ZKG INTERNATIONAL

ISSN: 2366-1313

Role and Efficacy of Deep Learning in Segmentation, Classification, and Prediction of Brain Tumour

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Abstract

Due to a significant increase in occurrence over the past few years, brain tumours are currently the tenth largest typical kind of tumour affecting both adults and children. If found early enough, it will be one of the most treatable types of tumours Scholars and experts have been researching to create cutting-edge techniques and ways to identify the type and stage of the tumour. Methods using Magnetic Resonance Imaging(MRI) have several benefits over alternative methods. Additionally, brain cancers can be automatically classified using an MRI scan without any intrusive procedures, eliminating biopsy and enhancing the safety of the diagnosis process. Following the years 2000 and the late 1990s, the research community has put in a tremendous amount of effort to generate an automatic detection and categorization of brain tumours. There is a tonne of work on the topic because of segmentation usingregion growth, machine learning, and deep learning approaches are of particular interest. The division of malignant tumours into their numerous histological kinds has been accomplished in the field with excellent performance results. This study's objective is to give an exhaustive evaluation of the latest developed, methodology for segmenting and classifying large brain tumour algorithms while considering cutting-edge approaches and their effectiveness. Deep learning has thereby radically altered and enhanced approaches for accurate detection, prognosis, and diagnosis innumber of healthcare domains, including pathology, brain tumour, lung cancer, abdomen, cardiac, and retina. This article aims to discuss the main deep learning concepts pertinent to the research of brain tumours given the variety of uses for deep learning (e.g., segmentation, classification, prediction, evaluation.). Condensing a sizable number of scientific contributions to the topic, this work gives a review (i.e., deep learning in brain tumour analysis).

1. Introduction

People's health can be spared,or the injury to your health associated with an illness or accident can be minimized by the early detection of abnormalities in medicine. Among the clinical abnormalities are things like glaucoma, diabetic retinopathy, interstitial lung diseases, heart problems, tuberculosis, and cancers [1]. Cancer is a top factor of mortality globally, based on research by the (WHO)World health organization [3]. The total number of people who develop cancer is expected to double in the next years, according to forecasts [2]. The chance of death can be decreased with early cancer detection and treatment. The effects of various malignancies, including lung, prostate, blood, brain, and others, on the human body are numerous. Experts have extensively researched these issues. However, the quality of diagnosis is constantly in demand, thus many kinds of studies are being conducted in this area. In this paper, we concentrate on brain tumours and present a comprehensive assessment of the definition, categorization, and detection of malignant tumours as well as the current use of machine learning and computer vision-based CAD systems.

Brain tumoursand their incidence

The human brain serves as a command center and is a crucial part of the neurological system that carries out daily tasks. The body's sensory organs send impulses or signals to the brain, which then receives them, processes them, makes the final judgments, and sends the information to the muscles. One of the most hazardous is brain tumourdisorder affecting the human brain when an uncontrolled mass of abnormal brain cells forms [4].

Brain tumour, which has increased morbidity of roughly the annual number of incidents reported, is the most fatal cancer. More than 250,000 brand-instances of the nervous system and brain cancer have been reported globally [5]. The only abnormally growing brain function that these tissues execute in brain tumours is unchecked cell proliferation. Brain tumours can lead to aberrant neurological conditions that enlarge and pressurize the brain. Additionally, they cause edema in the brain. The National Brain Tumour Foundation (NBTF) [6] reports that brain tumour deaths have increased by 300 percent in developing countries. 700,000 Americans have been maintaining a brain tumour, depending to data from the National Brain Tumour Society (USA) published in 2020. Over the last 30 years, the incidence of brain tumours has steadily climbed, much like other cancer forms. Rapid identification of a brain tumour might improve the prognosis and likelihood that the patient will recover after minor surgery, chemo, and radiotherapy.

According to recent population registration data for India [7], the second-most prevalent persistent illness in terms of human fatalities in India is cancer, which claims the lives of about 8 lac persons annually. In research on cancer cases in the Indian Territory published in 2016, the Indian Council of Medical Research (ICMR) estimated that there were 14 lac documented cases of the disease, possibly more. It also considered a number of cases that healthcare organizations failed to notify. The ICMR also found that, as of 2019, there were 25.8 new cases of cancer diagnosed per lac people, with a potential increase to 35 cases annually before 2029 [8]. Along with the United States and China, India has one of the top three global rankings for the number of cancer diagnoses. Additionally, it mentions Kerala, Tamil Nadu, and Delhi as important Indian states with about 2000 new instances of brain tumours reported daily. Among these data, it is predicted that over 1200 cases are in an advanced or later stage, which significantly lowers the survival rate (4–17 times) [9]. The second most prevalent cancer in women that results in mortality, after lung cancer, is a brain tumour. A recent study found that approximately 5 lac women died in 2015 as a result of brain tumours. Additionally, according to the World Health Organization (WHO), 1.5 million women may die from brain tumours [10]. The US, one of the most developed countries with the best healthcare system, also saw approximately 2.5 lac people with brain tumours and 40.000 fatalities in 2017 [10]. This kind of malignancy affects 5 to 10 persons per 100,000 individuals in India and is rising.Malignancies, which help compensateforchildren develop malignancies at a rate of 26% second most prevalent malignancy when considering children's brains and central nervous systems.

1.1. Types of brain tumour

The world health organization categorised Brain tumours into four groups based on whether they were malignant or benign (Grades I–IV). The two basic techniques for locating and examining BTs are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [11]. Malignant BTs in Grades III and IV proliferate rapidly, move to other body areas, and harm healthy cells. So, based on MRI and other imaging, early BT diagnosis and classification assist doctors in planning the best course of treatment [12]. Gliomas, pituitary tumours, and meningiomas are the three main forms of brain tumours. Pituitary BTs, which form in the brains basal layer and pituitary glands where several essential hormones for the body are produced, are often benign [13]. Gliomas are produced by the glial cells in the brain. Meningioma cancers typically develop on the brain and spinal cord's protective membrane [14]. Discriminate between normal and abnormal brain matter is necessary for the diagnosis of Brain Tumour. Variations in shape, size, and position make detection of brain tumour more difficult and are still an open challenge. Table 1 presents a brief overview of different grades of brain tumour.

