funding for the project. All authors have full access to all the data in this study.

Data availability: The data extraction matrix of this study is available in the Supplementary Information files.

Ethical approval: Not applicable. No human subjects involvement.

Guarantor: Professor Theodoros N. Arvanitis (TNA) is the guarantor for this study.

Funding: The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the Health Data Research UK (grant number HDR-3001).

ORCID iDs: Jayendra M Bhalodiya  <https://orcid.org/0000-0001-6540-6835>
Theodoros N Arvanitis  <https://orcid.org/0000-0001-5473-135X>

Supplemental material: Supplemental material for this article is available online.

References

- Lam WWM, Poon WS and Metreweli C. Diffusion MR imaging in glioma: does it have any role in the pre-operation determination of grading of glioma? *Clin Radiol* 2002; 57: 219–225.
- Louis DN, Perry A, Wesseling P, et al. The 2021 WHO classification of tumors of the central nervous system: a summary. *Neuro Oncol* 2021; 23: 1231–1251.
- Price SJ. The role of advanced MR imaging in understanding brain tumour pathology. *Br J Neurosurg* 2007; 21: 562–575.
- Nilsson M, Englund E, Szczepankiewicz F, et al. Imaging brain tumour microstructure. *Neuroimage* 2018; 182: 232–250.
- Menze BH, Jakab A, Bauer S, et al. The multimodal brain tumor image segmentation benchmark (BRATS). *IEEE Trans Med Imaging* 2015; 34: 1993–2024.
- Bakas S, Akbari H, Sotiras A, et al. Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features. *Sci Data* 2017; 4: 170117.
- Işin A, Direkoğlu C and Şah M. Review of MRI-based brain tumor image segmentation using deep learning methods. *Procedia Comput Sci* 2016; 102: 317–324.
- Angulakshmi M and Lakshmi Priya GG. Automated brain tumour segmentation techniques—a review. *Int J Imaging Syst Technol* 2017; 27: 66–77.
- Wadhwa A, Bhardwaj A and Singh Verma V. A review on brain tumor segmentation of MRI images. *Magn Reson Imaging* 2019; 61: 247–259.
- Abd-Ellah MK, Awad AI, Khalaf AAM, et al. A review on brain tumor diagnosis from MRI images: practical implications, key achievements, and lessons learned. *Magn Reson Imaging* 2019; 61: 300–318.
- AGPL. Zotero, <https://www.zotero.org/>.
- Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Br Med J* 2021; 372. Epub ahead of print 2021. DOI: 10.1136/bmj.n71
- Njeh I, Sallemi L, Ben AI, et al. 3D Multimodal MRI brain glioma tumor and edema segmentation: a graph cut distribution matching approach. *Comput Med Imaging Graph* 2015; 40: 108–119.
- Menze BH, Van Leemput K, Lashkari D, et al. A generative probabilistic model and discriminative extensions for brain lesion segmentation—with application to tumor and stroke. *IEEE Trans Med Imaging* 2016; 35: 933–946.
- Osman AFI. Automated brain tumor segmentation on magnetic resonance images and patient’s overall survival prediction using support vector machines. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2018; 10670 LNCS: 435–449.
- Chen X, Nguyen BP, Chui CK, et al. Automated brain tumor segmentation using kernel dictionary learning and superpixel-level features. *2016 IEEE Int Conf Syst Man, Cybern SMC 2016 – Conf Proc* 2017: 2547–2552.
- Juan-Albarracín J, Fuster-García E, Manjón J V, et al. Automated glioblastoma segmentation based on a multiparametric structured unsupervised classification. *PLoS One* 2015; 10: 1–20.
- Zhao Z, Yang G, Lin Y, et al. Automated glioma detection and segmentation using graphical models. *PLoS One* 2018; 13: 1–22.
- Kapás Z, Lefkovits L, Iclánzan D, et al. Automatic brain tumor segmentation in multispectral MRI volumes using a random forest approach. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2018; 10749 LNCS: 137–149.
- Latif G, Butt MM, Khan AH, et al. Automatic multimodal brain image classification using MLP and 3D glioma tumor reconstruction. In: *2017 9th IEEE-GCC Conference and Exhibition (GCCCE)*. IEEE, 2017, pp. 1–9.
- Lu Y and Chen W. Automatic multimodal brain-tumor segmentation. In: *Proceedings - 5th International Conference on Instrumentation and Measurement, Computer, Communication, and Control, IMCCC 2015*. IEEE, 2016, pp. 939–942.
- Kadkhodaei M, Samavi S, Karimi N, et al. Automatic segmentation of multimodal brain tumor images based on classification of super-voxels. *Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS* 2016; 2016–October: 5945–5948.
- Lee J, Kim SJ, Chen R, et al. Brain tumor image segmentation using kernel dictionary learning. *Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS* 2015; 2015–November: 658–661.
- Ellwaa A, Hussein A, AlNaggar E, et al. Brain tumor segmentation using random forest trained on iteratively selected patients. In: Crimi, et al. A (ed) *BrainLes*. Springer, Cham: LNCS, 2016, pp.129–137.
- Zhan T, Shen F, Hong X, et al. A glioma segmentation method using cotraining and superpixel-based spatial and clinical constraints. *IEEE Access* 2018; 6: 57113–57122.
- Bakas S, Reyes M, Jakab A, et al. Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge. *arXiv*, <http://arxiv.org/abs/1811.02629> (2018).
- Lefkovits S, Szilágyi L and Lefkovits L. *Brain tumor segmentation and survival prediction using a cascade of random forests*. Cham: Springer International Publishing, Epub ahead of print 2019, DOI: 10.1007/978-3-030-11726-9.
- Kao P-Y, Ngo T, Zhang A, et al. Brain tumor segmentation and tractographic feature extraction from structural MR images for overall survival prediction. In: Crimi, et al. A (ed) *BrainLes 2019, LNCS*, Springer, Cham: Springer International Publishing, pp.128–141.
- Baid U, Talbar S and Talbar S. Brain tumor segmentation based on non-negative matrix factorization and fuzzy clustering. *BIOIMAGING 2017 – 4th Int Conf Bioimaging, Proceedings; Part 10th Int Jt Conf Biomed Eng Syst Technol BIOSTEC 2017* 2017; 2017-Janua: 134–139.
- Rios Piedra EA, Ellingson BM, Taira RK, et al. Brain tumor segmentation by variability characterization of tumor boundaries. In: A. Crimi, et al. (Eds.): *BrainLes 2016, LNCS*, pp. 206–216.
- Li Y, Jia F and Qin J. Brain tumor segmentation from multimodal magnetic resonance images via sparse representation. *Artif Intell Med* 2016; 73: 1–13.

