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ORIGINAL RESEARCH

Deep learning neural networks for medical image segmentation of brain tumours for diagnosis: a recent review and taxonomy

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Abstract
Brain tumour identification with traditional magnetic resonance imaging (MRI) tends to be time-consuming and in most cases, reading of the resulting images by human agents is prone to error, making it desirable to use automated image segmentation. This is a multi-step process involving: (a) collecting data in the form of raw processed or raw images, (b) removing bias by using pre-processing, (c) processing the image and locating the brain tumour, and (d) showing the tumour affected areas on a computer screen or projector. Several systems have been proposed for medical image segmentation but have not been evaluated in the field. This may be due to ongoing issues of image clarity, grey and white matter present in a scan image, lack of knowledge of the end user and constraints arising from MRI imaging systems. This makes it imperative to develop a comprehensive technique for the accurate diagnosis of brain tumors in MRI images. In this paper, we introduce a taxonomy consisting of 'Data, Image segmentation processing, and View' (DIV) which are the major components required to develop a high-end system for brain tumour diagnosis based on deep learning neural networks. The DIV taxonomy is evaluated based on system completeness and acceptance. The utility of the DIV taxonomy is demonstrated by classifying 30 state-of-the-art publications in the domain of medFical image segmentation systems based on deep neural networks. The results demonstrate that few components of medical image segmentation systems have been validated although several have been evaluated by identifying role and efficiency of the components in this domain.

Keywords Taxonomy · Medical image segmentation · Magnetic resonance imaging (MRI) · Brain tumour · Deep neural networks (DNN) · Diagnosis · Image contrast · Image clustering · Re-clustering · Image pixels · Tumour boundaries

Abbreviations

MRI	Magnetic resonance imaging
MCFM	Modified fuzzy C-means
CLE	Confocal laser endomicroscopy
CNN	Convolutional neural networks
DCNN	Deep conventional neural network
ACM	Active contour models
CRFs	Conditional random fields
FCNN	Fully convolutional neural network
LHNPSO	Low-discrepancy sequence initialized particle swarm optimization algorithm with high-order nonlinear time-varying inertia weight
KFECSB	Kernelized fuzzy entropy clustering with spatial information and bias correction
RF Classifier	Random forests classifier

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1 Introduction

Brain image segmentation processing is the subject of a significant body of research that aims to develop systems for accurate cancer diagnosis, capable of differentiating tumour affected from healthy tissue. This is achieved by image preprocessing, clustering, and post-segmentation processes to enhance contrast in the raw or processed Magnetic Resonance Imaging MRI data, using clustering algorithms for automatic segmentation of images into different parts and fine-tuning the output data to eliminate bias. This process enhances accuracy of MRI images making tumour-affected regions easily identifiable (Chen et al. 2017a, b) through greater clarity of images, thus eliminating the issues faced in manual segmentation processes.

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Tools and techniques used for automated image segmentation are mainly VoxResNet, a 3D residual network (Li et al. 2016) which hierarchically stacks multiple layers of neurons to form a low, middle and high feature-based representation, with the 2D deep residual network being extended to 3D to obtain more representative data. This improves contrast of images by eliminating noise in the raw MRI data (Lim and Mandava 2018). Limitations arise from data processing which is limited to small data sets—no testing has so far been carried out on large datasets (Litjens et al. 2017).

Izadyyazdanabadi et al. (2018) used an intraoperative data collection process based on Confocal laser endomicroscopy (CLE) images and Convolutional Neural Networks (CNN) are used for learning the underlying feature representations. A CNN consists of an input layer, several convolutional layers, pooling layers, fully connected layers and an output layer. The main limitation of this technique is that it is still in the development stage and more tests are required before it can be implemented.

This short discussion demonstrates that researchers generally address different aspects of the meta-problem of brain tumour segmentation. However, the relationship between these approaches is unclear. This leads to a range of problems that hinder the advance of this field. One of these is the absence of comparability of methods. Furthermore, to advance research into brain tumour segmentation, it needs to be possible to combine existing methods to take advantage of valuable insights. To overcome these barriers, we propose a comprehensive taxonomy of components for brain tumour segmentation as a guide for future research.

Based on the critique offered earlier of data, image segmentation processing and view, the following modifications are proposed to overcome these limitations of comparability and combination of methods:

Data: The Modified Fuzzy C-means (MFCM) algorithm (Vishnuvarthanan et al. 2018) is added to the process, capable of processing large volumes of data which improves contrast and clustering, when combined with Contrast Limited Adaptive Histogram Equalisation during the image pre-processing. However, whilst this leads to improved levels of contrast, the proposed algorithm is unable to retrieve losses that occurred during this stage. This is overcome through re-clustering after segmentation.

Image Segmentation Processing: The threshold value from the Bacteria Foraging Optimisation (BFO) algorithm (Karthikumar and Chitra 2019) is added for fine-tuning the segmentation, resulting in clearer identification of tumour boundaries between dense edema and healthy tissue thereby increasing the accuracy of the MRI images.

View Identification of the dense edema is the third factor of the proposed framework.

To develop the DIV, thirty journal articles were evaluated providing an insight into past and present technologies used for MRI image segmentation. Based on completeness and outcomes, the DIV was developed from six of the most impressive recent works and then used to evaluate the six systems and validate the DIV.

The remainder of this paper is organised as follows: Sect. 2 defines the image segmentation process and discusses the importance of image segmentation in the medical field. This is followed by a review of existing literature related to image segmentation. Section 3 presents the taxonomy, its components and sub-components. Verification of these components can be found in Sect. 4 together with evaluation and verification has also been performed. Conclusion is drawn in Sect. 5.

2 Previous work

Studies in this section show the different approaches and varied areas of interest of researchers.

2.1 Diagnosis by human agents

An overview of existing systems was carried by Pak et al. (2017), with a focus on enhancing the accuracy of brain tumour diagnosis using MRI scans. The authors' main aim was to develop methods for judging the intensity (i.e. age and rate of growth) of tumours. This was also the aim of Raju et al. (2018) and Nithila and Kumar (2017), who investigated accuracy in terms of MRI imaging. They concluded that this process is prone to errors as MRI scanned images must be analysed by human agents. On the same issue, Ali and Yangyu (2017) concluded that the manual segmentation depends on the expertise of physicians which means that sometimes the type tumour may be incorrectly identified resulting in misdiagnosis. Banerjee et al. (2018) stressed the loss of time in arriving at a conclusive outcome with manual segmentation, stressing the danger in the case of aggressive cancers.

2.2 Automated diagnosis

Chen et al. (2017a, b), enhanced human diagnosis through a 3D supervoxel-based learning method which classifies healthy brain tissue, tumour core, and oedema for accurate diagnosis. Larger than normal voxels allowed for more accurate segmentation of tumours. This technique uses raw MRI data and patient-specific data as input (see also Singh and Bala 2018; Cole et al. 2018). In the pre-processing stage, Eddy current distortions are removed from DTI data using Eddy correct software. This is followed by a clustering process to segment the MRI image and identify tumour regions (Na et al. 2018), These combined results indicate that the accuracy of identifying the tumour regions is increased but the system does not provide appropriate techniques for viewing the output.

Such omission was also found in the work of Sompong and Wongthanavasu (2017). Here, the Kernelized Fuzzy Entropy Clustering (KFEC) algorithm facilitates automated segmentation of brain tissue from MRI images. Optimization of images is achieved using an LHNPSO algorithm which eliminate bias in images (Pham et al. (2018). Ba Nabizadeh and Kubat (2017) modified the KFEC and evaluated the proposed algorithm (KFECSB) by testing performance on different benchmark images. This technique enhances the accuracy of raw MRI image and hence, the issues related to image distortions and noise are minimised. However, this also reduces the quality of the original data as post-processing is not performed (Kaya et al. 2017).

A range of different segmentation techniques can be found in four recent works. Thus, Pinto et al. (2018) utilised an Extremely Randomized Trees technique for automatic tumour segmentation. This is achieved by training and testing the classifier. Imperfections in the MRI images are corrected using an N41TK method. In contrast, Fageot and Al-Kadi (2017) used the histogram matching method during this stage for ensuring identical intensity distribution of the same sequence. After pre-processing, local and contextual features are extracted using non-linear transformations. Here, the image classification is performed to segment the brain into several parts for identifying the tumour accurately, a method used recently also by Koley et al. (2016) and Farhi et al. (2017) incorporated an Active Contour Models technique to develop an automatic segmentation process with higher accuracy for detecting the tissue of a brain tumour. This leads to more accurate diagnosis of the brain tumour (Gibson et al. 2018), According to Subudhi et al. (2016) this framework also returns the output as a parameter of the simulated optical correlation.

These works are the result of experiments with a range of techniques; however, they all address single aspects of a much larger system.

2.3 Diagnosis using neural networks

A range of researchers studied accuracy of diagnosis if the diagnostic process is automated using deep learning technology.

Saha et al. (2016) proposed the addition of an MFCM algorithm to resolve the issue of accuracy as clustering and re-clustering of MRI images highlight the affected areas more clearly leading to more accurate diagnosis of the tumour. Chen et al. (2018) identified additional benefits from the addition of the MFCM as the type of a tumour can also be identified which enhances accuracy of the image segmentation. It also ensures that the tumour boundaries are identified accurately which provides information about tumour size and volume.

Zhao et al. (2018) emphasised the importance of removing bias from image although this resulted in over-performing the task obtaining an incorrect output of the processed image. This may result in incorrect identification of the tumour-affected regions and incorrect diagnosis (Bonte et al. 2018). Izadyyazdanabadi et al. (2018) investigated the intraoperative data collection process using Confocal laser endomicroscopy (CLE) images and CNN for learning the underlying feature representations. They were able to supplement MRI data; however, Al-Milaji et al. (2017) claim that this technique is still in the development stage and more tests must be performed for actual analysis of the accuracy that can be achieved. Amin et al. (2018) reported improved diagnosis with Deep Conventional Neural Network (DCNN) which can be used for early detection of tumours by segmenting MRI images using Active Contour Models (ACM). They based their positive results on a comparison with the BRATS 2013 dataset. The same system was deployed by Cabria and Gondra (2017), but here results indicated errors related to classification. They also showed non-overlapping tissue boundaries which impact the accuracy of the segmentation technique.