Table .1. Brain tumour grades, and their characteristics

	WHO Grade	Characteristics	Types of Tumour
Low grade	Grade I	• Benign or less malignant • Potentially treatable with just surgery • Non-infiltrative • Long-term viability • Slowly expanding	• Pilocytic astrocytoma • Craniopharyngioma • Gangliocytoma • Ganglioglioma
	Grade II	• Relative slowly expanding. • Slight infiltration. • Possibly repeat in a better standard.	• “Diffuse” astrocytoma. • Pineocytoma • Pure oligodendroglioma
High grade	Grade III	• Malevolent	• Anaplastic astrocytoma

ISSN: 2366-1313

		• Infiltrative • Consistently repeat as a better standard.	• Anaplastic ependymoma • Anaplasticoligodendroglioma
	Grade IV	• Most malignant • Tremendous expansion, combative. • Extremely pervasive. • Frequent reoccurrence. • Susceptible to Necrosis.	• Gliobastoma Multiforme • Pineoblastoma • Medulloblastoma • Ependymoblastoma

1.2. Automated diagnosis and the role of computer vision

Considering the facts presented above, designating these three distinct tumour characteristics is an important phase in a patient's medical diagnostic procedure. Specialists in medicine have said for a long time that identifying brain cancers in clinics using human interpretation might be challenging. More reliable early tumour detection techniques are thus desperately needed, including computer-aided diagnosis (CAD) [15]. Many the use of clinical applications that depend on identifying features from clinical images, including attempting to differentiate between healthful and sick tissue, have significantly relied on CAD techniques [16].

The primary objective is the use of computers in brain tumour diagnostics to compile specialized content about the kind, existence, and location of the tumour. In order to properly diagnose and treat cancer, information from clinical imaging is used. Brain tumours can be automatically diagnosed by employing a range of hierarchically structured methodologies. At each level of the hierarchy, a different approach to arranging, classifying, choosing, and explaining data is required. Despite some advancements in this area, doctors still make manual tumour forecasts. This is likely because of an interaction breakdown among physicians and scientists. A powerful automatic method due to the premature identification of brain tumours is necessary to assist minimize a measure of survival [17]. Brain tumours are diagnosed using three important procedures: tumour sensing, segmentation, and classification. Different tumour tissues are separated from one another in MRI images of brain tumours using segmentation techniques, and these tissues are then subjected to classification algorithms.

There were several advancements in the field of computer technology brain tumour diagnosis over the past ten years. These tools are always availableto help uncertain specialists of the nature of the tumours seeing or who want to examine them more. Methods for medical imaging are essential for early tumour detection and bettering therapy options. Many intra operative diagnostic techniques, including CT, MRI, SPECT, PET, and X-rays are employed to research brain tumours [18]. An essential stage of diagnosis is utilizing non-intrusive technology to find brain tumours [19]. Table 2 presents a brief comparison on different imaging techniques such as CT, MRI, PET, SPECT, and Ultrasound where we describe their characteristics, advantages and disadvantages.

Table. 2. Different types of imaging techniques

	Imaging technique				
	CT	**MRI**	**PET**	**SPECT**	**Ultrasound**
Characteristics	X-ray body organs, then use a computer to generate a sequence of cross-sectional images.	Create "slices" that depict the human body by using magnetic signals.	Example of a nuclear imaging approach that uses tracers to diagnose disorders.	A non-invasive method that structures cross-sectional images of radiotracers inside the human body.	The method is based on sound waves with a high temporal frequency that can generate both quantitative and qualitative diagnostic data using a variety of approaches.

Advantages	✓ Wide-angle view ✓ Identification of even minute variations between bodily tissues ✓ A deep penetration rates. ✓ Superior spatial clarity	✓ Greater realism ✓ Able to display anatomical details. ✓ Utilizes no ionizing radiation	✓ Effective at differentiating between benign and malignant conditions. ✓ Heightened sensitivity	✓ Images with no background ✓ Establish neurodegenerative disorders. ✓ Heightened sensitivity (lower than PET)	✓ Superior spatial clarity ✓ Low price ✓ Security profile ✓ Non-invasive ✓ No radioactivity
Disadvantages	✓ Small sensitivity ✓ Radiation ✓ High doses for each test ✓ Price ✓ Poor contrast in soft tissue	✓ Strong magnetic fields are disruptive. ✓ Unsuitable for those who have metallic equipment, such as pacemakers. ✓ Limited throughput ✓ Price	✓ Poor spatial resolution ✓ Radiation ✓ High prices ✓ The most expensive method ✓ Movement artifacts ✓ A lower level of resolution than CT and MRI	✓ Blurring effects are generated. ✓ Cannot anticipate neuropsychological impairments. ✓ Poor spatial resolution ✓ Radiation	✓ Operator specific ✓ Complicated lung and bone image ✓ Limitation of resolution
Radiation source and type	✓ X-rays (ionizing)	✓ Electric & Magnetic Fields (Nonionizing)	✓ Positron (ionizing)	✓ Photons (ionizing)	✓ Sound waves (Nonionizing)

In order to help in diagnosis, medical imaging techniques can reveal details on the location, sizing, form, and classification of brain tumours. Because it has a broad capacity to define soft tissue, unlike additional methods of medical imaging, MRI is considered a typical instrument for delivering comprehensive facts on anatomy and physiology, and tissues [20]. Segmentation is a crucial first step when determining a brain tumour's cause. Therefore, getting the proper identification may be aided by the early detection of malignant tumours.

Because of their excellent outcomes, AI-based approaches are employed to detect brain tumours [21]. Due to significant developments in medical science, AI technologies are now being used in e-healthcare systems. These methods aid subject-matter specialists in giving patients better medical care [22]. AnArtificial Intelligence (AI) system is trained to become an "expert system" using Machine Learning (ML) for image classification. It makes use of secure medical images from the industry that can be applied to training and diagnostics. The categorization of medical images is focused on extracting features while pre-processing; for instance, brain scans were employed to establish and categorize the tumour's kind. A collectionof data sets, including databases of medical images, can be used with various classification algorithms, including PNN, K-NN, ANN, SVM, and BPNN [23].

1.3 Brain tumour segmentation and classification

Segmentation andclassification of brain tumours are regarded as crucial steps of the automated module in this area of brain cancer analysis. The basic structures required to perform tumour segmentation and classification, as well as their brief descriptions, are provided in this section.

1.3.1.Braintumour segmentation

In computer vision, the phrase is image fragmentation to describe the division of a digital image into several portions, each having its own characteristics. In many photographs, it is utilized to identify objects and their borders. It is necessary to distinguish between abnormal brain tissues, such as active cells, a necrotic core, and edema, and healthy brain tissues, such as GM, WM, and CSF, to segment a brain tumour.

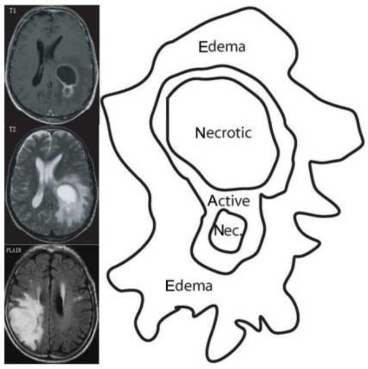

Fig.1.The three different brain tumour MRI images on the left include T1 with contrast, T2, and FLAIR images, while the three main parts of the segmented brain tumour are shown on the right.