32. Anwar SM, Yousaf S and Majid M. Brain tumor segmentation on multimodal MRI scans using EMAP algorithm. *Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS* 2018; 2018–July: 550–553.
33. Agn M, Puonti O, Rosenschöld PMA, et al. Brain tumor segmentation using a generative model with an RBM prior on tumor shape. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2016; 9556: 168–180.
34. Lefkovits L, Lefkovits S and Szilágyi L. Brain tumor segmentation with optimized random forest. In: A. Crimi, et al. (Ed.): *BrainLes 2016, LNCS*, pp. 88–99.
35. Pinto A, Pereira S, Correia H, et al. Brain tumour segmentation based on extremely randomized forest with high-level features. *Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS* 2015; 2015–Novem: 3037–3040.
36. Kaur T, Saini BS and Gupta S. A joint intensity and edge magnitude-based multilevel thresholding algorithm for the automatic segmentation of pathological MR brain images. *Neural Comput Appl* 2018; 30: 1317–1340.
37. Serrano-Rubio JP and Everson R. Brain tumour segmentation method based on supervoxels and sparse dictionaries. In: A. and Crimi, et al. (Eds.): *BrainLes 2019, LNCS*. Springer, Cham: Springer International Publishing, pp. 210–221.
38. Ma C, Luo G and Wang K. Concatenated and connected random forests with multiscale patch driven active contour model for automated brain tumor segmentation of MR images. *IEEE Trans Med Imaging* 2018; 37: 1943–1954.
39. Meier R, Knecht U, Wiest R, et al. CRF-Based brain tumor segmentation: Alleviating the shrinking bias. In: A. Crimi, et al. (Ed.): *BrainLes 2016, LNCS*, pp. 100–107.
40. Abbasi S and Tajeirpour F. Detection of brain tumor in 3D MRI images using local binary patterns and histogram orientation gradient. *Neurocomputing* 2017; 219: 526–535.
41. Selvapandian A and Manivannan K. Fusion based glioma brain tumor detection and segmentation using ANFIS classification. *Comput Methods Programs Biomed* 2018; 166: 33–38.
42. Bakas S, Zeng K, Sotiras A, et al. GLISTRboost: combining multimodal MRI segmentation, registration, and biophysical tumor growth modeling with gradient boosting machines for glioma segmentation. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2016; 9556: 144–155.
43. Pinto A, Pereira S, Rasteiro D, et al. Hierarchical brain tumour segmentation using extremely randomized trees. *Pattern Recognit* 2018; 82: 105–117.
44. Pei L, Reza SMS and Iftkharuddin KM. Improved brain tumor growth prediction and segmentation in longitudinal brain MRI. In: *Proceedings – 2015 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2015*. IEEE, 2015, pp. 421–424.
45. Steed TC, Treiber JM, Patel KS, et al. Iterative probabilistic voxel labeling: automated segmentation for analysis of the cancer imaging archive glioblastoma images. *Am J Neuroradiol* 2015; 36: 678–685.
46. Le Folgoc L, Nori A V, Ancha S, et al. Lifted auto-context forests for brain tumour segmentation. In: A. Crimi, et al. (Eds.): *BrainLes 2016, LNCS*, pp. 171–183.
47. Agn M, Munck af Rosenschöld P, Puonti O, et al. A modality-adaptive method for segmenting brain tumors and organs-at-risk in radiation therapy planning. *Med Image Anal* 2019; 54: 220–237.
48. Szilágyi L, Iclánzan D, Kapás Z, et al. Low and high grade glioma segmentation in multispectral brain MRI data. *Acta Univ Sapientiae, Inform* 2018; 10: 110–132.
49. Bonte S, Goethals I and Van Holen R. Machine learning based brain tumour segmentation on limited data using local texture and abnormality. *Comput Biol Med* 2018; 98: 39–47.
50. Ali HAM, Ahmed MAA and Hussein EM. MRI brain tumour segmentation based on multimodal clustering and level-set method. 2018 *Int Conf Comput Control Electr Electron Eng ICCCEEE* 2018 2018; 1–5.
51. Phophalia A and Maji P. Multimodal brain tumor segmentation using ensemble of forest method. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2018; 10670 LNCS: 159–168.
52. Mote SR, Baid UR and Talbar SN. Non-negative matrix factorization and self-organizing map for brain tumor segmentation. *Proc 2017 Int Conf Wirel Commun Signal Process Networking, WiSPNET* 2017 2018; 2018-Janua: 1133–1137.
53. Tustison NJ, Shrinidhi KL, Wintermark M, et al. Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation (simplified) with ANTsR. *Neuroinformatics* 2015; 13: 209–225.
54. Meier R, Karamitsou V, Habegger S, et al. Parameter learning for CRF-based tissue segmentation of brain tumors. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2016; 9556: 156–167.
55. Szilágyi T, Brady M and Berényi E. Phase congruency map driven brain tumour segmentation. In: *SPIE Medical Imaging 2015: Image Processing*. 2015, p. 941330.
56. Pinto A, Pereira S, Dinis H, et al. Random decision forests for automatic brain tumor segmentation on multi-modal MRI images. *Proc – 2015 IEEE 4th Port Meet Bioeng ENBENG 2015*. Epub ahead of print 2015. DOI: 10.1109/ENBENG.2015.7088842.
57. Zeng K, Bakas S, Sotiras A, et al. Segmentation of gliomas in pre-operative and post-operative multimodal magnetic resonance imaging volumes based on a hybrid generative-discriminative framework. In: A. Crimi, et al. (Eds.): *BrainLes 2016, LNCS*, pp. 184–194.
58. Alberts E, Charpiat G, Tarabalka Y, et al. A nonparametric growth model for brain tumor segmentation in longitudinal MR sequences. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2016; 9556: 69–79.
59. Seow P, Win MT, Wong JHD, et al. Segmentation of solid subregion of high grade gliomas in MRI images based on active contour model (ACM). *J Phys Conf Ser* 2016: 1–5. Epub ahead of print 2016; 694. DOI: 10.1088/1742-6596/694/1/012043
60. Shanker R, Singh R and Bhattacharya M. Segmentation of tumor and edema based on K-mean clustering and hierarchical centroid shape descriptor. *Proc - 2017 IEEE Int Conf Bioinforma Biomed BIBM 2017* 2017; 1105–1109.
61. Zhao J, Meng Z, Wei L, et al. Supervised brain tumor segmentation based on gradient and context-sensitive features. *Front Neurosci* 2019; 13: 1–11.