A Fully Convolutional Neural Network (FCNN) formed the basis of the work of Chen et al. (2017). The FCNN was used in conjunction with CRF to develop a model based on deep learning medical image segmentation and N41TK (improved N3 bias correction) for removing the bias from MRI scans, differentiating gliosis and gliomas thereby enhancing the accuracy of the diagnosis. Charron et al. (2018) used three different models, segmenting the image into image slides in three different views and voting based fusion to fuse the segmentation results. FCNN with CRF was also the basis of research by Essadike et al. (2018). In the post-processing stage, the parameters were based on the BRATS 2013 dataset. The researchers were positive about the outcomes, although the same process was used by Rajinikanth et al. (2017), who claim the segmentation performance is affected in this technique because the number of pixels varies in the image slices.

Different deep learning systems were used by Valable et al. (2017) who relied on an intraoperative data collection process which enables automatic selection of a diagnostic image by revealing the obstruction of blood in the image. After acquiring this image, annotation of the image is done in two stages i.e., initial and validation reviews. As per Havaei et al. (2017), in the initial review phase, all images are reviewed in detail whereas, during the validation process, the database of images is divided into development and test datasets (Havaei et al. 2017), Saha et al. (2016) found that Convolutional Neural Networks (CNN) are used to learn the underlying feature representation. CNN consist of an input layer, several convolutional layers, pooling layers, fully connected layers and an output layer (Valverde et al. 2017).

Raju et al. (2018) argued that, although new techniques have been developed, accuracy of results has not been improved since only data and image segmentation component were considered and the third important component, view, was ignored. This is important because physicians and radiologists will be able to provide accurate diagnosis only if appropriate tools are used for analysing the MRI image (Li et al. 2016),

From the insights gained from the above research, diagram was designed mapping the processes of VoxResNet for the development of effective brain segmentation systems (Fig. 1).

The works discussed earlier used only two factors while performing brain tumour segmentation: pre-processing and segmentation of supervoxels which compromised the accuracy of the process.

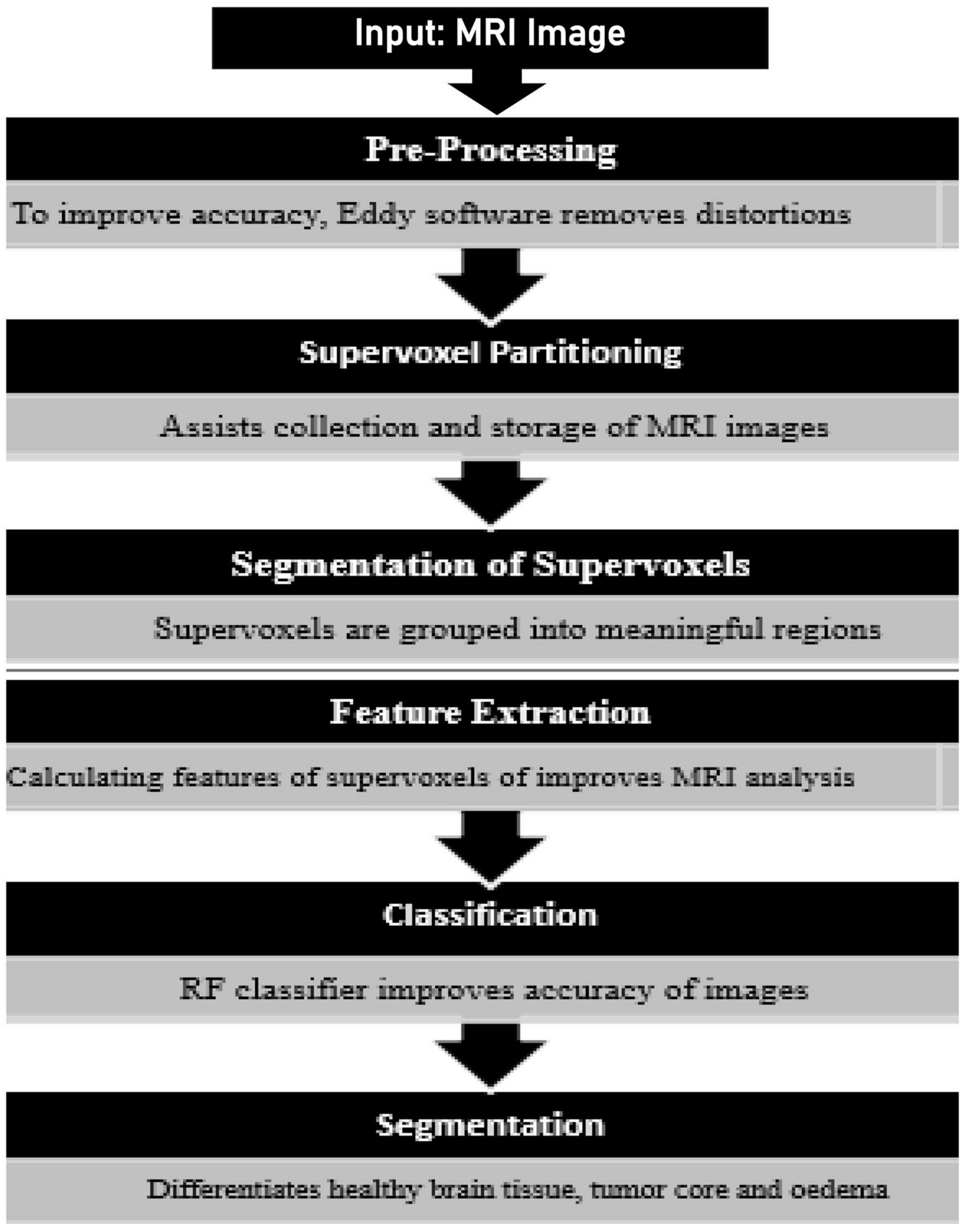


Fig. 1 Diagram depicted the process flow of VoxResNet

3 Taxonomy for deep learning neural networks for medical image segmentation of a brain tumour for diagnosis

3.1 Proposed system: data, image segmentation processing, and view (DIV)

The data, image segmentation processing and view (DIV) taxonomy was created based on the review of both the traditional and latest techniques used in Magnetic Resonance Imaging (MRI) brain image segmentation. It is also based on my personal learning and factual involvement working with and improvising solutions of Medical Image Segmentation (MIS) systems using deep neural networks for brain tumour diagnosis. We have created a taxonomy that takes into consideration the most relevant and appropriate factors for the evolution, validation, and evaluation of such systems with the help obtained from domain experts of MIS systems who

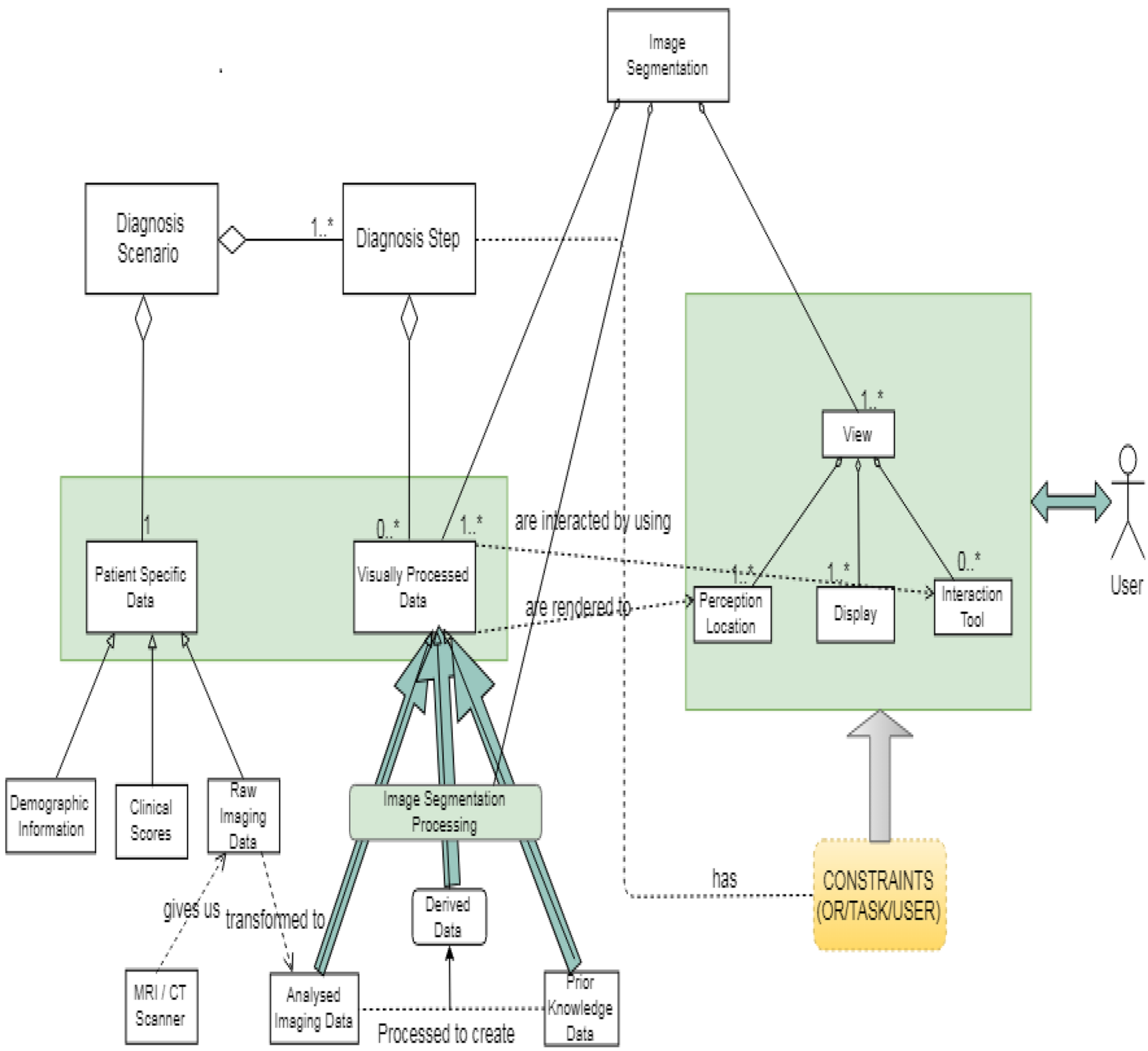


Fig. 2 The above figure shows the three factors of our Image Segmentation taxonomy (i.e., data, image segmentation processing and view), as well as the classes and subclasses (solid-line arrows) that represent them. The relationships between them (dashed-line arrows) are also shown. Numbers in the figure specify the cardinality of the relationships. The image segmentation processing is associated with both visually processed data and view classes. The view is the component that is interacted with by the user and therefore, the component which is most limited by constraints

used deep neural networks, and based on the analysis of 30 exceptional papers from Q1–3 level journals (Fig. 2).