Based on how much human engagement segmenting a brain tumour is broadly categorized into three types: manual segmentation, semiautomatic segmentation, and fully automatic segmentation.

1.3.2.Manual Segmentation

With manual segmentation, the tumour regions are manually labeled or painted around using specialized tools. The education, experience, and comprehension of the brain the human body's structure operator have a major influence on the accuracy of segmentation results. Manual segmentation is frequently used as the benchmark for semi-automated and completely automatic segmentation, despite being laborious and time-consuming [24].

1.3.3. Semi-Automatic Segmentation

Segmentationwhich issemi-automatedcombine computer and human skills. Initializing the segmentation process, receiving feedback, and assessing segmentation outcomes all require user input [25]. Despite taking less time than manual segmentation techniques, semi-automatic segmentation methods still rely on the operator to produce the desired results.

1.3.4. Fully Automatic Segmentation

Human intervention is not needed during the fully automatic segmentation of brain tumours. The segmentation problems are resolved by combining artificial intelligence and prior knowledge. Discriminating and generating methods are additional categories for fully automatic segmentation techniques. Classification techniques frequently use supervised learning, which involves learning from a sizable dataset the correlations between the input image and the human-annotated data. Over the past few years, this group has made substantial use of traditional machine learning techniques, which rely on manually created features [24]. Due to the intricacy of medical images, many techniques might not be able to fully use the training data. Due to their outstanding interpretation in computer vision applications and their ability to directly learn features from data, deep learning techniques have recently gained popularity [26]. On the other hand, generic techniques draw on a prior understanding of the location and characteristics of diverse tissue types.Accuracy problems and other computational difficulties plague manual and semi-automatic segmentation techniques. Deep Learning Techniques have also produced positive outcomes in the biomedical field. To produce the final segmentation map, UNet, a deep learning-based architecture, formulates encoder and decoder modules [26].

1.4Brain tumour classification

To categorize and recognize groups of images or matrices within an image in line with predefined criteria, image classification is necessary. The categorization law may be applied by a single or several spectrum or morphological classification methods. The two major types of image classification techniques are supervised and unsupervised techniques.

(a) Unsupervised Classification

No training data is used in the automated, unsupervised classification technique. This demonstrates that Machine Learning Algorithms are used to analyzeundefined group information through the discovery of concealed characteristics or material groupings without the need for human involvement [27].

(b) Supervised classification technique

Supervised image classification techniques require previously classified reference samples of brain tumour images that are annotated by qualified doctors to train the classifier and subsequently identify new, confusing data (the ground truth). The supervised classification methodology is the method of visualizing, picking, and training data samples from an image and categorizing them according to pre-selected groupings, such as background, foreground, lesion, etc.

1.5. Contribution

The complete article presents a literature review about brain tumour detection, segmentation and classification. We briefly study about the traditional machine learning approaches, and their drawbacks in this domain. Later, we describe the importance of deep learning approaches in medical domain and presented a brief discussion on existing deep-learning based approaches for brain tumour segmentation. We also present the major research gaps and challenges faced in the brain tumoursegmentation.

1.6. Organization

In Section II of this paper, the most recent strategies for segmenting brain tumours using various deep learning and machine learning techniques are discussed. In a similar vein, we further this section's a discussion of imagecategorization techniques depending on deep learning and Conventional Machine Learning. The problems and research limitations in this area are discussed in Section III. Section IV also covers the work's future scope and concluding remarks.

2. Literature review

The detection and categorization of brain tumours employing a variety of imaging techniques, notably those obtained utilizing MRI brain scans, has recently seen widespread usage of ML and DL approaches. The most recent and pertinent research pertaining to the study in this paper is presented in this section.

2.1. Brain tumour segmentation

The process of brain tumour segmentation involves identifying and quantifying the size of the tumour regions, which may or may not have vascularization, necrotic tissue, and edema (swelling near the tumour). It is possible to determine strange spots by contrasting aberrant regions with normal tissue. BT segmentation can be broadly categorized into three categoriesdepending on the level of human involvement: manual segmentation, semi-automatic segmentation, and fully automatic segmentation.

2.1.1. Traditional methods

The classification model is trained using specific attributes in machine learning-based strategies for segmenting brain tumours. Authors in [28] reported the challenges in segmentation due to location, shape, and characteristic of cells. The procedures utilized to analyze MRI images are pre-processing, extraction, classification, and post-processing. For segmentation, classifier algorithms like SVM, Adaboost, and Random Forest (RF) are used. These three classifiers' segmentation of brain tumours was compared in this study.

Image Processing is used to build animage of the skeletal system makeup of the human body, as stated in [29]. Images from MRIs offer images of the aberrant human brain that can be used to spot tumour cells. These aid in identifying the internal organization of the human brain and scanning it to precisely identify cells. Wavelet-based region segmentation and Gray Level Co-occurrence Matrix (GLCM) feature extraction make up the suggested work.

Tissues of the body throughout the body are employed to analyze brain tumour cells using MRI [30]. In this study, MRI segmentation was carried out using several threshold approaches and algorithms. In a highly

ISSN: 2366-1313

effective way, the segmentation method was used to automatically identify the location and borders of brain pathology. The brain area can also be qualitatively analyzed using this method to separate tumour cells with high sensitivity levels.

Image processing is utilized in the medical industry to find aberrant cells in the body, as explained in [31]. This study used MRI and Fluid-Attenuated Inversion Recovery (FLAIR) technology to automatically identify and predict the presence of tumour cells and healthy cells in the brain [32]. The classification of each pixel method and the best pixel technique were applied. To assure better segmentation results, characteristics such as curvatures, Gabor textons, structural evaluation, and luminosity were examined. To classify each super pixel as a tumour or not, the Extremely Randomized Tree (ERT) classifier was used with a support vector machine. The suggested technique of segmenting brain tumour cells using ERT classifiers carried out categorization quickly and frequently.

According to [33], brain tumour cells cause cancer. A prevalent kind of brain tumour that results in mortality is gliomas. This study developed an automated segmentation technique for MRI-based glioma detection. Since tumour cells were chosen using this region's subdivided spectrum and image luminosity method was more successful than the other way. This technology identified brain tumours with accuracy, and it performed well with better noise reduction and a precise segmentation strategy.