62. Bharath HN, Colleman S, Sima DM, et al. Tumor segmentation from multimodal mri using random forest with superpixel and tensor based feature extraction. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2018; 10670 LNCS: 463–473.
63. Shanker R and Bhattacharya M. Brain tumor segmentation of normal and lesion tissues using hybrid clustering and hierarchical centroid shape descriptor. *Comput Methods Biomech Biomed Eng Imaging Vis* 2019; 7: 676–689.
64. Barbosa M, Moreira P, Ribeiro R, et al. Automatic classification and segmentation of low-grade gliomas in magnetic resonance imaging. In: A. M. Madureira, et al. (Eds.): *SoCPaR 2018, AISC*. 2020, pp. 43–50.
65. Sharif M, Amin J, Raza M, et al. Brain tumor detection based on extreme learning. *Neural Comput Appl* 2020; 32: 15975–15987.
66. Gyorfı A, Csaholczi S, Fulop T, et al. Brain tumor segmentation from multi-spectral magnetic resonance image data using an ensemble learning approach. *IEEE Trans Syst Man, Cybern Syst* 2020–October; 2020: 1699–1704.
67. Csaholczi S, Iclánzan D, Kovács L, et al. Brain tumor segmentation from multi-spectral MR image data using random forest classifier. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 12532 LNCS: 174–184.
68. Pei L, Bakas S, Vossough A, et al. Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. *Biomed Signal Process Control* 2020; 55: 101648.
69. Kaur T, Saini BS and Gupta S. A novel fully automatic multilevel thresholding technique based on optimized intuitionistic fuzzy sets and tsallis entropy for MR brain tumor image segmentation. *Australas Phys Eng Sci Med* 2018; 41: 41–58.
70. Mostafaie F, Teimouri R, Shahre Babak ZN, et al. Region of interest identification for brain tumors in magnetic resonance images. 2020 *28th Iran Conf Electr Eng ICEE 2020* 2020; 1–5.
71. Soltaninejad M, Yang G, Lambrou T, et al. Supervised learning based multimodal MRI brain tumour segmentation using texture features from supervoxels. *Comput Methods Programs Biomed* 2018; 157: 69–84.
72. Cordier N, Delingette H and Ayache N. A patch-based approach for the segmentation of pathologies: application to glioma labelling. *IEEE Trans Med Imaging* 2016; 35: 1066–1076.
73. Bhattacharya D and Sinha N. An improved approach of high graded glioma segmentation using sparse autoencoder and fuzzy c-means clustering from multi-modal MR images. In: *SPIE Medical Imaging 2018: Biomedical Applications in Molecular, Structural, and Functional Imaging, 11-13 Feb. 2018*. 2018, p. 38.
74. Song B, Chou C-R, Chen X, et al. Anatomy-guided brain tumor segmentation and classification. In: A. Crimi, et al. (Eds.): *BrainLes 2016, LNCS*, pp. 162–170.
75. Meier R, Porz N, Knecht U, et al. Automatic estimation of extent of resection and residual tumor volume of patients with glioblastoma. *J Neurosurg* 2017; 127: 798–806.
76. Reyes AM DL, Buemi M E, Aleman MN, et al. Development of a graphic interface for the three-dimensional semiautomatic glioblastoma segmentation based on magnetic resonance images. In: *Congreso Argentino de Ciencias de la Informatica y Desarrollos de Investigacion, CACIDI 2018*. 2018. Epub ahead of print 2018. DOI: 10.1109/CACIDI.2018.8584357.
77. Porz N, Habegger S, Meier R, et al. Fully automated enhanced tumor compartmentalization: man vs. machine reloaded. *PLoS One* 2016; 11: 1–16.
78. Velazquez E R, Meier R, Dunn WD, et al. Fully automatic GBM segmentation in the TCGA-GBM dataset: prognosis and correlation with VASARI features. *Sci Rep* 2015; 5: 1–10.
79. Yushkevich PA, Pashchinskiy A, Oguz I, et al. User-guided segmentation of multi-modality medical imaging datasets with ITK-SNAP. *Neuroinformatics* 2019; 17: 83–102.
80. Ren Y, Sun P and Lu W. *Overall survival prediction using conventional MRI features*. Springer, Cham: Springer International Publishing. 2020. Epub ahead of print 2020. DOI: 10.1007/978-3-030-46643-5_24.
81. Zhao X, Wu Y, Song G, et al. 3D Brain tumor segmentation through integrating multiple 2D FCNNs. In: *BrainLes, LNCS*, pp. 138–149.
82. Jesson A and Arbel T. Brain tumor segmentation using a 3D FCN with multi-scale loss. In: *BrainLes, LNCS*, pp. 138–149.
83. Shaikh M, Anand G, Acharya G, et al. Brain tumor segmentation using dense fully convolutional neural network. In: *BrainLes, LNCS*, pp. 138–149.
84. Casamitjana A, Puch S, Aduriz A, et al. 3D convolutional neural networks for brain tumor segmentation: a comparison of multi-resolution architectures. In: *BrainLes*. 2016, pp. 150–161.
85. Albiol A, Albiol F. Extending 2D deep learning architectures to 3D image segmentation problems. In: *BrainLes*. Springer International Publishing, pp. 73–82.
86. Puybureau E, Tochon G, Chazalon J, et al. Segmentation of gliomas and prediction of patient overall survival: a simple and fast procedure. In: *BrainLes*. Springer International Publishing, pp. 199–209.
87. Sedlar S. Brain tumor segmentation using a multi-path. In: *BrainLes*. 2018, pp. 403–422.
88. Perkuhn M, Stavrinou P, Thiele F, et al. Clinical evaluation of a multiparametric deep learning model for glioblastoma segmentation using heterogeneous magnetic resonance imaging data from clinical routine. *Invest Radiol* 2018; 53: 647–654.
89. Chen W, Liu B, Peng S, et al. Computer-aided grading of gliomas combining automatic segmentation and radiomics. *Int J Biomed Imaging* 2018; 2018: 1–11.
90. Kamnitsas K, Ferrante E, Parisot S, et al. Deepmedic for brain tumor segmentation. In: *BrainLes*. 2016, pp. 138–149.
91. Kamnitsas K, Bai W, Ferrante E, et al. Ensembles of multiple models and architectures for robust brain tumour segmentation. In: *BrainLes*. 2018, pp. 450–462.
92. Laukamp KR, Thiele F, Shakirin G, et al. Fully automated detection and segmentation of meningiomas using deep learning on routine multiparametric MRI. *Eur Radiol* 2019; 29: 124–132.
93. Feng X, Tustison N and Meyer C. Brain tumor segmentation using an ensemble of 3d u-nets and overall survival prediction using radiomic features. In: *BrainLes*. Springer International Publishing, pp. 279–288.