Based on this review and prior knowledge related to image segmentation of MRI images, it was concluded that physicians should be equipped with the latest techniques to facilitate classification of normal and affected tissues of the brain to identify brain tumours and provide a diagnosis. The three main points that should be considered are:

1. the type of MRI data that should be acquired,
2. the type of brain image segmentation through clustering techniques and the post-processing steps for enhancing the accuracy of the image
3. how results need to be displayed for the diagnosis of brain tumours. Hence, the classification of the MIS system has been based on three factors; data, image segmentation processing, and view (DIV).

The first factor in the DIV taxonomy is data and includes visually processed and patient data which have properties of dimensionality, semantics and modality. We also consider the way in which the data is acquired preoperatively and whether the data indicates a real or virtual object during the end view of the image segmentation process. The above classes are used for classification during the image segmentation process. This latter process, during which tools or algorithms are used for transforming the data into pictorial or visual representations, is the second factor. The different methods of segmentation of images is evaluated and, in some cases, post-processing is carried out to enhance accuracy of the segmentation results. The objective is to highlight the tumour regions to increase the accuracy of the diagnosis. The third factor deals with the type of view obtained from the visualization process and includes the type of display used. The three components and their classes with their most important attributes and values have been tabled below (Table 1).

In the above table, the three components of the DIV taxonomy and their classes with their most suitable attributes and their values that have been identified. It demonstrates that image segmentation processing is associated with both visually processed data and view classes (Table 1). The main purpose of the above table is to analyse the Main Attributes and Common Instances of the DIV components. This allows selecting of the factors and the most suitable sub-classes for the success of a research project. Figure 3 below depicts the diagnostic process.

3.2 Data

The data that has been considered as one of the important components of the proposed system is classified into two main subclasses as patient-specific data and visually processed data along with derived, analysed and prior knowledge data subclasses. The latter can be viewed directly; however, the raw images may also be modified into visually processed data. The details of the different classes of data and their subclasses, their attributes and their common instances used in the taxonomy, are shown in Fig. 4, which also provides a clear specification of all types of data which can be used by the physician.

In Fig. 4, most of the relevant attributes and examples are shown. Arrows in the diagram are depicting the inheritance, and the rounded shapes are representing the instances of the class. The detailed data classes and their subclasses are included in the taxonomy to specify the data types. The purpose of using the data component in the classification is to highlight the importance data availability to the end user.

The main purpose of using data as a part of the classification is to explain the importance of selecting the appropriate MRI image that is used for segmentation for accurate identification of tumour affected areas. Selecting a suitable image not only minimises the time taken for segmentation, but it also highlights the important features for differentiating tumour from normal tissues. The raw MRI image may contain bias which has to be eliminated to identify the affected areas. The processed data provides an appropriate diagnosis of patients and reduces the time taken by the physician for accurate analysis of MRI data. Furthermore, patient-specific information such as BMI and sugar levels, is used for determining the type of diagnosis that can be provided according to the present health condition of the patient. MRI and CT scan images considered as input images which are processed to improve accuracy by reducing noise and other distortions.

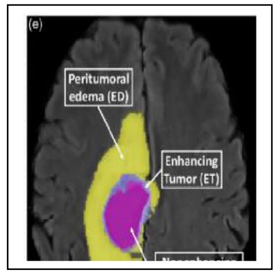
'Data' may have a range of different source. Thus, raw imaging data is the image obtained by MRI or CT scans which provides information regarding the status of the brain tumour. MRI scans are performed for identification of the presence of a tumour. This is basic information since it only provides a limited amount of information. In some cases, colours are used for accurate analysis of a tumour. However, visual data are patient data obtained from the MRI database, other clinical databases and MICCAI brain tumour datasets (Naito et al. 2017). Visual data consists of any information that can be viewed for ascertaining the health condition of the patients. Medical records may be printed or in image form. For instance, the blood report and sugar levels are printed whereas MRI scan results are obtained in the form of images. The information obtained by analysing these reports is vital as it enables to provide appropriate diagnosis. Image analysis data is the information obtained by ascertaining the volume, size and extent of a brain tumour and derived data is the output obtained by measuring the tumour boundaries. These are the images which have been transformed to create a specific data object. The difference is that

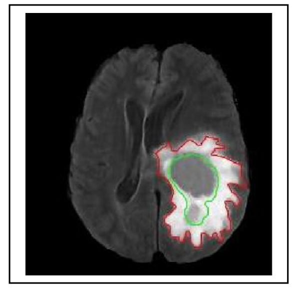
Table 1 Main attributes and common instances of the DIV components

Factor/class	Main attributes	Common instances
Data	Dimensions	0D, 1D, 2D, 3D, 4D, 5D
Raw data imaging	Time of acquisition	Pre-op
	Sensors of acquisition	Functional Magnetic Resonance Imaging, CT scan, Angiography, Magnetic Resonance Imaging, Diffusion Tensor Imaging, Medical images, Confocal laser endomicroscopy images
Visual data	Data object	Virtual, real
	semantics	Operational, strategic, anatomical
	Databases	Multimodal Brain Tumour Image Segmentation Challenge (BRATS) database, Clinical database, Patients MRI database, Brain Tumour Image Segmentation (BRATS) Benchmark dataset, Database of images, Virtual skeleton database, MICCAI brain tumour dataset
Image analysis data	Primitives of data	Volume, surface, wireframe, contour, line, mesh
Derived data	Fundamental process	Measurements (volume of the tumor, aregion of interest distance), labels, uncertainty
Data of prior knowledge	Fundamental model	Symptoms and nature of an illness, the uncertainty of system, tool models, labels
Image segmentation processing	Algorithms	Brain Extraction Tool Algorithm, VosRexNet algorithm, Propagation algorithm, Fuzzy C-means algorithm, Homogeneity-and Object-feature based Random Walks algorithm, Modified Fuzzy C-means algorithm, Random Forests Classification algorithm, grow cut algorithm, 3DACWE algorithm, Saliency detection algorithm, Voxel clustering algorithm
	Techniques	Conditional Random Fields, Fully Convolutional Neural Networks, Brain metastases automatic segmentation, 3D convolutional neural network
	Methods and models	Union Segmentation, Bayesian Fuzzy clustering, Kernelized fuzzy Entropy clustering, Back-StO2-MRI approach, Local and Non-local Active Contour Models, Sensitivity and Cohen's kappa segmentation, voting based fusion method, 3Dsupervoxel based learning method
	Classifiers, filters, infrastructure, frameworks	Random Forest classifier, Gabor Filters, NiftyNet infrastructure, TensorFlow Framework, Gaussian filter, Extremely Randomized Trees Potential Field Segmentation, Intersection Segmentation
	Tools for segmentation	Vander Lugtcorrelator, Matlab, Caffe library, Confocal imaging instrument, IPlan software, Eddy correct software, Functional Magnetic Resonance Imaging tool, Brain extraction tools
Thresholding	Algorithms based on histograms	Pixels less than 128 are considered in this category
Edge-based segmentation	Edge filters	Boundaries of connected regions
Region-based segmentation	Algorithms	Measurement of boundaries
View	Mixed reality	Virtual reality, Augmented reality
Perception location	Location	Patient, a digital display, a surgical tool, real environment
Display	Device	MRI scanning device, touchscreen, screen/monitor, laser, wall, holography, multi-view lenticular display, augmented microscope, TensorBoard Visualization
Interaction tools	Tools for hardware interaction	Keyboard, Mouse, haptic device
	Tools for visual interaction	Object view change, changing object properties, windowing/transfer functions, clipping planes, volume cutting

the raw MRI image is directly obtained by performing MRI scans and the image analysis data undergoes changes before the physicians study the image to identify a brain tumour. Prior knowledge data consists of details regarding the patient's history of illness which is useful while providing the diagnosis (Banerjee et al. 2018). This data can be surgery details, prior measurements, and any other information that is useful for ascertaining the health condition of patients. Segmentation of MRI data is effective in bringing the tumour to prominence and identifying the tumour core and the area of the oedema (surrounding tissue) which may carry spawns of the tumour.

Images 1=3





This image shows a colour-enhanced tumour (without segmentation)
Copyright: Getty Images

Tumour images after segmentation
Copyright: Researchgate

The image segmentation processing in the DIV taxonomy identifies the best technique among all the available techniques for accurate detection and segmentation of MRI images for brain tumour diagnosis. This is of high importance as the raw MRI data is further processed and its accuracy is enhanced to intensify the contrast of images through clustering and classification. The components, their subclasses, attributes and common instances are shown in Fig. 5.

The purpose of considering image segmentation component for the DIV taxonomy is that it enables to remove the bias present in raw MRI images by eliminating noise and other distortions. It is used to identify the best techniques and algorithms for best results. Clustering and classification ensure that the accuracy of the raw image is enhanced so that the tumour regions can be identified. The edge-based and region-based segmentation highlights the tumour boundaries and hence, the physicians will be able to accurately differentiate the tumour from normal tissue. Clustering techniques (i.e. Conditional Random Fields and 3D convolutional neural network) are used to achieve the objective of segmenting the raw MRI images automatically. This is more advantageous when compared with the traditional modes of identifying the tumour affected areas manually as the latter has limitations. Thus, we consider the automatic image segmentation component as indispensable as it eliminates bias. The subcomponents of image segmentation processing are classified as.