2.2.2 Deep-learningbased methods

Deep learning algorithms are a subclass of machine learning algorithms that build up a hierarchy of increasingly more complex representations of the original input. In this part, we discuss Deep Learning methods for classifying brain cancers. With a focus on architectural comparisons, this article strives to deliver a complete technical study of deep learning-based brain tumour segmentation methods. We are interested in analyzing how various designs impact how deep neural networks function for segmenting brain tumours as well as the possibility of further enhancing various learning approaches for a variety of issues. We discuss a variety of high-level inspections, such as efficient architecture design, its significance, computational performances, etc.An example of a convolutional neural network is one that incorporates convolutional operations into some of its layers.Medical image segmentation has recently seen the widespread application of a number of convolutional neural network-based network models, including Network in Network [34], VGG [35], GoogleNet [36], Res-Net [37], InceptionV3, etc. Among these, the VGG network stands out since it has a strong capacity for feature extraction and is ensure confluence in the event of shorter training cycles. However, once the network depth increases beyond a certain point, gradient explosion, and disappearance occur, which will cause the optimization effect to begin to diminish to deal with the problem of network degradation,

(a) GoogLeNet, ResNet, and VGG-basedarchitectures for segmentation

Szegedy et al. [35] introduced Inception, often known as GoogLeNet, as a fresh deep learning structure in 2014. Instead of calling it GoogleNet, experts refer to it as GoogLeNet since it honors the memories of the pioneering LeNet visual recognition model. From a different angle, Inception enhances performance by making intelligent use of computational resources to extract more features with comparable computational complexity and enhance the outcomes. A deep learning structure can extract more features since it can add more layers with the same receptive field.

Inception V2 was developed in 2015 which had a smaller internal covariate shift [38]. The efficiency of GoogLeNet's computation was increased the following year by Szegedy et al. [35], and to highlight the change, it is typically referred to as Inception-v3. The Inception is constantly enhanced, and it is integrated with other models to produce better results for certain jobs.

Deepak, et al's [39] application of deep transmission of knowledge to the classification of three various kinds of brain cancers was novel. Additionally, GoogLeNet was employed as a pre-trained model to categorize several forms of brain tumours for the first time. Additionally, the completely linked layer of GooLeNet was deleted, and the final three layers were changed to conform the intended subdomain. Amin, et al. [40] evaluate Alex and Google networks later in 2019 using the most challenging datasets for Medical Image Computing and Computer-Assisted Intervention (MICCAI) and finally achieve a mean accuracy of over 85%. Table III is a list of related work.

Rehman, et al. [41] mentioned the CE-MRI dataset from figShare once more in 2020. Additionally, they evaluated how well AlexNet, GoogleLeNet, and VGG16 performed when used as pre-trained models. Additionally, a fully automatic solution for the categorization problem is presented by Chelghoum, et al. [42].

And both achieve a respectable training outcome with a VGG accuracy of 98.70%. However, Rehman, et al. [49] concentrated on contrasting several transfer learning approaches, namely freeze and fine-tuning. Based on training duration and epoch numbers, Chelghoum et al. [42] provide the nine seasoned classifiers' general categorization precision designs. KULKARNI, et al. [43] used a proprietary dataset to evaluate the effectiveness of cutting-edge transfer discovering technologies on the binary problem. The result showed that all the improved models performed admirably in every situation. Anjum, et al. [44] evaluated the reliability of binary classification of brain cancers using GoogLeNet in more recent work, and they came up with a respectable result of 99.33% total accuracy (TA).

The University of Oxford's Visual Geometry Group [45], which collaborated with Google DeepBrain and placed second in ILSVRC-2014, created VGG. Both VGG and GoogleNet are effective in image visual recognition jobs, and they each receive unique features for their successful efforts. Additionally, because of its regular design and stackable convolutional blocks, VGG sometimes outperformed GoogLeNet in studies on the identification of brain tumours via transfer learning. VGG is frequently referred to as VGG-16 because it has 13 convolutional layers where all the 3 are connected layers. It has a more complex architecture than AlexNet and more parameters. VGG16 and VGG19 are two of the six distinct structures that make up VGGNet. Table 3 contains a list of related works.

Table .3. comparative analysis of brain tumour segmentation methods

Reference	Year	Dataset	Size of Dataset	Performance
Cruz Roa [46]	2015	Private dataset	10 pathology slide case	VGG6: 76.60%
Chato et al [47]	2017	Brats 2017	163 samples in Brats 2017	AlexNet =91% VGGNet= 86.4%
Swati et al [48]	2019	CE MRI	3064 abnormal brain CE-MRI	Accuracy =94.82%
Rehman et al [41]	2020	CE MRI	3064 abnormal brain CE-MRI	Finetuned VGG=98.69
Chelghoum et al [50]	2020	CE MRI	3064 abnormal brain CE-MRI	VGG =98.71
Ahuja et al [49]	2020	Brats 2019	155 slices	VGG=99.82
Kora et al. 50]	2021	CE MRI	3064 abnormal brain CE-MRI	VGG = 98.16
Chelghoum et al [42]	2020	CE-MRI dataset	3064 abnormal MRI	98.71% accuracy by using VGG16 for 90 epoch
Kaur et al. [94]	2020	Harvard repository, figshare, and clinical dataset	V1: 50T2, V2: 74 T2 Clinical: 500, Figshare: 3064	94% and 95.92% accuracy by using AlexNet
Divya [52]	2020	CE-MRI dataset	3064 abnormal CE MRI	Maximum accuracy of 98.67%
Alnemer [54]	2021	Kaggle repository	7023 MR image	Accuracy =98.7% with data augmentation
Polat [53]	2021	CE-MRI dataset	3064 CE MRI	Highest accuracy =99.02
Kulkarni [43]	2021	Private dataset	100 benign and 100 malignant	93.7% precision, and 96.77 f1-score
Ananda Kumar et al [55]	2022	Brats MRI dataset	NA	Highest accuracy 99.57