94. Tuan TA, Tuan TA and Bao PT. Brain tumor segmentation using bit-plane and UNET. In: *BrainLes*. Springer International Publishing, pp. 466–475.
95. Kim G. Brain tumor segmentation using deep fully convolutional neural networks. *BrainLes* 2018; 10670: 344–357.
96. Kermi A, Mahmoudi I and Khadir MT. Deep convolutional neural networks using U-net for automatic brain tumor segmentation in multimodal MRI volumes. In: *BrainLes*. Springer International Publishing, pp. 37–48.
97. Baid U, Talbar S, Rane S, et al. Deep learning radiomics algorithm for gliomas (DRAG) model: A novel approach using 3D UNET based deep convolutional neural network for predicting survival in Gliomas. In: *BrainLes*. Springer International Publishing, pp. 369–379.
98. Sun J, Chen W, Peng S, et al. DRRNet: dense residual refine networks for automatic brain tumor segmentation. *J Med Syst* 2019; 43: 1–9.
99. Cahall DE, Rasool G, Bouaynaya NC, et al. Inception modules enhance brain tumor segmentation. *Front Comput Neurosci* 2019; 13: 1–8.
100. Xu Y, Gong M, Fu H, et al. Multi-scale masked 3-D U-net for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
101. Isensee F, Kickingereder P, Wick W, et al. No new-net. *BrainLes* 2019; 2: 380–392.
102. Chen W, Liu B, Peng S, et al. S3D-UNet: Separable 3D U-net for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
103. Mehta R and Arbel T. 3D U-Net for brain tumour. In: *BrainLes*. Springer International Publishing, pp. 254–266.
104. Weninger L, Rippel O, Koppers S, et al. Segmentation of brain tumors and patient survival prediction: methods for the BraTS 2018 challenge. In: *BrainLes*. Springer International Publishing, pp. 380–392.
105. Gering D, Sun K, Avery A, et al. Semi-automatic brain tumor segmentation by drawing long axes on multi-plane reformat. In: *BrainLes*. Springer International Publishing, pp. 380–392.
106. Beers A, Chang K, Brown J, et al. Sequential neural networks for biologically-informed glioma segmentation. In: *SPIE Medical Imaging*. 2018, p. 108.
107. Sun L, Zhang S and Luo L. Tumor segmentation and survival prediction in glioma with deep learning. In: *BrainLes*. Springer International Publishing, pp. 380–392.
108. Hasan SMK and Linte CA. A modified u-net convolutional network featuring a nearest-neighbor re-sampling-based elastic-transformation for brain tissue characterization and segmentation. In: *IEEE Western New York Image and Signal Processing Workshop (WNYISPW)*. IEEE, 2018, pp. 1–5.
109. Gholami A, Subramanian S, Shenoy V, et al. A novel domain adaptation framework for medical image segmentation. In: *BrainLes*. Springer International Publishing, pp. 289–298.
110. Li H, Li A and Wang M. A novel end-to-end brain tumor segmentation method using improved fully convolutional networks. *Comput Biol Med* 2019; 108: 150–160.
111. Stawiaski J. A pretrained densenet encoder for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 105–115.
112. Carver E, Liu C, Zong W, et al. Automatic brain tumor segmentation and overall survival prediction using machine learning algorithms. In: *BrainLes*. Springer International Publishing, pp. 406–418.
113. Wang G, Li W, Ourselin S, et al. Automatic brain tumor segmentation using convolutional neural networks with test-time augmentation. In: *BrainLes*. 2019, pp. 61–72.
114. Isensee F, Kickingereder P, Wick W, et al. Brain tumor segmentation and radiomics survival prediction: contribution to the BRATS 2017 challenge. In: *BrainLes*. 2018, pp. 287–297.
115. Myronenko A. 3D MRI brain tumor segmentation using autoencoder regularization. In: *BrainLes*. Springer International Publishing, pp. 380–392.
116. Vaidhya K, Thirunavukkarasu S, Alex V, et al. Deep convolutional encoder networks for multiple sclerosis lesion segmentation. In: *BrainLes*, pp. 144–155.
117. Alex V, Vaidhya K, Thirunavukkarasu S, et al. Semisupervised learning using denoising autoencoders for brain lesion detection and segmentation. *J Med Imaging* 2017; 4: 1.
118. Rezaei M, Harmuth K, Gierke W, et al. A conditional adversarial network for semantic segmentation of brain tumor. In: *BrainLes*, pp. 138–149.
119. Li Z, Wang Y and Yu J. Brain tumor segmentation using an adversarial network. In: *BrainLes*, pp. 138–149.
120. Mok TCW and Chung ACS. Learning data augmentation for brain tumor segmentation with coarse-to-fine generative adversarial networks. In: *BrainLes*. Springer International Publishing, pp. 70–80.
121. Yao H, Zhou X and Zhang X. Automatic segmentation of brain tumor using 3D SE-inception networks with residual connections. In: *BrainLes*. Springer International Publishing, pp. 380–392.
122. Castillo LS, Daza LA, Rivera LC, et al. Brain tumor segmentation and parsing on MRIs using multiresolution neural networks. *BrainLes* 2018; 10670: 138–149.
123. Pourreza R, Zhuge Y, Ning H, et al. Brain tumor segmentation in MRI scans using deeply-supervised neural networks. In: *BrainLes*, pp. 138–149.
124. Tchikindas L, Sparks R, Baccon J, et al. Segmentation of nodular medulloblastoma using random walker and hierarchical normalized cuts. *IEEE Annu Northeast Bioeng Conf NEBEC* 2011 2011; 1–2.
125. Chandra S, Vakalopoulou M, Fidon L, et al. Context aware 3D CNNs for brain tumor segmentation. In: *BrainLes*, pp. 380–392.
126. Pawar K, Chen Z, Shah NJ, et al. Residual encoder and convolutional decoder neural network for glioma segmentation. *BrainLes* 2018; 10670: 138–149.
127. Benson E, Pound MP, French AP, et al. Deep hourglass for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
128. Li Y and Shen L. Deep learning based multimodal brain tumor diagnosis. In: *BrainLes*, pp. 138–149.
129. McKinley R, Meier R and Wiest R. Ensembles of densely-connected CNNs with label-uncertainty for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
130. McKinley R, Jungo A, Wiest R, et al. Pooling-free fully convolutional networks with dense skip connections for