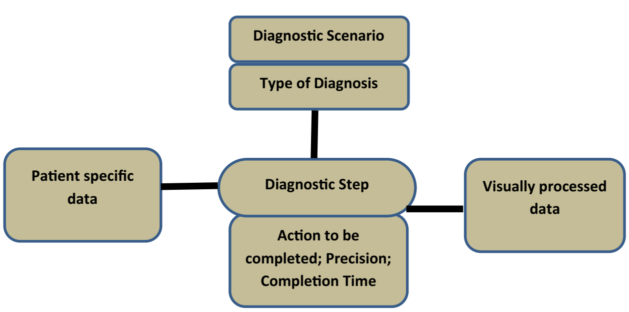


Fig. 3 The diagnostic scenario describes the type of diagnosis and the number of diagnostic steps that are executed to provide the diagnosis, whereby each step describes the action, its associated precision, and completion time. Each diagnosis step is associated with visually processed data and, therefore, indirectly with the view

3.3 Sub-components

The sub-components are assigned a range of functions. The purpose of thresholding is to identify the ways in which the pixels can be enhanced to improve the clarity of the output. It is an important factor while performing image segmentation as it becomes easier to classify the brain image into various sections. This permits focus on the section that contains the abnormality (Essadike et al. 2018). The image segmentation processing is designed to locate the tumour affected tissues and hence, it is important that the healthy tissues are separated. This is ensured by providing different colours on the MRI image which increases the accuracy of the segmentation results (Zhao et al. 2018), while region-based segmentation is used as identifier of tumour boundaries. This is done to ascertain the size and volume of the tumour and hence, appropriate diagnosis can be made. A further sub-component is perception location. That part of the environment which is studied in order to benefit from the image segmentation processing. The perception location consists of patient and the environment in which the physician performs routine tasks. For determining the perception location, three factors are considered; whether it is appropriate for the physician to consider other options for viewing, whether other people involved in MRI scans benefit and whether the equipment used for studying the MRI images inappropriately placed in the MRI scan room. The final sub-component is the view which enables the end user to view the output of the segmentation process. Interaction tools are computers, projectors, etc. for displaying the output so that physicians

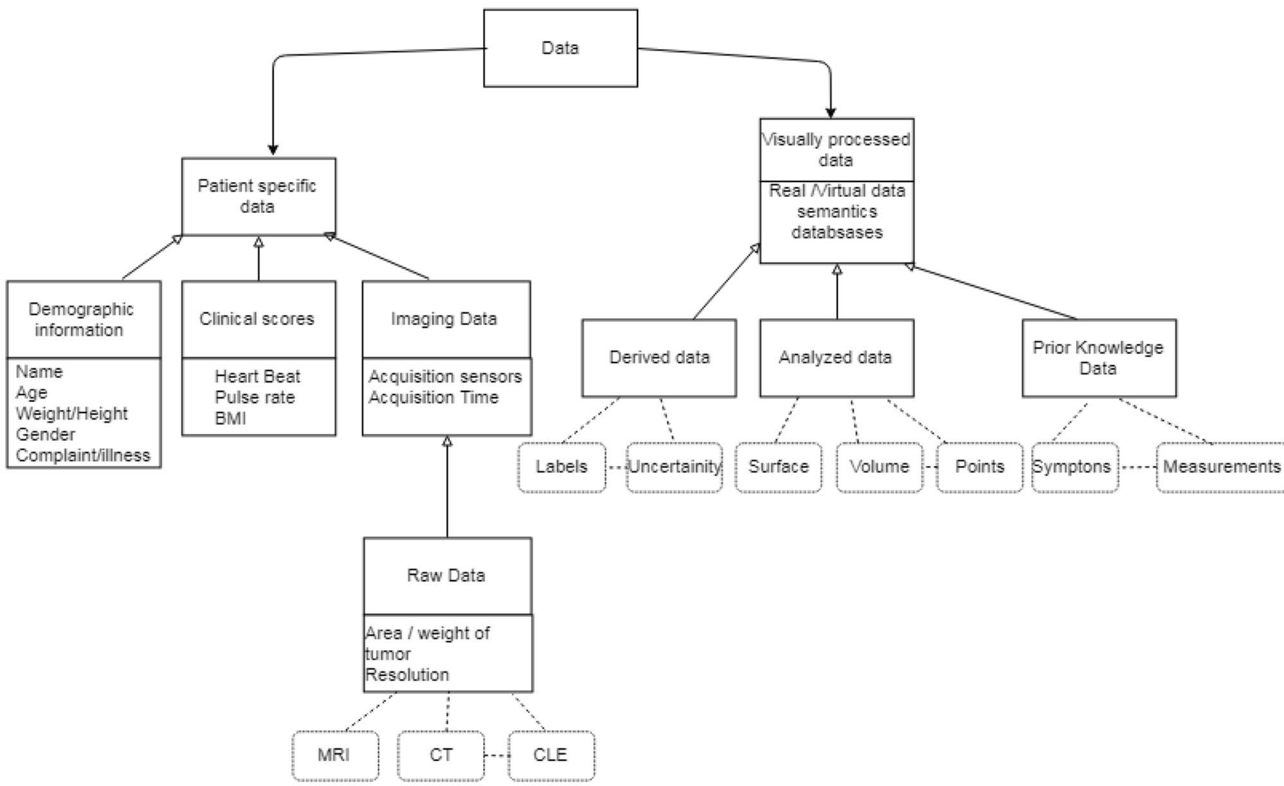


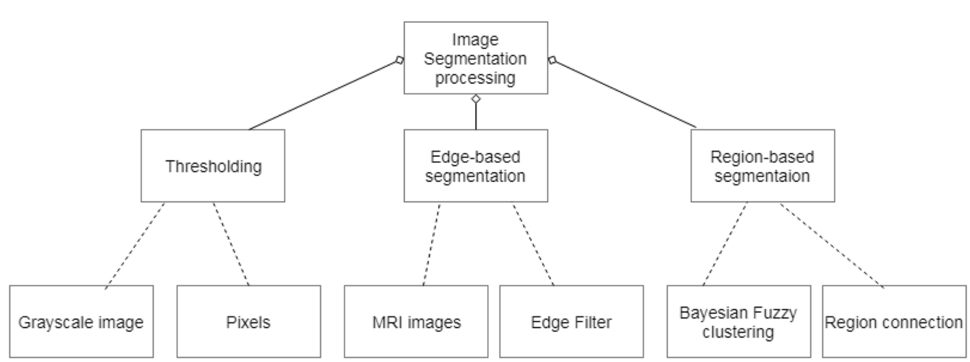
Fig. 4 Data classes, their most relevant attributes and an instances are presented here. The different types of data are patient-specific and visually processed. The solid arrow represents inheritance, and the rounded squares represent examples of how the image segmentation processing is associated with both visually processed data and view classes

and radiologists can identify the tumour affected areas. The various devices used for displaying the information include MRI scan machines, monitors, augmented microscopes, and TensorBoard Visualization. This provides a description for the system in terms of how and where the information is presented to the end user and how their interaction with the system can take place. The components, their subclasses, attributes and common instances are shown in Fig. 6.

The purpose of the view component in the DIV taxonomy is that it enables to display of the tumour affected regions to provide appropriate diagnosis. The interaction tools such as keyboard, mouse, windowing/transfer functions, and monitors are used to analyse the output received after performing the segmentation process. 'Eddy correct' software is used for classifying images to differentiate the tumour from normal tissues. The resulting output enables the physicians to accurately ascertain the type and volume of the tumour and make an accurate diagnosis. Hence, displaying the output plays an important role. The sub-components of view consist of perception location, display, and interaction tools.

Perception location is the part of the environment which is studied in order to benefit from the image segmentation processing. The perception location consists of patient and the environment in which the physician performs routine

Fig. 5 The main classes of the image segmentation processing, their subclasses, their most relevant attributes, and instances are depicted.The arrow heads represent inheritance, and dotted lines represent aggregation (i.e., "has a" relationships)



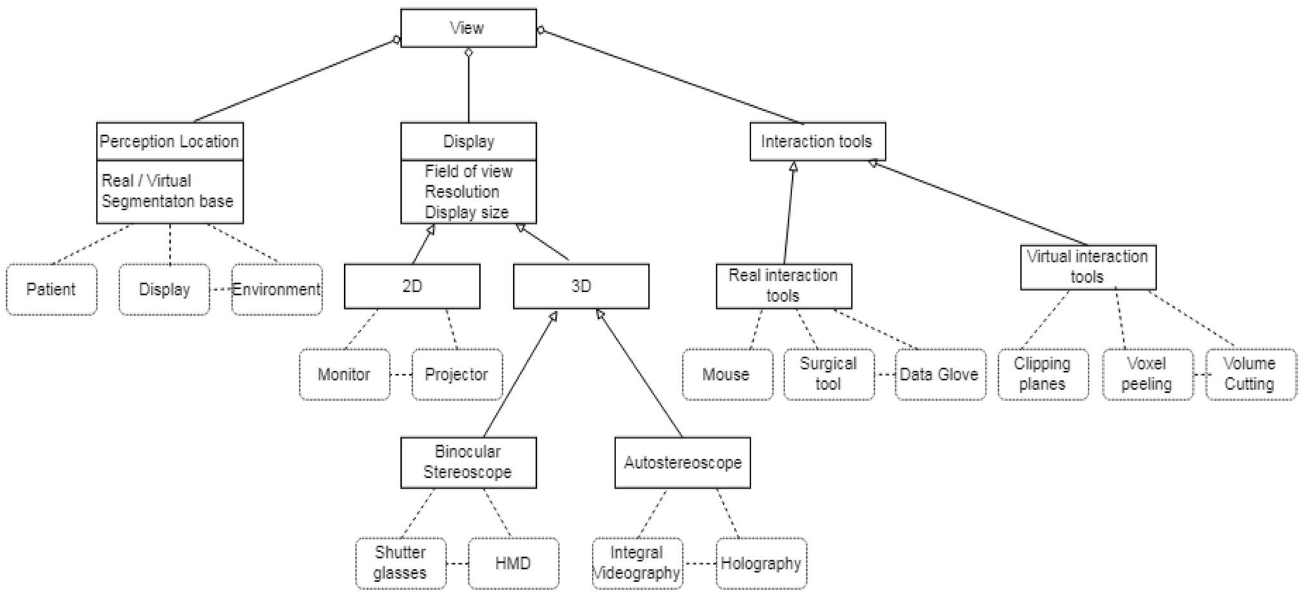


Fig. 6 The main classes of the view, their subclasses, and their most relevant attributes are depicted. The arrow heads represent inheritance, and the triangle arrow heads represent aggregation (i.e., "has a" relationships). Gray rounded squares represent example instances of a class

tasks. To determine the perception location, three factors are considered; whether it is appropriate for the physician to consider options of viewing other than the medical field, whether other people involved in MRI scans benefit and whether the equipment used for studying the MRI images is appropriately placed in the MRI scan room. Display contains the devices that are used for ascertaining the health condition of the patient, namely monitor, the MRI scan machine, and the augmented microscope. 3D imaging is used for accurate analysis of the MRI images as the brain parts are displayed. The physicians also use binocular stereoscopic displays and surgical microscopes for identifying the tumour. The Auto stereoscopic displays, which have been used in IGS, include multi-view lenticular displays and holography. Interaction tools are the hardware devices used for ascertaining the condition of the tumour. They are keyboard, mouse, and other optic devices (Cole et al. 2018). The interaction tools can be further classified as hardware interaction tools and virtual interaction tools. The examples of hardware interaction tools that are used in image segmentation are keyboard, mouse, Haptic devices, or data gloves. The virtual interaction tools include clipping panes, turning raw MRI image visibility on and off, and adjusting the colour, contrast and brightness of the raw data.