Cruz-Roa, et al. [46] used transfer learning in conjunction with VGGNet to perform a task for the timely identification of Medulloblastoma, a type of brain tumour. Additionally, the IBCa-CNN CNN model, another CNN model, was previously trained. However, these two models were trained in two separate fields, whereas the 2-layer CNN known as IBCa-CNN was trained to classify invasive breast cancer tumours. Following that, Chato, et al. [47] began a new transfer learning study using VGGNet. In BraTS 2017, 163 samples were considered, and because the dataset was specialized, it ended up becoming a multi-class classification problem. Although both AlexNet and VGG16 produced somewhat positive outcomes when used, VGG16 was still unable to fully demonstrate its power because of over-fitting and unfavorable transfer issues. The CE-MRI dataset from figshare was considered in 2019. Using transfer learning, various organizations experimented with binary and multiclass classification on the dataset. Rehman, et al. [41] utilized freeze and fine-tuned strategies to change the pre-trained models' layers and acquired a greater accuracy of 98.69% in even a multi-class classification, compared to 94.82% for the maximum accuracy in the work of Swati, et al. [48]. Additionally, Chelghoum, et al. [42] completed a difficult challenge in the same year, 2020, that included 9 pre-trained models for comparison in a multi-class classification test. They also kept track of the epochs that produced the best results, and they concluded that VGG16 could attain the maximum extent of 98.71% with 90 epochs. The performance of VGG in transfer learning advanced to a higher level almost immediately after the CE-MRI was tried. In more recent research, Ahuja, et al. [49] utilized the superpixelmethod for eliminating brain tumours and detect gliomas (of a certain type) using the BraTS 2019 dataset. Despite being a binary classification, the suggested system demonstrated the potential of VGG for tumour detection and produced a training accuracy of 99.82%. The CE-MRI dataset was retested in 2021 by Kora, et al. [50], who focused on the changes while using VGG-16 as a pre-trained model with a novel method of examining convolutional layers developed by the University of California. Researchers can study the filter kernel size of this layer on the original image, which has the added benefit of improving discriminating in terms of the receptive field. There are two benefits to the GoogLeNet-like nonlinearity of a collection of 3 by 3 convolutions merged into a single layer.The research on ResNet [51] was based on the degradation, which states that accuracy declines as neural network depth increases. Table 3 contains a list of related works.

Every cutting-edge model, including ResNet, demonstrates its potent capacity for prediction and classification. But Divya, et al. [52] employed the Contrast-Enhanced Magnetic Resonance Imaging dataset and focused on ResNet or ResNeXt with multi-class classification and achieved a maximum accuracy of 98.67%. In the following year, 2021, Polat, et al. [53] improved the work using the same dataset and Adadelta (a type of optimization technique). Using 7023 MR images from the Kaggle library, Alnemer, et al. [54] recognized four clinical stages of brain tumours almost simultaneously. After data augmentation, the proposed system, which is built on a modified ResNet152V2 network, achieved an overall accuracy of 98.9%. In more recent research, Kumar, et al. [55] explored the binary categorization of tumours using a novel technique dubbed Hyb-DCNN-ResNet152 TL.

(b) Deep Learning architectures for segmentation of brain tumours

The fundamental issue is that not all types of MRI are always accessible during clinical examinations. In this study, if one or more MR modalities are missing, we describe a novel brain tumour segmentation network based on the significant link between the MR modalities of the same patient. A segmentation network, a synthesizer with increased features and a connectivity constraint unit make up the proposed network. Using the existing modalities, the feature-enhanced generator produces an improved 3D image of the absent characteristic. In addition to requiring the generator to offer a feature-enhanced modality that the correlated restriction component can only be used to restrict correlations that are consistent with the accessible paradigms benefit from the paradigms' multiple-source connection. A multi-encoder-based U-Net segmentation network is employed to accomplish the final brain tumour segmentation [56].Hussain et al. [57] correlation design was made up by incorporating an inductive framework between a concurrent Convolutional neural network layer and a sequential CNN layer. The sequential Convolutional Neural Network architecture proposed by Saouli et al. [58] enables the simultaneous development and training of CNN models utilizing a progressive connection from end to end.

The fully convolutional network which uses mainly semantic segmentation is therefore better consistent with what is required to segment medical images. FCN and CRF were combined, according to Zhao et al. [59], to segment brain tumours. The technique uses segmented images of brain tumours to train segments are taken in two dimensions along the axisymmetric, tangential, and orthogonal planes. The segmentation speed is quicker and more efficient than previous segmentation techniques.Cinar et al. [60] presented UNet approach for medical image segmentation. This approach produces high DSC and PPV. To improve the model's capacity for discriminating, Zhou et al. [61] suggested a pyramid-shaped 3D atomic convolution feature. This model is utilized to separate tumours into various sizes. Then, it is advised to use a 3D extensive connectivity design, an enhancement to the original base [62] is developed, and using 3D convolution, a significant pyramidal component functionality is produced.

The SegNet model was suggested by Badrinarayanan et al. [63]. The model's 13-layer vgg-16 networkbased encoder may keep the location in consideration of data of the greatest pixel during its encoded process. The U-Net model based on FCN is one sort of frequently utilized paradigm for segmenting brain tumours. In this model, furthermore, the connection architecture consists ofcomprises an encoder and a decoder, and a leap interconnection in the U-Net networking will classify pathways, utilized to obtain figure's attributes to the decoder's path at the appropriate position, to get the direct sampling's characteristics from its coded stage into the process of decoding, discovering further precise qualities. Chen et al.[64] suggested a multi level deep network that can acquire and visualize multi-level data by including supplementary algorithms Multi-Level Deep Medical (MLDM) and U-Net to achieve image segmentation.Results of 83%, 73%, and 85% were obtained from the DSC, PPV, and TPR, respectively. Zhou et al. attempted to close the conceptual barrier between the encoder and decoder networksvisualizing things [65] and recommended several layered close correlationsapproaches to access the connections for the encoder and decoder. Alom et al proposal for inverted neuronal networks along with recurrent remnant convolutional neural networks based on U-Net are found in [66]. The outcome of the research shows that U-Net works better when the two types of network segmentation are aggregated than when U-Net is utilized alone. The attention residual U-Net, which combines the connectivity of residuals and the recurrent neural networks with the traditional U-Net network, was suggested by Zhang et al. [67] to enhance the segmentation of the behaviour of brain tumourMR images. The basic U-Net model as well as blocks for extensive supervisory, parallel concentration, multiple resolutions, and residuals have all been studied in [68].

A 3D convolution check was used to extend the original U-Net model, which Militaryi et al. [69] proposed as the foundation for the V-Net model. In order to segment the tumour more accurately than with direct V-Net segmentation, Cascaded V-Net was employed by Hua et al. [70] along with the approach of initially segmenting the entire tumour into sub-regions of the tumour. Cicek et al. [71] suggested a 3D U-Net model learn the characteristics of sparsely annotated volume images. In contrast to the restriction that deep neural networks are required for multi-scale feature extraction, Heetalwork's [72] built on the 3D U-Net and included a Hybrid Dilated Convolution (HDC) component to improve optical perception range of neurons. The computational complexity and the number of model characteristics might be minimized using shallow neural networks. Tsenget et al[73]propose an encoder/decoder with a When combined with MR visual information, the surface complexity of the cross-modal convolutional component of various modalities, and employing balanced and multi-stage retraining techniques concurrently, in order to address the issue content that is skewed, improved the methods of DSC, TPR, and PPV measure when compared to the traditional U-Net structure. The robust neural network technique developed by Isensee et al. [74] avoided overfitting and enhanced the U-Net network model by increasing the amount of data. In table 4, we present a brief comparison of traditional machine learning and deep learning based methods for segmentation of brain tumour.