- semantic segmentation, with application to brain tumor segmentation. In: *BrainLes*, pp. 138–149.
131. Naceur MB, Saouli R, Akil M, et al. Fully automatic brain tumor segmentation using end-to-end incremental deep neural networks in MRI images. *Comput Methods Programs Biomed* 2018; 166: 39–49.
 132. Islam M, Jose VJM and Ren H. Glioma prognosis: segmentation of the tumor and survival prediction using shape, geometric and clinical information. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 133. Islam M and Ren H. Multi-modal PixelNet for brain tumor segmentation. In: *BrainLes*, pp. 138–149.
 134. Puch S, Sanchez I, Hernandez A, et al. Global planar convolutions for improved context aggregation in brain tumor segmentation. In: *BrainLes*, pp. 380–392.
 135. Randhawa RS, Modi A, Jain P, et al. Improving boundary classification for brain tumor segmentation and longitudinal disease progression. In: *BrainLes*, pp. 65–74.
 136. Zhou C, Chen S, Ding C, et al. Learning contextual and attentive information for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 137. Banerjee S, Mitra S and Shankar BU. Multi-planar spatial-convnet for segmentation and survival prediction in brain cancer. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 138. Wang Y, Li C, Zhu T, et al. Multimodal brain tumor image segmentation using WRN-PPNet. *Comput Med Imaging Graph* 2019; 75: 56–65.
 139. Colmeiro RGR, Verrastro CA and Grosjes T. Multimodal brain tumor segmentation using 3D convolutional networks. In: *BrainLes*, pp. 138–149.
 140. Hua R, Huo Q, Gao Y, et al. Multimodal brain tumor segmentation using cascaded V-Nets. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 141. Han W-S and Han IS. Neuromorphic neural network for multimodal brain image segmentation and overall survival analysis. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 142. Choudhury AR, Vanguri R, Jambawalikar SR, et al. Segmentation of brain tumors using DeepLabv3+. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 143. Grivalsky S, Tamajka M and Benesova W. Segmentation of gliomas in magnetic resonance images using recurrent neural networks. In: *2019 42nd International Conference on Telecommunications and Signal Processing, TSP 2019*. IEEE, 2019, pp. 539–542.
 144. Kori A, Soni M, Pranjal B, et al. Ensemble of fully convolutional neural network for brain tumor segmentation from magnetic resonance images. In: *BrainLes*. Springer International Publishing, pp. 380–392.
 145. Fidon L, Li W, Garcia-Peraza-Herrera LC, et al. Generalised Wasserstein dice score for imbalanced multi-class segmentation using holistic convolutional networks. In: *BrainLes*, pp. 138–149.
 146. Jungo A, McKinley R, Meier R, et al. Towards uncertainty-assisted brain tumor segmentation and survival prediction. In: *BrainLes*, pp. 138–149.
 147. Zhou F, Li T, Li H, et al. TPCNN: two-phase patch-based convolutional neural network for automatic brain tumor segmentation and survival prediction. In: *BrainLes*, pp. 138–149.
 148. Yang T, Song J and Li L. A deep learning model integrating SK-TPCNN and random forests for brain tumor segmentation in MRI. *Biocybern Biomed Eng* 2019; 39: 613–623.
 149. Chahal ES, Haritosh A, Gupta A, et al. Deep learning model for brain tumor segmentation analysis. *2019 3rd Int Conf Recent Dev Control Autom Power Eng RDCAPE 2019 2019*; 378–383.
 150. Zhang D, Song Y, Liu D, et al. *Efficient 3D depthwise and separable convolutions with dilation for brain tumor segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2019, DOI: 10.1007/978-3-030-35288-2_45.
 151. Kaldera HNTK, Gunasekara SR and Dissanayake MB. MRI based glioma segmentation using deep learning algorithms. In: *International Research Conference on Smart Computing and Systems Engineering (SCSE)*. 2019. Epub ahead of print 2019. DOI: 10.23919/SCSE.2019.8842668.
 152. Derikvand F and Khotanlou H. Patch and pixel based brain tumor segmentation in MRI images using convolutional neural networks. *5th Iran Conf Signal Process Intell Syst ICSPIS 2019 2019*; 18–19.
 153. Wacker J, Ladeira M and Nascimento JEV. Transfer learning for brain tumor segmentation. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2021; 12658 LNCS: 241–251.
 154. Derikvand F and Khotanlou H. Brain tumor segmentation in MRI images using a hybrid deep network based on patch and pixel. *Iran Conf Mach Vis Image Process MVIP 2020*; 2020–Febru: 5–9.
 155. Ali M, Gilani SO, Waris A, et al. Brain tumour image segmentation using deep networks. *IEEE Access* 2020; 8: 153589–153598.
 156. Hamghalam M, Lei B and Wang T. Convolutional 3d to 2d patch conversion for pixel-wise glioma segmentation in MRI scans. In: Crimi A and Bakas S (eds) *Brainles 2019, LNCS 11992*. Springer, Cham: Springer International Publishing, 2020, pp.3–12.
 157. Mzoughi H, Njeh I, Ben SM, et al. Glioblastomas brain tumor segmentation using optimized U-Net based on deep fully convolutional networks (D-FCNs). *2020 Int Conf Adv Technol Signal Image Process ATSIP 2020 2020*; 1–6.
 158. Amian M and Soltaninejad M. *Multi-resolution 3d CNN for MRI brain tumor segmentation and survival prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI:10.1007/978-3-030-46640-4_21.
 159. Michael Mahesh K and Arokia Renjit J. Multiclassifier for severity-level categorization of glioma tumors using multimodal magnetic resonance imaging brain images. *Int J Imaging Syst Technol* 2020; 30: 234–251.
 160. van der Voort SR, Incekara F, Wijnenga MMJ, et al. WHO 2016 subtyping and automated segmentation of glioma using multi-task deep learning. *arXiv* 2020; 1–49.
 161. Qamar S, Jin H, Zheng R, et al. 3D hyper-dense connected convolutional neural network for brain tumor segmentation. *Proc - 2018 14th Int Conf Semant Knowl Grids, SKG 2018 2018*; 123–130.
 162. Hu Y and Xia Y. 3D deep neural network-based brain tumor segmentation using multimodality magnetic resonance sequences. In: *BrainLes*, pp. 138–149.