4 Example instantiation of the data, image segmentation processing and view

Appropriate elements for the image segmentation process are selected to ensure accuracy of the MRI image. Only relevant were considered to develop the proposed DIV framework. Papers from 2016 to 2018 were considered so that the latest techniques can be reviewed, and the best possible solution be proposed. Chen et al. (2018) and Essadike et al. (2018) proposed systems based on rapid sequencing which enhances the accuracy of the segmentation. Similarly, Pham et al. (2018) used a clustering algorithm programmed for identifying tumour tissues for g better results. From 30 papers, only two works were considered as then remaining were either too dated or their results did not provide the expected accuracy.

4.1 Data

Raw imaging data are MRI and CT scans that reveal tumor affected areas and the volume of brain tumours, obtained through the image segmentation process to enhance accuracy of the raw MRI images. The segmented image data is further divided into visual data, image analysis data, derived data and prior knowledge data. The visual data is the anatomical information of the patient, whereas image analysis data and derived data provide information related to the volume of a tumor. Prior knowledge data provides information related to the techniques used previously for determining size and volume of a brain tumour. All these types of data are used for accurately identifying the condition of a brain tumour and make the diagnosis (Ilunga-Mbuyamba et al. 2017a, b). The initial output of images from an MRI scan is 'raw data' as it contains all information of the brain tumour. This raw image is then used for the segmentation of the brain for any signs of a tumour. Algorithms are used on this image obtain more detailed information about the tissue and the tumour (Soltaninejad et al. 2018). Visual data denotes the difference between virtual and real segmentation. This analysis is carried out using simulation software (semantics) to obtain segmented images of the brain. The visualization processing forms part of the DIV. Image analysis data is included in the DIV as it represents the step that adjusts volume, surface, and contours before commencing the segmentation process. This data is derived by performing edge-based classification and Super Voxel techniques. This is the output of the pre-processing process performed by an RF classifier to enhance the accuracy of the raw MRI image to remove bias from the image to increase output accuracy. Most of the journals completely ignored the prior knowledge data and only focused on deriving the output by considering the MRI data as input. We have, nevertheless, included this component in the DIV because it is essential to know the medical history of the patient.

4.2 Image segmentation processing

All papers provided an insight regarding the different ways in which the segmentation process can be performed. The 30 that were selected used clustering, classification and algorithms such as fuzzy c-means. The segmentation techniques preferred by the authors have been shown in Table 2.

Table analysis In the above table, the appropriate factors of image segmentation process, the various components are determined to check if the techniques enhance the accuracy of the MRI image. From 30 papers, only two are considered as the others were either of previous years or their results did not provide the expected accuracy (Table 2). The main objective of Table 2 is to extract the DIV Classification of Medical Image Segmentation of Brain Tumour to identify the best method.

In the above table, algorithms, features and advantages are analyzed and compared to find the best technology. Only papers from 2016 to 2018 are considered so that the latest techniques can be reviewed, and the best possible solution be proposed (Table 3). The main aim of this table is to compare features, advantages and algorithms used in the different publications. From the above table the components of the DIV taxonomy are defined and described separately. The purpose of the above table is to describe the components and sub-classes of the DIV taxonomy to identify advantages for diagnosing brain tumours.

Description In the above table, 30 papers are presented, showing the processes used. Only two journals are considered as remaining (Table 4). The main purpose of above table is to evaluate and indicate the processes used in different publications to extract suitable components for the evaluation of the DIV taxonomy.

Description In the above table, algorithms, features and advantages are analyzed and compared to find the best technology. The journals from 2016 to 2018 are considered so that the latest techniques can be reviewed and the best possible solution using the latest technology can be proposed (Table 5).

Thresholding classifies pixels based on the range of values in which the pixel lies. Pixels with the values less than 128 are placed in one category and the remainder in another. The boundaries between adjacent pixels in different categories are superimposed on the original image. Clustering algorithms are used for enhancing the accuracy of the results (Essadike et al. 2018). Different types of filters such as NT41K are used for classifying the image with a view to enhancing the contrast in the MRI image. This is done to differentiate the tumour tissues from the normal ones, enhancing the accuracy of the raw data (Zhao et al. 2018) Fusion techniques are used for grouping pixels of the same category. This ensures that the pixels of the same value are placed above the image to identify the tumour. This results in the identification of the tumour boundaries. All papers focused on improving the segmentation process but ignored the view of the final output of the segmentation process. However, the display tools that can be used by physicians and radiologists have been discussed in all the papers. In most of the journals, the MRI scan machine has been considered as the perception location because the output derived from the MRI scans has been used as the input for further improvement. The DIV uses all output devices including display monitor as perception location. The display devices have been used to evaluate the quantity and volume of the brain tumour in almost all papers. The microscope-assisted guided intervention for evaluating the volume and size of the tumour has also been used along with the monitors. The proposed system contains both hardware and software interaction tools for identifying the tumour regions. Most of the journals either used hardware or software interaction tools but none provided solutions related to this component.

Table 2 DIV classification of medical image segmentation of brain tumour

Reference	Domain	Data input	Data	Image segmentation	View
Amin et al. (2018)	Brain tumour diagnosis	2D MR image scans (patch-based approach)	Improved segmentation and classification of images	Deep neural networks segment different types of tumours	Accurate classification and segmentation of a brain tumour
Banerjee et al. (2018)	Brain tumour	Brain tumor images (Raw imaging data)	Automated delineation process of tumor segmentation	Salient Tumour location is used for defining colour difference between the patches	Accurate analysis of tumour and enhanced speed of diagnosis process
Bonte et al. (2018)	Brain tumour	MR images scans (2D images)	Automatic segmentation of braintumour	Image Pre-processing is done for Re-slicing and co-registration of images	Achieving a high level of accuracy in brain tumour segmentation
Cabria et al. (2017)	Medical industry	Images from functional MRI	Accurately identifying the volume of white matter hyper	Support Vector Regression and radio wave frequency is used for identifying white matter hyper	Enhancing brain MRI procedure by introducing convolutional networks
Charron et al. (2018)	Brain tumour diagnosis	Images from functional MRI	Accurately identifying brain metastases	The use of the 3D convolutional neural network for segmenting brain metastases	Detect and segment brain metastases on multimodal MRI
Chen et al. (2018)	Medical industry	MR images (3D visual image)	Automatic segmentation of 3D images enables accurate segmentation of the brain tissues	VoxResNet is used for automatic segmentation of images	Developing an advanced technique for automated segmentation of the brain structure
Cole et al. (2018)	Brain tumour	Samples of the different tumours	The samples of different types of tumours are processed	The rapid sequencing of the whole genomes' id performed	Reclassification and updates on the classification of tumour types and intensity
Essadike et al. (2018)	Brain tumour	Vander LugtCorrelator algorithm	Automatic detection of tissue region with abnormal conditions	The tailoring of all types of a braintumour is performed here	Image segmentation of the tumorous area with higher accuracy and faster segmentation
Fahri et al. (2017)	Brain tumour	MRI (raw imaging data	Improved speed of iteration and accuracy of segmentation	Level Set is used for the description of shapes	Accurate identification of accurate boundaries of the affected region
Gibson et al. (2018)	Medical imaging	2Dand3D (dimensionality) medical images (raw imaging data)	Simplifying deep learning platforms for conducting further research	The niftynet platform enables collecting required information	Deep learning platform ensures improved quality of medical care
Havaei et al. (2017)	Brain tumour	MR images (2D axial image)	Accurate and reliable segmentation of tumour tissues	The deep convolutional neural network helps in individual feature map biasing	Accurate and reliable segmentation system development is achieved
Hussain et al. (2017)	Medical industry	Automated brain tumour segmentation algorithm	Accurately identifying the brain tumour in MRI image	The deep convolutional neural network is used in brain tumour segmentation	Classifying the images accurately and detect a tumour affected area
Ibrahim et al. (2018)	Brain tumour	MR images (visualised imaging	Improving the performance of the active contour segmentation techniques	3DACWE is made for boundary detection of the object	Accurate segmentation of brain tumor images without edges for improvement of active contour is defined

Table 2 (continued)

Reference	Domain	Data input	Data	Image segmentation	View
Izadyyazdanabadi et al. (2018)	Neurosurgical	CLE images (raw imaging data)	Automatically detect the diagnostic CLE image for braintumour	Convolutional Neural Networks helps to identify the affected area	Automatically the selection of a diagnostic image for examination
Kawahara et al. (2017)	Brain network neurodevelopment	MR images (structural images)	Development of the neuron networks of the infants	Edge-to-edge layers aredone to filter the data	Accurate prediction of the motor outcomes
Li et al. (2016)	Brain tumour	MR images (raw imaging data)	Automatic and accurate segmentation of images	ITKN3 normalization is used for bias correction	Automatic detection and segmentation of the braintumour
Lim and Mandava (2018)	Brain tumour	Random walks algorithm	Small numbers of pixels are labelled by the user	The modelling of the image is done in the form of a graph	Segmentation of images of multi sequence brain tumour
Mbuyamba et al. (2017)	Brain tumour	MRI data (multimodal brain images)	Automatic segmentation of a brain tumour	Feature extraction is performed by extracting image samples	Achieving better results of segmentation
Mohan and Subashini (2018)	Brain tumour	MR images of the brain	The use of radio waves and magnetic field to produce detailed images	The radio waves manipulate the atoms of the body with the magnetic position	Classification and segmentation of a tumour through different techniques
Na et al. (2018)	Brain tumour	MR images (diffusion-weighted)	Concluding that adult survivors of paediatric brain tumours exhibit white matter topology	Quantification of estimated rotational and transactional displacement is done for assessing each participant	Indicating the networks of white matter disruptions caused due to treatments of Braintumour
Pak et al. (2017)	Brain tumour	Images from functional MRI	The activity of the brain is detected and measured with associated changes in blood flow	The fMRI scans the neural activity of the spinal cord and the brain	Interpretation of braintumour pre-surgical mapping and progression
Pham et al. (2018)	Brain tumour	Brain MRI images (raw imaging data)	Improving segmentation of images of MRI brain	Kernelized Fuzzy Entropy Clustering accurately segments the images	Achieving segmentation with satisfactory performance
Pinto et al. (2018)	Brain tumour	MRI (raw imaging data) sequences	Automatic detection of tissue region with abnormal conditions	The tailoring of all types of braintumour is performed here	Image segmentation of tumorous area—higher accuracy and faster segmentation
Rajinikanth et al. (2017)	Brain tumour	MR images (raw data)	Enhancement and extraction of tumour core and sector of edema from the brain MRI	Multi-level thresholdingremoves irrelevant information	Achieving better accuracy and precision for segmentation of braintumour
Raju et al. (2018)	Brain tumour	MRI images (visualized image)	Automatically segment the brain structure and classify the level of a tumour	HCS algorithm is integrated from CSA for calculating optimal weights to multi-SVNN	Classifying the brain tumour in MRI images