Table. 4. comparative analysis of traditional machine learning and deep-learningbased methods

	Method	Advantage	Disadvantage
• Traditional segmentation methods	• A segmentation technique using thresholds. • Regional-based segmentation approach • Method of segmentation based on fuzzy theory. • Edge monitoring-based segmentation technique	• Simple to apply, • Quick with calculations • Easy computation, • High precision, • Capable of parallel operation, • Little demand for images, • Sensitive to certain factors, • Effective noise cancellation, • Quick detection time	• Low accuracy • Inapplicable to small images • Reactive to sound • Simple to create a cavity. • Volume impact • Time-consuming
Traditional machine learning	• KNN • Random forest • SVM • Dictionary learning	• Straightforward, precise, • Successful noise reduction • Excellent fitting skills, • Effective noise cancellation, • Quick with calculations,	• Data correlation is necessary, • Complex mathematical operations • There are many features needed,

ISSN: 2366-1313

		• Reconcile data discrepancies, • Good performance, strong theoretical foundation, simple calculation, quick operation speed	• Information loss is simple, • Reliant on kernel functionality, • Low accuracy when multitasking; high data requirements.
Deep learning	• CNN • FCN • Encoder-decoder based	• Automatic feature extraction shared convolution kernel • There is no minimum image size, categorize each pixel. • Restoring pixel position information while recognizing multiscale features in combination with high and low-resolution information.	• Lack of interpretability, the knowledge that is quickly lost, the presence of local convergence. • Lack of spatial consistency, insensitivity to details, and non-real-time efficiency

2.3. Research Gaps in Segmentation models

While brain tumour segmentation has come a long way, there are still several problems that need to be overcome for cutting-edge deep learning techniques. The following categories might be used to group the difficulties in brain tumour segmentation:

- No location was given as Gliomas are caused by mutant sticky platelets that encircle nerve cells. Because squidgy particles are widely distributed throughout space, either High-Grade Glioma (HGG) or Low-Grade Glioma (LGG) may appear in the brain.
- Morphological uncertainty: The morphology, or dimension and form, of diverse brain malignancies, distinct greatly in contrast to a rigid item. A brain tumour's epithelium is made up of edema tissues, which display different fluid-like formations that rarely provide any context considering that the tumour's morphologies. Sub-regions of a tumour may also vary in size and shape.
- Low contrast: Images with striking vibrancy and density anticipated to contain a variety of image data. MRI images perhaps being of poor quality and low contrast as a result of the image projection and tomography procedure. The distinction between biological tissues is frequently hazy and difficult to make out. It is challenging to classify cells close to the boundary, which makes accurate segmentation more challenging to do.
- Bias in annotation Manual annotation heavily relies on personal expertise, which can induce a bias when labeling data. During the learning process, the segmentation algorithm is significantly impacted by the annotation biases.
- Imbalanced problem: The data-driven learning method is impacted by the imbalanced problem because large tumour regions may have a significant impact on the retrieved characteristics.

2.4. Brain tumour classification

According to recent research articles, supervised machine learning and image classification tasks were successfully completed using deep learning techniques and approaches. Brain tumours come in a variety of forms, such as gliomas, meningiomas, and pituitary tumours. Additional classifications for brain tumours include benign (low-grade I and II) and malignant (high-grade III and IV) tumours. Brain tumour classification is challenging since tumour tissue cells vary in size, location, contrast, and structure. Modern deep-learning techniques used to categorize the glioma, meningioma, and pituitary kinds of brain cancer, which are further split into axial, coronal, and sagittal planes.

Feature extraction, feature reduction, and classification during pre-processing are the several phases that make up classical ML approaches. The extraction of features is necessary for classification accuracy as it is a crucial step in conventional ML algorithms [75]. The two main types of feature extraction are. This first kind of feature extraction includes low-level (global) characteristics such as texture features and intensity, first-order statistics (such as mean, standard deviation, and skewness), and second-order statistics such as Gray-Level Co-occurrence Matrix (GLCM) [76], Wavelet Transform (WT), Gabor feature, and shape [77].

An approach for categorizing brain tumours using a combination of deep characteristics and machine learning classifiers is proposed by Kang et al. [78]. Our suggested approach uses the notion of transfer learning and makes use of several deep convolutional neural networks that have already been trained to extract deep features from brain Magnetic Resonance Imaging (MRI) images. The deep properties that were extracted are subsequently evaluated by numerous machine learning classifiers.

Raza et al. [79] Hand-crafted features are necessary for the conventional ML classifiers, which takes a lot of effort. Contrarily, DL has recently been extensively employed for classification and detection tasks due to its relatively robust feature extraction capabilities. Therefore, using a fundamental Convolutional Neural Network (CNN) architecture, in this paper, we introduce a hybrid deep learning model called Deep Tumour Net for the classification of three different types of brain tumours (BTS): glioma, meningioma, and pituitary tumours. The foundation was provided by the GoogLeNet architecture of the CNN model. When developing the hybrid Deep Tumour Net approach, the last five levels of GoogleNet were removed, and fifteen new layers were inserted in their stead.

According to Kumar et al. [80], the drawbacks of deep networks include over-fitting and the disappearing gradient problem. For the purpose of vanishing gradient and over-fitting issues, we have suggested a deep network model in this research that makes use of ResNet-50 and global average pooling. In terms of global averages, the pooling layer has the following benefits: Due to the lack of parameter optimization, which inhibits over-fitting a layer below, it serves as a flattened layer for converting multidimensional extracted features into a one-dimensional feature set. Additionally, it requires less computing time than basic ResNet-50.

Kokkalla and others [81] categorization of brain tumours into three classes has proposed using an inception residual network-based network. High-level abstractions can be automatically discovered by the proposed model from the input images. The suggested architecture differs from state-of-the-art models in several ways, including an Inception residual network that was created to control the issue with gradient descent, is three thick layers connected to the output layer that enhanced the proposed model's effectiveness, leaky ReLU activation that prevented the disengagement strategy, the withering ReLU issue that was created to minimize model oversampling, and identical outcomes on noisy images.

The design of a two-channel deep neural networks for tumour detection categorization was proposed by Bodapati et al. [82]. In the beginning, InceptionResNetV2 and Xception networks' convolution blocks are used to extract local feature representations, which are then vectorized using suggested pooling-based approaches. The sort of tumour that is present in the photos can be determined with the use of a hypothesized attention mechanism that places more a focus on tumour areas and a decrease emphasis on non-tumour sections. The proposed two-channel approach enables end-to-end cooperative two sets of tumours are trained imageassumptions that lead to effective generalization.