163. Lachinov D, Vasiliev E and Turlapov V. Glioma segmentation with cascaded UNet. In: *BrainLes*. Springer International Publishing, pp. 380–392.
164. Cui S, Mao L, Jiang J, et al. Automatic semantic segmentation of brain gliomas from MRI images using a deep cascaded neural network. *J Healthc Eng* 2018; 2018: 1–14. Epub ahead of print 2018. DOI: 10.1155/2018/4940593
165. Liu C, Si W, Qian Y, et al. Multipath densely connected convolutional neural network for brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 81–91.
166. Ahuja S, Panigrahi BK and Gandhi T. Transfer learning based brain tumor detection and segmentation using super-pixel technique. 2020 *Int Conf Contemp Comput Appl IC3A 2020* 2020; 244–249.
167. Buatois T, Puybureau É, Tochon G, et al. Two stages CNN-based segmentation of gliomas, uncertainty quantification and prediction of overall patient survival. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 11993 LNCS: 167–178.
168. Wan Y, Rahmat R and Price SJ. Deep learning for glioblastoma segmentation using preoperative magnetic resonance imaging identifies volumetric features associated with survival. *Acta Neurochir (Wien)* 2020; 162: 3067–3080.
169. Rahmat R, Saednia K, Haji Hosseini Khani MR, et al. Multi-scale segmentation in GBM treatment using diffusion tensor imaging. *Comput Biol Med* 2020; 123: 103815.
170. Yang H-Y and Yang J. Automatic brain tumor segmentation with contour aware residual network and adversarial training. In: *BrainLes*. Springer International Publishing, pp. 380–392.
171. Hu X, Li H, Zhao Y, et al. Hierarchical multi-class segmentation of glioma images using networks with multi-level activation function. In: *BrainLes*. Springer International Publishing, pp. 380–392.
172. Dai L, Li T, Shu H, et al. Automatic brain tumor segmentation with domain adaptation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
173. Nuechterlein N and Mehta S. 3D-ESPNet with pyramidal refinement for volumetric brain tumor image segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
174. Noori M, Bahri A and Mohammadi K. Attention-guided version of 2D UNet for automatic brain tumor segmentation. 2019 *9th Int Conf Comput Knowl Eng ICCKE 2019* 2019; 269–275.
175. Agravat RR and Raval MS. Brain tumor segmentation and survival prediction. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 11992 LNCS: 338–348.
176. Xu H, Xie H, Liu Y, et al. *Deep cascaded attention network for multi-task brain tumor segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2019, DOI: 10.1007/978-3-030-32248-9_47.
177. Shanis Z, Gerber S, Gao M, et al. *Intramodality domain adaptation using self ensembling and adversarial training*. Springer, Cham: Springer International Publishing, 2019, pp. 90–98.
178. Cheng J, Liu J, Liu L, et al. Multi-level glioma segmentation using 3D U-net combined attention mechanism with atrous convolution. *Proc - 2019 IEEE Int Conf Bioinforma Biomed BIBM 2019* 2019; 1031–1036.
179. Chang K, Beers AL, Bai HX, et al. Automatic assessment of glioma burden: a deep learning algorithm for fully automated volumetric and bidimensional measurement. *Neuro Oncol* 2019; 21: 1412–1422.
180. Rosas González S, Birgui Sekou T, Hidane M, et al. 3D automatic brain tumor segmentation using a multiscale input U-Net network. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 11993 LNCS: 113–123.
181. Agravat RR and Raval MS. 3D semantic segmentation of brain tumor for overall survival prediction. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2021; 12659 LNCS: 215–227.
182. Xue Y, Xie M, Farhat FG, et al. *A multi-path decoder network for brain tumor segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_25.
183. Aledhari M and Razzak R. An adaptive segmentation technique to detect brain tumors using 2D UNet. *Proc - 2020 IEEE Int Conf Bioinforma Biomed BIBM 2020* 2020; 2328–2334.
184. Zhenyu Z, Gao S and Huang Z. An automatic glioma segmentation system based on a separable attention U-Net (SAUNet). In 2020 9th International Conference on Bioinformatics and Biomedical Science (ICBBS '20). New York, NY, USA: Association for Computing Machinery, 95–101. <https://doi.org/10.1145/3431943.3431959>
185. Dong H, Yu F, Jiang H, et al. Annotation-free gliomas segmentation based on a few labeled general brain tumor images. In: *IEEE 17th International Symposium on Biomedical Imaging (ISBI)*. Iowa City, Iowa, USA, 2020, pp. 354–358.
186. Sameer MA, Bayat O and Mohammed HJ. Brain tumor segmentation and classification approach for MR images based on convolutional neural networks. *Proc 2020 1st Inf Technol to Enhanc E-Learning other Appl Conf IT-ELA 2020* 2020; 138–143.
187. Naser MA and Deen MJ. Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images. *Comput Biol Med* 2020; 121: 103758.
188. Guo X, Yang C, Ma T, et al. *Brain tumor segmentation based on attention mechanism and multi-model fusion*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_5.
189. Wu P and Chang Q. Brain tumor segmentation on multimodal 3D-MRI using deep learning method. *Proc - 2020 13th Int Congr Image Signal Process Biomed Eng Informatics, CISP-BMEI 2020* 2020; 635–639.
190. Feng X, Tustison NJ, Patel SH, et al. Brain tumor segmentation using an ensemble of 3D U-nets and overall survival prediction using radiomic features. *Front Comput Neurosci* 2020; 14: 1–12.
191. Xu X, Zhao W and Zhao J. *Brain tumor segmentation using attention-based network in 3D MRI images*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_1.
192. Shi W, Pang E, Wu Q, et al. *Brain tumor segmentation using dense channels 2d u-net and multiple feature extraction networks*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46640-4_26.