Table 2 (continued)

Reference	Domain	Data input	Data	Image segmentation	View
Singh et al. (2018)	Brain tumour segmentation	MRI image (raw imaging data)	Removing inaccuracies in the images	Varied approaches to image segmentation are proposed for accurate segmentation	Preserving the image details by removing noise insensitiveness
Soltaninejad et al. (2018)	Brain tumour	MRI image segmentation	Accurately identifying the brain tumour in MRI image	Voxel-wise classification enhances weak image boundaries	Classifying the images as healthy brain tissue, tumour core, and oedema
Valable et al. (2017)	Brain tumour diagnosis	MRI approach (visual images)	Accurate identification of glioma cells	Tumour delineation helps to differentiate the tumours	Accurate mapping of Hypoxemia condition in the rats
Vishnuvarthanan et al. (2018)	Brain tumour	MRI images (raw imaging data)	Accurate segmentation and segregation of a tumour	Modified Fuzzy C-means fine-tunesthe segmentation	Identification of tumour regions bounded between dense edema and normal tissue
Zhao et al. (2018)	Brain tumour diagnosis	Images from functional MRI	Training FCNNs and CRFs helps to differentiate the gliosis and gliomas	MRI images are segmenting for identifying the affected area	Appropriate analysis of the status of a brain tumour

4.3 Image segmentation application

The research has been conducted with the aim of bringing clarity to the brain tumour diagnostic process. This has been achieved by observing all the functions and actions performed during the image segmentation and evaluating the best technique that can be used for classifying tumour affected areas.

4.4 Validation and evaluation

The validation and evaluation process analyse the effectiveness of techniques. The validation process ascertains the level of accuracy achieved and indicates that the proposed system was appropriately developed, and evaluation indicates the value of the proposed system. Table 6 summarises the validation and evaluation processes that were followed in the different publications.

Description Table 6 summarises validation and evaluation processes found in the 30 papers under investigation. It defines the result of the proposed techniques in comparison to the other existing techniques. The purpose of above table is to validate and evaluate the components and results related to the taxonomy.

Description In the above table, image type and components of image segmentation are discussed (Table 7). This represents the advantages and effectiveness of the DIV taxonomy which are evaluated. The objective of above table (Table 7) is to explain the image types and components involved in the taxonomy.

Validation techniques are used for analysing the effectiveness of any system. All authors have arrived at their conclusion by following different validation methods. For instance, Zhao et al. (2018) segmented brain images into slices and extracted image patches from image slices for resolving the issue of image segmentation. This was done to eliminate the bias in the raw MRI image. But the best solution came from Vishnuvarthanan et al. (2018) who used pre-processed images for clustered using an MFCM algorithm for calculating and assigning a membership function specification. The output is derived by evaluating the desired objective and comparing that with the actual output obtained after performing image segmentation.

A multi-model MRI dataset was used for generating supervoxels and partitioned using Voxel-wise classification to identify tumour affected areas (Soltaninejad et al. 2018). This resulted in the easy identification of a tumour as the tumour boundaries are highlighted. Izadyyazdanabadi et al. (2018), evaluated their results using the Dice similarity coefficient. This enhances the accuracy of the results obtained as the mathematical derivation is considered more accurate than other techniques, all of which are adopted to ascertain

Table 3 Features analysis and algorithms used in MIS of brain tumour

Author	Features						Algorithm/ technique	Process followed				Results		
	Normalisation	Image acquisition	Image imaging	Image clustering	Image evaluation	Deep learning		Pre-processing	Feature extraction	Classification	Evaluation	Bias correction	Tissue classification	Noise removal
Amin et al. (2018)			✓		✓		Convolutional Neural Networks		✓		✓		✓	
Cabria et al. (2018)		✓					Support Vector Regression algorithm				✓		✓	
Charron et al. (2018)			✓		✓		3D convolutional neural network (DeepMedic)	✓	✓		✓		✓	
Chen et al. (2018)		✓			✓			✓			✓		✓	
Gibson et al. (2018)						✓	TensorFlow framework			✓				
Havaei et al. (2017)			✓		✓			✓	✓	✓			✓	
Hussain et al. (2017)	✓	✓					Deep convolutional neural network	✓				✓		
Izadyyazdanabadi et al. (2018)		✓			✓		Deep learning image selection algorithm	✓		✓	✓			✓
Pham et al. (2018)		✓		✓	✓		LHNPSO algorithm			✓		✓		
Pinto et al. (2018)	✓	✓					Extremely Randomised Tree	✓	✓		✓	✓		
Raju et al. (2018)		✓			✓			✓	✓	✓			✓	
Singh et al. (2018)		✓		✓			Local and Non-local Fizzy C-means algorithm (LNLFCM)	✓			✓			✓

Table 3 (continued)

Author	Features						Algorithm/technique	Process followed				Results		
	Normalisation	Image acquisition	Image imaging	Image clustering	Image evaluation	Deep learning		Pre-processing	Feature extraction	Classification	Evaluation	Bias correction	Tissue classification	Noise removal
Valable et al. (2017)		✓		✓			StO2-MRI-approach		✓		✓		✓	
Vishnuvarthanan et al. (2018)		✓		✓			Modified Fuzzy C-means (MFCM) algorithm	✓		✓	✓		✓	
Zhao et al. (2018)	✓		✓		✓		Fully Convolutional Neural Networks	✓		✓	✓	✓		

the extent to which the contrast is enhanced, and the desired level of accuracy is achieved. The results are compared with the output obtained by performing image segmentation and raw MRI image. Further, results are compared with the output derived after performing other segmentation techniques. From all the above, there is not a complete match between most papers and the DIV. Figure 7 below provides a detailed analysis,

This figure highlights the overlap between the DIV taxonomy and other publications (Table 2). The percentage of papers which described the classes that represent each factor of the DIV taxonomy is as follows: 10% described the bias corrections that are used in the image segmentation process, while 90% included noise removal.

To validate the completeness of the DIV, the frequency of terms and the overlap between the DIV and the 30 publications was evaluated Table 8).

Table 8 shows the frequency of terms used by 30 researchers in this area of research. Most terms indicate a match as their rate of compatibility with the current research was above 50%. Exceptions are ‘pixels’, ‘guided’, ‘visualisation, ‘virtual’, ‘wireframes’, ‘Gaussian filter’, and some of the less common algorithms. Overall, therefore, there is a satisfactory fit of common terms.

4.5 Completeness

To ensure the completeness of the taxonomy, the most frequent terms are shown in the above table. The selected terms are checked, described and accounted for in terms of the DIV taxonomy. If more than one publication described the given term, only most recent publication was selected to avoid skewing the result. The frequent terms in the works were found with the help of DEVON think Pro tool. The first selected 30 terms are shown in the above Table 8.

They describe types of diagnosis and anatomy which are common in the selected papers. The lack of other common terms in the system leads us to believe that the DIV taxonomy is complete and its qualities and abilities are described in the system.

The mean squared error is the tool that is used to evaluate the efficiency of the proposed Modified Fuzzy C-means methodology (MFCM). With this tool, the quantities which are estimated are squared. This means that the square of all the average value of the error is done (Na et al. 2018). When represented equatorial, the square of the cumulative error values derived from the output image and the original image is expressed as MSE. The values of the MSE are required to be as low as possible for the segmentation result. The lower values of MSE indicates the better image segmentation result. This means that there are minimal chances of error occurrence in nature (Vishnuvarthana et al. 2018). The original and the output image can be examined in this model

Table 4 Evaluation of processes used in selected publications

Author	Image processing	Image clustering	Image classification	Image segmentation	Feature extraction	Image Post PROCESSING	Data storage
Amin et al. (2018)				✓	✓		
Banerjee et al. (2018)	✓	✓		✓			
Bonte et al. (2018)	✓		✓	✓		✓	
Cabria et al. (2017)				✓		✓	
Charron et al. (2018)	✓			✓			
Chen et al. (2018)	✓			✓		✓	
Cole et al. (2018)			✓	✓			
Essadike et al. (2018)	✓			✓			
Fahri et al. (2017)	✓	✓		✓		✓	
Gibson et al. (2018)							✓
Havaei et al. (2017)	✓			✓	✓		
Hussain et al. (2017)	✓			✓		✓	
Ibrahim et al. (2018)	✓			✓	✓	✓	
Izadyyazdanabadi et al. (2018)		✓	✓	✓			
Kawahara et al. (2017)	✓			✓		✓	
Li et al. (2016)	✓			✓		✓	
Lim and Mandava (2018)	✓	✓		✓			
Mbuyamba et al. (2017)			✓		✓		
Na et al. (2018)	✓		✓	✓		✓	
Pak et al. (2017)			✓	✓		✓	
Pham et al. (2018)		✓		✓		✓	
Pinto et al. (2018)			✓	✓		✓	
Rajinikanth et al. (2017)	✓	✓		✓		✓	
Raju et al. (2018)			✓	✓	✓	✓	
Singh et al. (2018)		✓		✓		✓	
Soltaninejad et al. (2018)	✓		✓	✓	✓	✓	
Valable et al. (2017)	✓	✓		✓			
Vishnuvarthanan et al. (2018)	✓	✓		✓			
Zhao et al. (2018)	✓		✓	✓		✓	

to get exact results. The MSE values are used for the identification of the level of deformation in the segmented output image (Nabizadeh and Kubat 2017).

It is important to evaluate the DIV taxonomy. For this, qualitative and quantitative approaches are used for accessing the classification. Vishnuvarthanan et al. (2018) proposed the use of a "goodness of fit" approach (Fig. 8).

The evaluation of the level of tolerance for the image towards the noise is that of the peak signal to noise ratio (Vishnuvarthanan et al. 2017). This is used to describe the tolerance level that is possessed by an image from the intruding noise signals. If the PSNR value remains high, then the effect of the noise signal to the image would be low. A variable MAX is used to denote the number of pixels that are there in the input image, and the MSE values are used to assist the prediction of the PSNR values (Namburu et al. 2017) (Fig. 9).