The four stages of Sasank et al. [83]tumour classification from MRI undergoes 4 different phases they are pre-processing , segmentation, feature extraction, andclassification. During pre-processing, the Laplacian of Gaussian (LoG) and Contrast Limited Adaptive Histogram Equalization (CLAHE) are used. Following that, three distinct extraction techniques are used to extract the characteristics from the segmented image. However, it is often possible to find the extracted features in huge dimensions along with both relevant and unrelated features. Before the tumour classification stage, an optimization-based feature selection procedure is added to help decrease that. For classification, a Kernel-Based Soft-plus Extreme Learning Machine (KSELM) is employed.

A trained GoogleNet can be employed to extract characteristics from the brain Magnetic Resonance images, Deepak and Ameer [39] were able to classify three different forms of brain cancers with 98% accuracy. ResNet-50, and VGG-16 models using transfer learning techniques were employed by Saxena et al. [84] to categorize brain tumour data. The ResNet-50 model recorded a 95% accuracy rate, which was the highest. CNN designs have been used in studies [85] to categorize brain cancers. The Convolution Neural Network topologies draws characteristics from brain MRI data. The main goal of these suggested models is to identify the optimal deep-learning model that correctly categorizes MR images of the brain. A multi-pathway CNN architecture was reported by Francisco et al. [86] gliomas, meningiomas, and pituitary tumours are three examples of brain tumours that can be automatically segmented, utilizing a dataset from a T1-weighted, contrast-enhanced MRI that was made accessible to the public, they tested their suggested model and achieved 97.3% accuracy. Their training process is, nevertheless, rather expensive. To detect the purpose of detecting brain tumours from MR image data, Demir et al. [87] suggested a brand-new and efficient method based on a deep auto-encoder. Convolutional layers were employed in place of dense layers in the deep auto-encoder structure. The deep auto-encoder model's final encoded layer provided access to the deep feature sets. With the variance threshold technique, the deep characteristics were diminished. The several classifiers used for classification technique, including Support Vector Machines (SVM), Decision Trees (DT), K-Nearest Neighbours (KNN), and ensembles.

An automatic technique that can perform the cataloging of tumours with MRI was conceived and created by Neelima et al. [88]. Pre-processing is referred to as the first step in normalizing intensity. Here, min-max normalization is used for pre-processing. With the help of the Optimal DeepMRSeg strategy, segmentation is carried out. DeepMRSegment is trained using the recently developed Sailfish Political Optimizer (SPO) algorithm. Combining the Political Optimizer and the Sailfish Optimization Algorithm (SOA), the suggested SPO is created (PO).The data augmentation is carried out followed by Convolutional Neural Network (CNN) features,Data augmentation such as random translation, random left or right flipping, brightness, rotation, or contrast change can be carried out by CNN. After that, to classify the data a Generative Adversarial Network is used and it is trained using a Conditional Autoregressive Value at Risk-based Sailfish Political Optimizer (CAViaR-SPO), which combines CAViaR, SOA, and PO.

A new pre-processing technique that enhances the categorization of MGMT promoter methylation directly from MRI scans was introduced by Das et al. [89]. By artificially generating missing slices, we create a technique that may be utilized to normalize MRI data into a single spatial plane with uniform slice thickness. In addition to MGMT promoter methylation identification, the proposed approach can be useful for other purposes. For instance, an MRI scan can be used to diagnose GBM or Alzheimer's disease. These approaches can also be used on MRI images produced by various clinical conditions thanks to the normalization process enabled by the IS-Gen. MRI scan analysis-based deep learning models can be applied to the IS-Gen in a variety of ways.

Data collection, preparation, and application are the three key elements that makeup Khan et al’s [90] suggest brain tumour diagnosis system. Data collection is the first layer, where raw data is gathered. The second layer (pre-processing layer) was then used to handle, transport, and standardize this natural material. The consistent data will be forwarded to CNN's third layer, the prediction layer. Variables served as input and output in the data acquisition layer. The precision and miss rate of the issue are calculated in the final layer, known as the performance evaluation layer. The formation of brain tumours was concluded in the key location. Table 5 presents a brief comparison of aforementioned deep learningbased methods.

Table 5. comparative analysis of different deep learning based methods for segmentation and classification

Ref	Approach	Advantages	Limitations	Results
[87]	Deep learning, machine learning, and AI-driven image analysis.	While the data in this area is still new, we can yet produce better results.	Conclusions and potential problems need to be extensively investigated.	At every stage of the workflow, significant variability is still present in AI-driven imaging analysis, which is the focus of ongoing research and the subject of several papers.
[88]	Bio geography-based optimization	The results indicate that the suggested model enhanced precision by 2.206% while increasing accuracy by 4.22%.	Deflections exist in tumour detection	An algorithm for segmenting the brain tumour region in Magnetic Resonance Imaging has been proposed in this research.
[89]	Adversarial learning	6% increase in accuracy. Able to correctly recommend chemotherapy treatment options to 46,141 patients compared to 41,409 patients by the	Usage of reorientingstep in the pre-processing pipelines.	The pre-processing technique described in this work enhances the classification of MGMT promotor methylation obtained directly from MRI scans. By artificially generating missing slices, the technique can be utilized to standardize MRI data into a single spatial plane with uniform slice

		baseline model.		thickness.
[90]	Deep learning	This model overcomes precise segmentation of brain tumours.	Model accuracy is 92.13% which is just 7% superior to existing methods.	In the current study, CNN is used to propose a hierarchical deep-learning-based classification of brain tumours. The input was divided into four groups by the model: glioma, meningioma, pituitary, and no tumour.
[91]	Principle component analysis, k means clustering algorithm	Improved brain tumour detection method using the k-means algorithm. PCA efficiently and quickly detects human brain cancers.	The 2019 WHO worldwide classifications of diseases are not used, and it is applied to a tiny dataset.	PCA outperform all other systems currently in use. Brain tumours are accurately recognized in a short amount of time because of the 95% accuracy that was attained.
[92]	Deep learning	Reduce the expense of diagnostic and recurrent imaging, and speed up the detection of brain tumours.	Model is trained only on datasets available not verified on real-life data	Finding out whether MRI scans of a brain tumour are accurate to 100% and validated to 99.28% is a simple, quick, and effective learning method.
[93]	Hybrid machine learning algorithms.	The suggested method outperformed the current approaches in terms of results. The model's accuracy was roughly 96.47%.	The classification technique for brain tumours does not use a hybrid deep learning approach with a deep transfer learning model.	This study suggested a therapeutic therapy method based on patient-estimated brain tumours that is unsupervised.