193. Baid U, Shah NA and Talbar S. Brain tumor segmentation with cascaded deep convolutional neural network. In: Crimi A and Bakas S (eds) *Brainlesion: glioma, multiple sclerosis, stroke and traumatic brain injuries. BrainLes 2019. Lecture notes in computer science, vol 11993*. Springer, Cham: Springer International Publishing, 2020, pp. 90–98.
194. Feng X, Dou Q, Tustison N, et al. *Brain tumor segmentation with uncertainty estimation and overall survival prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46640-4_29.
195. Long J, Ma G, Liu H, et al. Cascaded hybrid residual U-Net for glioma segmentation. *Multimed Tools Appl* 2020; 79: 24929–24947.
196. Kotowski K, Nalepa J and Dudzik W. *Detection and segmentation of brain tumors from MRI using U-nets*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_17.
197. Banerjee S, Arora HS and Mitra S. *Ensemble of CNNs for segmentation of glioma sub-regions with survival prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_4.
198. Bangalore Yogananda CG, Wagner B, Nalawade SS, et al. *Fully automated brain tumor segmentation and survival prediction of gliomas using deep learning and MRI*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_10.
199. Ribalta Lorenzo P, Marcinkiewicz M and Nalepa J. *Multi-modal U-Nets with boundary loss and pre-training for brain tumor segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_13.
200. Peng S, Chen W, Sun J, et al. Multi-Scale 3D U-nets: an approach to automatic segmentation of brain tumor. *Int J Imaging Syst Technol* 2020; 30: 5–17.
201. Dutta J, Chakraborty D and Mondal D. *Multimodal segmentation of brain tumours in volumetric MRI scans of the brain using time-distributed U-Net*. Springer Singapore, Epub ahead of print 2020, DOI: 10.1007/978-981-13-9042-5_62.
202. Wang F. Neural architecture search for gliomas segmentation on multimodal magnetic resonance Imaging, <http://arxiv.org/abs/2005.06338> (2020).
203. Juan-Albarracín J, Fuster-García E, del Mar Álvarez-Torres M, et al. Oncohabitats glioma segmentation model. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 11992 LNCS: 295–303.
204. Yin Y. Partial view segmentation: a novel approach to the brain tumor segmentation. 2020 *IEEE 3rd Int Conf Comput Commun Eng Technol CCET 2020* 2020; 76–79.
205. Yi L, Zhang J, Zhang R, et al. *SU-Net: an efficient encoder-decoder model of federated learning for brain tumor segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-61609-0_60.
206. Yin P, Hu Y, Liu J, et al. *The tumor mix-up in 3D unet for glioma segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_26.
207. Kim S, Luna M, Chikontwe P, et al. *Two-step u-nets for brain tumor segmentation and random forest with radiomics for survival time prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46640-4_19.
208. Kot E, Krawczyk Z, Siwek K, et al. U-Net and Active Contour Methods for Brain Tumour Segmentation and Visualization. *Proc Int Jt Conf Neural Networks*. Epub ahead of print 2020. DOI: 10.1109/IJCNN48605.2020.9207572.
209. Bangalore Yogananda CG, Shah BR, Vejdani-Jahromi M, et al. A novel fully automated MRI-based deep-learning method for classification of IDH mutation status in brain gliomas. *Neuro Oncol* 2020; 22: 402–411.
210. Dong H, Yang G, Liu F, et al. Automatic brain tumor detection and segmentation using U-net based fully convolutional networks. *Commun Comput Inf Sci* 2017; 723: 506–517.
211. Russo C, Liu S and Ieva AD. Spherical coordinates transformation pre-processing in Deep Convolution Neural Networks for brain tumor segmentation in MRI. 1–26.
212. Rezaei M, Yang H and Meinel C. Voxel-GAN: adversarial framework for learning imbalanced brain tumor segmentation. In: *BrainLes*. Springer International Publishing, pp. 380–392.
213. Carver EN, Dai Z, Liang E, et al. Improvement of multiparametric MR image segmentation by augmenting the data with generative adversarial networks for glioma patients. *Front Comput Neurosci* 2021: 1–10. Epub ahead of print 2021; 14. DOI: 10.3389/fncom.2020.495075
214. Hamghalam M, Wang T and Lei B. High tissue contrast image synthesis via multistage attention-GAN: application to segmenting brain MR scans. *Neural Netw* 2020; 132: 43–52.
215. Stefani A, Rahmat R and Harris-Birtill D. *Autofocus net: auto-focused 3D CNN for brain tumour segmentation*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-52791-4_4.
216. Din NKAM and Rahni AAA. Evaluation of a deep learning based brain tumour segmentation method. In: *Journal of Physics: Conference Series* 2020. Epub ahead of print 2020. DOI: 10.1088/1742-6596/1497/1/012009
217. Vu MH, Nyholm T and Löfstedt T. Multi-decoder networks with multi-denoising inputs for tumor segmentation. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2021; 12658 LNCS: 412–423.
218. Vu MH, Nyholm T and Löfstedt T. Tunet: end-to-end hierarchical brain tumor segmentation using cascaded networks. *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)* 2020; 11992 LNCS: 174–186.
219. Casamitjana A, Cata M, Sanchez I, et al. Cascaded V-Net using ROI masks for brain tumor segmentation. In: *BrainLes*, pp. 138–149.
220. Lopez MM and Ventura J. Dilated convolutions for brain tumor segmentation in MRI scans. In: *BrainLes*, pp. 138–149.
221. Chang PD. Fully convolutional deep residual neural networks for brain tumor segmentation. In: *BrainLes*, pp. 108–118.
222. Ermiş E, Jungo A, Poel R, et al. Fully automated brain resection cavity delineation for radiation target volume definition in glioblastoma patients using deep learning. *Radiat Oncol* 2020; 15: 1–10.
223. Banerjee S, Mitra S, Sharma A, et al. A CADe system for gliomas in brain MRI using convolutional neural networks, <http://arxiv.org/abs/1806.07589> (2018).