According to Vishnuvarthanan et al. (2017), Meningioma, a tumour which affects the meningeal layer of patients can be identified partially by BFO based MFCM and it can be referred in the segmentation result. The proposed system fails to detect this Meningioma, but this can be corrected. The other error in the detection is that the system failed to detect a tumour present in the pituitary adenomas from the input image (Sompong and Wongthanavasu 2017).

4.6 Goodness of fit and completeness

For the evaluation of the DIV taxonomy, overlapping terms between the taxonomy and literature are evaluated against the terms found in the selected journals. It becomes difficult to automate this method because most of the terms are often dependent. The term overlap among the taxonomy and the corpus depends on the previous analysis of 17 selected journals.

Table 5 Features analysis and algorithms used in MIS of brain tumour

Author	Features							Algorithm/ technique	Process followed				Results			
	Normalisation	Image acquisition	Image imaging	Image clustering	Image evaluation	Deep learning	Re-clustering		Pre-processing	Feature extraction	Classification	Evaluation	Bias Correction	Tissue classification	Storing stored data	Noise removal
Amin et al. (2018)			✓		✓			Convolutional Neural Networks		✓		✓		✓		
Cabria et al. (2017)		✓						Support Vector Regression algorithm				✓		✓		
Charron et al. (2018)			✓		✓			3D convolutional neural network (DeepMedic)	✓	✓		✓		✓		
Chen et al. (2018)		✓			✓				✓			✓		✓		
Gibson et al. (2018)						✓		TensorFlow framework			✓				✓	
Havaei et al. (2017)			✓		✓				✓	✓	✓			✓		
Hussain et al. (2017)	✓	✓						Deep convolutional neural network	✓				✓			
Izadyyazdanabadi et al. (2018)		✓			✓			Deep learning image selection algorithm	✓		✓	✓				✓
Pham et al. (2018)		✓		✓	✓			LHNPSO algorithm			✓		✓			
Pinto et al. (2018)	✓	✓						Extremely Randomised Tree	✓	✓		✓	✓			
Raju et al. (2018)		✓			✓				✓	✓	✓			✓		
Singh et al. (2018)		✓		✓				Local and Non-local Fizzy C-means algorithm (LNLFCM)	✓			✓				✓

Table 5 (continued)

Author	Features							Algorithm/technique	Process followed				Results			
	Normalisation	Image acquisition	Image imaging	Image clustering	Image evaluation	Deep learning	Re-clustering		Pre-processing	Feature extraction	Classification	Evaluation	Bias Correction	Tissue classification	Storing stored data	Noise removal
Valable et al. (2017)		✓		✓				StO2-MRI-approach		✓		✓		✓		
Vishnuvarthanan et al. (2018)		✓		✓			✓	Modified Fuzzy C-means (MFCM) algorithm	✓		✓	✓		✓		
Zhao et al. (2018)	✓		✓		✓			Fully Convolutional Neural Networks	✓		✓	✓	✓			

To ensure the completeness of the taxonomy, the most frequent terms are chosen in the above table. The selected terms are checked and described into the account by the DIV taxonomy. If more than one publication described in the given system then only most recent publication was selected to avoid skewing the results. The frequent terms in the works are found with the help of DEVON think Pro tool. The first selected 30 terms are shown in Table 8.

The lack of other common terms in the system leads the user to believe that the DIV taxonomy is complete and its qualities and abilities are described in the system. The evaluation of the DIV system and other mixed systems regarding accuracy, clustering, classification, etc., is important for the acceptance of systems. However, one purpose of the DIV taxonomy is to define all the components which should be evaluated and not specific evaluations.

5 Discussion

Here we discuss the elements of brain segmentation that were not addressed in the 30 papers are discussed, and the need for their inclusion is justified (Pham et al. 2018). The CLAHE is discussed which shows that the tumour region is hidden in the segmentation of the MR images. The parts of the brain that are not highlighted in the segmentation are not mentioned in the literature. Therefore, the importance of such hidden areas in the identification of the actual tumor is described (Dou et al. 2017).

The pre-processing by Contrast Limited Adaptive Histogram Equalization (CLAHE) is a component of the system which is used to pre-process the input image. Furthermore, Vishnuvarthan et al. (2018) suggested that the CLAHE supports the improvement in levels of contrast for the input image. The CLAHE is used to enhance the boundary visualization of the image between the tissue and the tumor region that are present in the input images of the MR brain image (Naito et al. 2017). The functionality of both the BFO and the MFCM can provide good identification of the boundaries in between of the edema regions and tissue. The CLAHE performs well as compared to AHE. The CSF and the nasal sinuses regions are crucial for the segmentation process which cannot be neglected (Zhao et al. 2018). There are chances of a tumor present in this region or near this region. These regions are difficult to identify along with the edema portion of the brain. Both the CSF and the nasal sinuses are considered for the pre-processing to correctly identify the tumour region (Pan et al. 2017). Most papers proposed using normal detection and classification techniques such as feature extraction and classification which can, however, result in incorrect output as the images may be over-rectified and may lose original data. Similarly, applying an incorrect

Table 6 Validation and evaluation of medical image segmentation of brain tumour

References	Domain	Component evaluated	Criteria	Validation method	Results
Amin et al. (2018)	Brain tumour diagnosis	Brain tumour segmentation	Convolutional Neural Networks	DCNN is explored for brain tumour segmentation classification	Segmentation of different types of brain tumours is done
Banerjee et al. (2018)	Brain tumour	Brain tumour segmentation	Saliency map modification	Saliency detection algorithm is used for defining one or more salient regions of image	Definition of colour difference between the patches is produced
Bonte et al. (2018)	Brain tumour	Brain tumour segmentation	Feature extraction	Voxels assignment is done to the highest probability tissue after estimation of tissue probabilities at the post-processing stage	The disconnected part with the largest size is selected as the region of the tumour
Cabria et al. (2017)	Medical industry	Brain tumour segmentation	Based on physics concepts a new algorithm for the segmentation is used	Potential field clustering and the Adaptive potential threshold is calculated	Physics concepts make the segmentation more accurate
Charron et al. (2018)	Brain tumour	Brain metastases automatic segmentation	3D convolutional neural network (DeepMedic)	Detection and segmentation performance are evaluated by applying Dice similarity coefficient	Detecting and segmenting brain metastases on multimodal MRI
Chen et al. (2018)	Medical industry	Brain tumour segmentation	VoxResNet for volumetric image segmentation	2D deep residual network is extended to 3D deep residual network to get more representative data	Volumetric feature representation learning is strengthened
Cole et al. (2018)	Brain tumour	Brain tumour segmentation	Clinical characteristics	The diagnostic criteria of inclusion for patients was identified	Different medical and pathological characteristics were obtained
Essadike et al. (2018)	Brain tumour	Brain tumour segmentation	Active Contour Models	A mathematical formula is derived	The timorous area is segmented accurately
Fahri et al. (2017)	Brain tumour	Brain tumour detection and segmentation	Level Set	Adaptive algorithm is used for description of shapes and track that affects interfaces	Improvement of efficiency
Gibson et al. (2018)	Medical imaging	Deep learning infrastructure	Developing NiftyNet infrastructure	The tensorflow framework is used for defining an interface and TensorBoard visualization for visualising2D and 3D images	Simplifying the learning platforms for conducting further research
Havaei et al. (2017)	Brain tumour	Brain tumour segmentation	Back-propagation algorithm	A mathematical formula is derived for achieving accurate segmentation of shape and size of the tumour	Achieving Weight learning ability and individual feature map biasing
Hussain et al. (2017)	Medical industry	Brain tumour segmentation	Deep convolutional neural network (DCNN	The convolutional layers are overlapped to form hierarchical fashion for the feature of maps	Accurately determine the tumour

Table 6 (continued)

References	Domain	Component evaluated	Criteria	Validation method	Results
Ibrahim et al. (2018)	Brain tumour	Brain tumour segmentation	Segmentation	Use of 3DACWE is made for segmentation that is used for boundary detection of the object	The specificity, accuracy of the image segmentation is achieved
Izadyyazdanabadi et al. (2018)	Neurosurgical	Brain tumour segmentation	Intraoperative data collection process	CLE imaging acquisition instrument is used along with intraoperative CLE imaging process to acquire a CLE image	Intraoperative mapping of CLE images with respect to the site of the biopsy can be done
Kawahara et al. (2017)	Brain network neurodevelopment	Applications of neuroimaging	BrainNetCNN architecture	BrainNetCNN architecture is composed here with convolutional layers and fully connected (FC) layers	Variety of BrainNetCNN architecture configurations is tested
Li et al. (2016)	Brain tumour	Brain tumour segmentation	Pre-processing	For bias field correction use of ITKN3 normalization tools are used	Different fields are used for bias correction
Lim and Mandava (2018)	Brain tumour	Brain tumour segmentation	Homogeneity-and Object-feature based Random Walks (HORW) algorithm	HORW algorithm is used After identification of images with tumor and segmentation is done	Illustrates the distribution of intensity of the tumor
Mbuyamba et al. (2017)	Brain tumour	Brain tumour segmentation	Image classification	The success rate of the image classification was used for evaluation of the selection system	A large amount of usage for the purpose of supervised learning
Na et al. (2018)	Brain tumour	Deficits of paediatric brain tumors in the adult survivors	Tractography Construction	Used the diffusion MATLAB toolbox of PANDA toolkit and pipeline diffusion of MRI images	Possible streamlines constructions are performed
Pak et al. (2017)	Brain tumour	Neurosurgical operations of the brain tumors	BOLD tissue framework	Deoxygenated Haemoglobin is modulated by several factors by deriving BOLD signals	Based on a framework of mass conservation of oxygen is achieved
Pham et al. (2018)	Brain tumour	Brain tumour segmentation	Kernelized Fuzzy Entropy Clustering	The optimization of the objective is done using LHNPSO algorithm	Better segmentation of brain images
Pinto et al. (2018)	Brain tumour	Brain tumour segmentation	Extremely Randomized Trees (ERT)	ERT Classifier is applied in two stages for training and testing	ERT classifier learns patterns from the annotated data
Rajinikanth et al. (2017)	Brain tumour	Brain tumour segmentation	Multi-level thresholding	Grouping similar values of pixels for locating and examining significant available information from the images	Irrelevant information is not considered

Table 6 (continued)