224. Wang Y, Li C, Zhu T, et al. A deep learning algorithm for fully automatic brain tumor segmentation. *Proc Int Jt Conf Neural Networks* 2019; 2019–July: 1–5.
225. Wu W, Li D, Du J, et al. An intelligent diagnosis method of brain MRI tumor segmentation using deep convolutional neural network and SVM algorithm. *Comput Math Methods Med* 2020; 2020: 1–10. Epub ahead of print 2020. DOI: 10.1155/2020/6789306
226. Alqazzaz S, Sun X, Yang X, et al. Automated brain tumor segmentation on multi-modal MR image using SegNet. *Comput Vis Media* 2019; 5: 209–219.
227. Zarrar MK, Hussain F, Khan MM, et al. Latest trends in automatic glioma tumor segmentation and an improved convolutional neural network based solution. *MACS 2019 - 13th Int Conf Math Actuar Sci Comput Sci Stat Proc*. Epub ahead of print 2019. DOI: 10.1109/MACS48846.2019.9024815.
228. Zhou Z, He Z, Shi M, et al. 3D dense connectivity network with atrous convolutional feature pyramid for brain tumor segmentation in magnetic resonance imaging of human heads. *Comput Biol Med* 2020; 121: 1–11.
229. Guo X, Yang C, Lam PL, et al. *Domain knowledge based brain tumor segmentation and overall survival prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46643-5_28.
230. Ngo DK, Tran MT, Kim SH, et al. Multi-task learning for small brain tumor segmentation from MRI. *Appl Sci* 2020; 10: 1–16.
231. Nie Y, Ding H, Shang Y, et al. Spatial attention-based efficiently features fusion network for 3D-MR brain tumor segmentation. *Proc 2020 IEEE Int Conf Prog Informatics Comput PIC* 2020 2020; 67–74.
232. Liu S and Guo X. *Improving brain tumor segmentation with multi-direction fusion and fine class prediction*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-46640-4_33.
233. Jia H, Xia Y, Cai W, et al. *Learning high-resolution and efficient non-local features for brain glioma segmentation in MR images*. Springer, Cham: Springer International Publishing, Epub ahead of print 2020, DOI: 10.1007/978-3-030-59719-1_47.
234. Dorent R, Booth T, Li W, et al. Learning joint segmentation of tissues and brain lesions from task-specific hetero-modal domain-shifted datasets. *Med Image Anal* Epub ahead of print 2021; 67: 1–16. DOI: 10.1016/j.media.2020.101862
235. Acharya M, Alsadoon A, Al-Janabi S, et al. MRI-based diagnosis of brain tumours using a deep neural network framework. *CITISIA 2020 - IEEE Conf Innov Technol Intell Syst Ind Appl Proc* 2020; 1–5.
236. Zhong L, Li T, Shu H, et al. (TS)2WM: tumor segmentation and tract statistics for assessing white matter integrity with applications to glioblastoma patients. *Neuroimage* 2020; 223: 117368.
237. Zeineldin RA, Karar ME, Coburger J, et al. Deepseg: deep neural network framework for automatic brain tumor segmentation using magnetic resonance FLAIR images. *Int J Comput Assist Radiol Surg* 2020; 15: 909–920.
238. Kawa J, Rudzki M, Pietka E, et al. Computer aided diagnosis workstation for brain tumor assessment. *Proc 22nd Int Conf Mix Des Integr Circuits Syst Mix* 2015 2015; 98–103.
239. Sauwen N, Sima DM, Van Cauter S, et al. Hierarchical non-negative matrix factorization to characterize brain tumor heterogeneity using multi-parametric MRI. *NMR Biomed* 2015; 28: 1599–1624.
240. Fathi Kazerooni A, Mohseni M, Rezaei S, et al. Multi-parametric (ADC/PWI/T2-w) image fusion approach for accurate semi-automatic segmentation of tumorous regions in glioblastoma multiforme. *Magn Reson Mater Physics, Biol Med* 2015; 28: 13–22.
241. Sauwen N, Acou M, Sima DM, et al. Semi-automated brain tumor segmentation on multi-parametric MRI using regularized non-negative matrix factorization. *BMC Med Imaging* 2017; 17: 1–14.
242. Lu M, Zhang X, Zhang M, et al. Non-model segmentation of brain glioma tissues with the combination of DWI and fMRI signals. *Biomed Mater Eng* 2015; 26: S1315–S1324.
243. Rahmat R, Brochu F, Li C, et al. Semi-automated construction of patient individualised clinical target volumes for radiotherapy treatment of glioblastoma utilising diffusion tensor decomposition maps. *Br J Radiol* Epub ahead of print 2020; 93: 1–7. DOI: 10.1259/bjr.20190441
244. Zhang X, Dou W, Zhang M, et al. A framework of automatic brain tumor segmentation method based on information fusion of structural and functional MRI signals. *Proc 2016 8th IEEE Int Conf Commun Softw Networks, ICCSN 2016* 2016; 625–629.
245. Sun R, Wang K, Guo L, et al. A potential field segmentation based method for tumor segmentation on multi-parametric MRI of glioma cancer patients. *BMC Med Imaging* 2019; 19: 1–9.
246. Artzi M, Blumenthal DT, Bokstein F, et al. Classification of tumor area using combined DCE and DSC MRI in patients with glioblastoma. *J Neurooncol* 2015; 121: 349–357.
247. Beigi M, Safari M, Ameri A, et al. Findings of DTI-p maps in comparison with T2/T2-FLAIR to assess postoperative hyper-signal abnormal regions in patients with glioblastoma 08 information and computing sciences 0801 artificial intelligence and image processing. *Cancer Imaging* 2018; 18: 1–7.
248. Huber T, Alber G, Bette S, et al. Reliability of semi-automated segmentations in glioblastoma. *Clin Neuroradiol* 2017; 27: 153–161.
249. Nitsch J, Klein J, Dammann P, et al. Automatic and efficient MRI-US segmentations for improving intraoperative image fusion in image-guided neurosurgery. *NeuroImage Clin* 2019; 22: 101766.
250. Niyazi M, Brada M, Chalmers AJ, et al. ESTRO-ACROP guideline ‘target delineation of glioblastomas’. *Radiother Oncol* 2016; 118: 35–42.
251. Guo L, Wang G, Feng Y, et al. Diffusion and perfusion weighted magnetic resonance imaging for tumor volume definition in radiotherapy of brain tumors. *Radiat Oncol* 2016; 11: 1–13.
252. Kono K, Inoue Y, Nakayama K, et al. The role of diffusion-weighted imaging in patients with brain tumors. *Am J Neuroradiol* 2001; 22: 1081–1088.
253. Massimino M, Biassoni V, Gandola L, et al. Childhood medulloblastoma. *Crit Rev Oncol Hematol* 2016; 105: 35–51.
254. Lassaletta A and Ramaswamy V. Medulloblastoma in adults: they’re not just big kids. *Neuro Oncol* 2016; 18: 895–897.