References	Domain	Component evaluated	Criteria	Validation method	Results
Raju et al. (2018)	Brain tumour	Brain tumour segmentation	Bayesian Fuzzy clustering	Identification of core and the edema regions by defining Bayesian parameters	Improved flexibility and capability of classifying the image
Singh et al. (2018)	Brain tumour	Brain tumour segmentation	Fuzzy C-means (FCM) algorithm	Image pixels are grouped using clustering algorithm of Fuzzy C-means	Similar pattern images are found that suffer with distortions of noise
Soltaninejad et al. (2018)	Brain tumour	Brain tumour segmentation	3Dsupervoxel based learning method is used	The multi-model MRI dataset is used for generating supervoxels and partitioned using Voxel-wise classification	MRI images are collected and stored
Valable et al. (2017)	Brain tumour diagnosis	Mapping the hypoxemia condition	StO2-MRIapproach	A mathematical formula is derived	The type of same tissue intensity translates variations
Vishnuvarthanan et al. (2018)	Brain tumour	Brain tumour segmentation	Modified Fuzzy C-means (MFCM) algorithm	The pre-processed images are clustered using MFCM algorithm for calculating membership function	Each point of data associated with the cluster gets an assigned membership function specification
Zhao et al. (2018)	Brain tumour	Brain tumour segmentation	Conditional Random Fields is used	The brain images are segmented into slices and Local regions called image patches are extracted from image slices	The image segmentation problem is solved

Table 7 Table illustrating Image types and Components Evaluation

Author	Image type			Component evaluated			Display		Image		Advantages	Effectiveness of results		
	Functional MRI I images	2Dand3D medical images	MRI (Multi,modal)	Brain tumor segmentation	Neuro-surgical operations tumours	Neuroimaging	MRI scanning device	Projector	Raw data	Process image		High	Medium	Low
Banerjee et al. (2018)	✓			✓							Definition of colour difference between the patches is produced		✓	
Bonte et al. (2018)		✓				✓					Different types of tumour types and classes are classified		✓	
Cole et al. (2018)				✓				✓		✓	Different medical and pathological characteristics were obtained		✓	
Essadike et al. (2018)	✓			✓				✓			The tumorous and non-tumorous area is identified		✓	
Fahri et al. (2017)	✓					✓		✓			The minimization of computed energy is achieved		✓	
Ibrahim et al. (2018)		✓			✓					✓	Segmentation of three-dimensional brain tumor is achieved		✓	

Table 7 (continued)

Author	Image type			Component evaluated			Display		Image		Advantages	Effectiveness of results		
	Functional MRI I images	2Dand3D medical images	MRI (Multi,modal)	Brain tumor segmentation	Neuro-surgical operations tumours	Neuroimaging	MRI scanning device	Projector	Raw data	Process image		High	Medium	Low
Kawahara et al. (2017)	✓					✓					Input dimensionality is reduced			✓
Li et al. (2016)				✓							Different fields are used for bias correction		✓	
Lim and Mandava (2018)	✓			✓					✓		Illustrates the distribution of intensity of the tumour		✓	
Mbuyamba et al. (2017)			✓		✓		✓				The features of different image samples are extracted and evaluated		✓	
Na et al. (2018)			✓			✓	✓				Possible streamlines constructions performed		✓	
Pak et al. (2017)					✓						Delivery of blood oxygen to the brain is identified			✓
Rajinikanth et al. (2017)	✓			✓					✓		Irrelevant information is not considered		✓	

Table 7 (continued)

Author	Image type			Component evaluated			Display		Image		Advantages	Effectiveness of results		
	Functional MRI I images	2Dand3D medical images	MRI (Multi,modal)	Brain tumor segmentation	Neuro-surgical operations tumours	Neuroimaging	MRI scanning device	Projector	Raw data	Process image		High	Medium	Low
Soltaninejad et al. (2018)		✓		✓			✓			✓	Enhancing weak image boundaries is done by combining all MRI modalities	✓		

clustering technique may result in highlighting normal tissue regions along with those that are tumour affected. Therefore, these techniques must be used depending on the image pixel and the quality of the raw MRI image. The papers showed clear understanding of the interaction tools used for providing the output obtained after performing the image segmentation process.

6 Conclusion

This research has aimed to develop a framework that can improve image segmentation techniques for accurate diagnosis. The accuracy of MRI images can be increased through better segregation of tumours from normal tissue. The results indicate that by using a Modified Fuzzy C-means technique, the accuracy of the diagnosis can be enhanced, and a framework developed which supports automated image segmentation rather than a manual technique. Identifying brain tissues using MRI images is a tedious and time-consuming process and it requires expert knowledge. These limitations can be overcome by using Modified Fuzzy C-means which removes bias in the image and accurately identifies tumor-affected areas.

The DIV taxonomy contains a detailed analysis and comparison of 30 state-of-the art solutions for performing brain image segmentation accurately. While conducting the analysis, it was noted that only three journals considered using these three components of the taxonomy. The remainder considered only two factors namely data and image segmentation and ignored the third important factor, which is view. The proposed solution provides a comprehensive framework which has been developed considering all three factors and hence, it overcomes the limitations of the state-of-the-art solutions. The classification table has been prepared to illustrate the main components and their corresponding sub-components.

The outcome further indicates that most of the papers used numerical measurements for validation of their results, while a small number applied multiple techniques to evaluate the accuracy achieved by image segmentation. It is important to develop new methods for processing raw MRI data because the existing techniques do not provide comprehensive solutions for the issues faced by physicians. Future work needs to focus on further enhancing quality of the image segmentation and processing large volumes of raw MRI data efficiently.

Fig. 7 The percentage of components or classes which were described in the selected publications is shown. For example, 60 percent of the papers described the type of image analysis data that are used in their image segmentation system

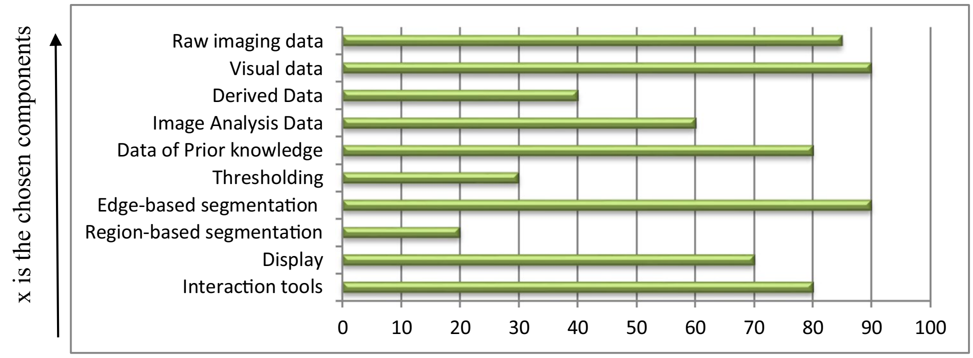
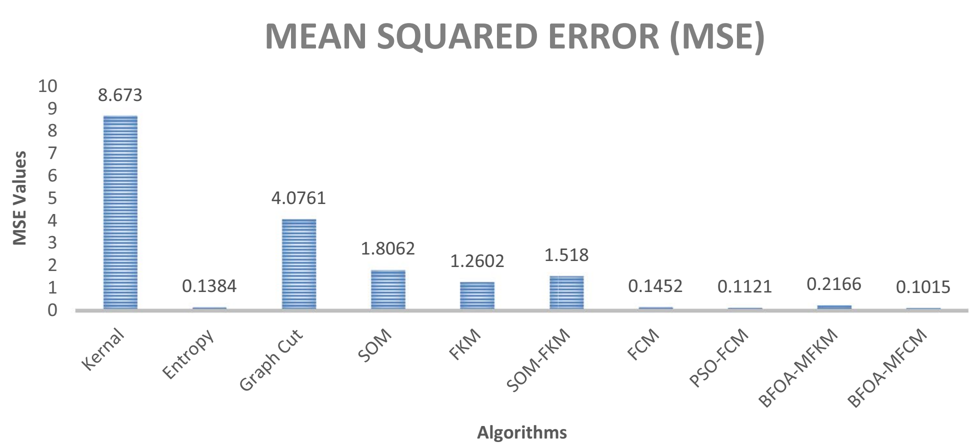


Table 8 Frequency of terms used in 30 chosen publications

Term	Frequency	Term	Frequency	Term	Frequency
Reality and real	70	Guided	23	Model	102
Medical	89	Patient	87	Time	87
surgery and surgical	103	Data	76	Assisted	94
Display	162	Augmented	55	Target (s)	52
Needle	99	Visualisation	45	Accuracy	123
Method	76	Virtual	33	Operative	78
Interaction tool	89	Gaussian filter	12	Voxel clustering algorithm	43
Pixel	32	Brain Extraction Tool Algorithm	21	Database	54
Haptic device	93	Voxel clustering algorithm	34	Data object	49
Gabor filters	81	Random forests Classification algorithm	56	Wireframes	24

Fig. 8 Mean squared error representation of the input image



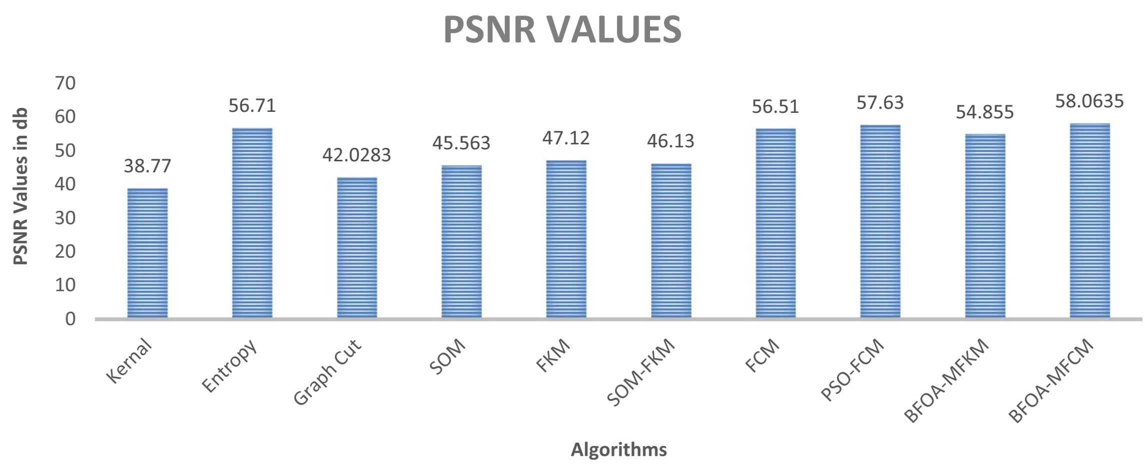


Fig. 9 The above figure shows the Peak Signal to Noise ratio of the image which describes the level of noise in the segmented image

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