According to Islam et al. [91], current methods (such as wavelet transform, Fuzzy C-means, random forest, and Artificial Neural Network (ANN)) can detect brain cancers, but with poor precision and a longer execution time (in minutes). In this study, we offer an improved method for the rapid and accurate diagnosis of human brain tumours using the Template-based K-means (TK) algorithm, super-pixels, and Principal Component Analysis (PCA). First, we use super-pixels and PCA to extract key features that help detect brain cancers with accuracy. Then, accuracy is improved by employing a filter to enhance the image. Finally, the TK-means clustering technique is used to segment the images to find the brain tumour.

Almadhoun and others, [92] in this article, various methods, and strategies for employing deep learning to create a model for brain tumour detection are reviewed. Finding a reliable and efficient method to identify brain tumours using MRI is the aim in order to support the brain in making decisions quickly, accurately, and simply. According to a recent World Health Organization research from February 2018, the Asian continent has the greatest death rate from brain tumours or other diseases of the Central Nervous System (CNS). Early tumourdetection is crucial in order to save many of these lives.

Rinesh and others [93] This study uses several techniques on hyperspectral images to examine tumour localization in the brain. Using k-based clustering techniques like a k-nearest neighbor and k-means clustering, the tumour is found. Both methods use the firefly algorithm, an optimization technique, to determine the value of k. The manual calculation for determining K's ideal value to partition the brain areas is reduced by optimization methods. The multilayer feed-forward neural network is used to label the various parts of the brain.

3. Research Challenges

Utilizing deep learning methods and algorithms to interpret brain tumour images poses a variety of special difficulties. A difficult barrier to the use of deep learning techniques is the dearth of substantial training datasets. Many PACS, MRI, and CT systems have been deployed in various hospitals during the past ten years, producing a large number of medical images. In certain other fields, image data are employed in purpose-specific, well-organized digital archives. In the future, it is anticipated to be simpler to introduce structured labelling reports in the healthcare industry, particularly for the study of brain tumours. To train the purpose of training deep learning algorithms, researchers have requested task-specific and text-free reports from domain specialists (such as pathologists and radiologists) who specialize in the segmentation, prediction, and categorization of images.It takes a lot of time and demands a high degree of knowledge, which is difficult in brain tumour analysis, to label temporized images. Slice-by-slice annotations are difficult and time-consuming operations that are required for the training of deep learning algorithms that segment tumours, typically in 3D networks. Another significant drawback of deep learning algorithm is their inability to learn effectively from small amounts of visual data. Many researchers have exclusively used 2D segmentation to train their 3D segmentation algorithms. BraTS datasets are frequently used to assess tumour analysis algorithms and to forecast a tumour in brain MRIs. Radiologists have annotated four different tumour types in this dataset. When using these data to train a deep learning system, extra modelling of uncertainty and noise in the standard reference is required. Although some scholars have offered remedies by explicitly including label uncertainty in the loss function, this problem is still unresolved. Unbalanced class representation is another issue with data. To construct new lesions of brain tumours, for instance, by scaling and rotation, data augmentation techniques are applied, although this could lead to class imbalance. To address the class imbalance, data augmentation techniques are widely used. However, the majority of deep learning techniques and architectural designs used in the analysis of brain tumours still focus on classifying patches rather than determining their physical locations. A potential fix for this is to feed the complete image into the deep network, which may then learn using a variety of techniques. Another study challenge is that, often, researchers utilize the same fixed size for a kernel to slice an image, which may obscure some relevant information from another region that the kernel ignores. A few researchers have experimented with slicing the image data into different kernel sizes, but further research is required in this field.

4. Conclusion and future scope

By segmenting and categorizing brain tumours, the task may be automated, which will improve diagnosis, treatment planning, and patient follow-up. With the use of numerous approaches, such as conventional image processing, shallow machine learning, and deep learning techniques, the automation of brain tumour segmentation and classification tasks has undoubtedly evolved. Creating a fully autonomous system which can be installed on the hospital floor is still challenging. This paper has explored several key elements, state-of-the-art techniques, and tools to implement autonomous brain tumour segmentation algorithms. The robustness of expert performance is still lacking in deep learning techniques, despite the tremendous advances made in the field. Several important designs, such as ensemble methods and U-Netbased models, have shown considerable promise for improving the state-of-the-art with proper, pre-processing,weight initialization, sophisticated training schemes, and strategies to address inherent class imbalance issues. The shortage of a sizable medical training database is a major factor in the poor performance of many segmentation algorithms.

References

1. Yadav, S. S., & Jadhav, S. M. (2019). Deep convolutional neural network based medical image classification for disease diagnosis. Journal of Big Data, 6(1), 1-18.
2. Jiao Z, Gao X, Wang Y, Li J (2016) A deep featurebased framework for breast masses classification. Neurocomputing 197:221–231
3. World Health Organization. (2022). World health statistics 2022: monitoring health for the SDGs, sustainable development goals.
4. Shaik, N. S., &Cherukuri, T. K. (2022). Multi-level attention network: application to brain tumour classification. Signal, Image and Video Processing, 16(3), 817-824.
5. World Health Organization. Fact Sheet Cancer. Available online: https://www.who.int/news-room/fact-sheets/detail/cancer
6. Abdelaziz, S., & Lu, S. (2019). K-means algorithm with level set for brain tumour segmentation. *Indonesian Journal of Electrical Engineering and Computer Science*, *15*(2), 991-1000.
7. Malvia, S., Bagadi, S. A., Dubey, U. S., & Saxena, S. (2017). Epidemiology of breast cancer in Indian women. Asia-Pacific Journal of Clinical Oncology, 13(4), 289-295.
8. Sharma, A. K., Nandal, A., Dhaka, A., Koundal, D., Bogatinoska, D. C., &Alyami, H. (2022). Enhanced watershed segmentation algorithm-based modified ResNet50 model for brain tumour detection. BioMed Research International, 2022.
9. Liyanage, U. A., & Samaranayake, U. M. J. E. (2019). Evidence based mammography screening: is evidence changing?. *therapy*, *11*(13), 14.
10. R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2017,” American Cancer Society, vol. 67, no. 1, pp. 7–30, 2017.

ISSN: 2366-1313

11. Samee, N. A., Mahmoud, N. F., Atteia, G., Abdallah, H. A., Alabdulhafith, M., Al-Gaashani, M. S., ... & Muthanna, M. S. A. (2022). Classification Framework for Medical Diagnosis of Brain Tumour with an Effective Hybrid Transfer Learning Model. *Diagnostics*, *12*(10), 2541.
12. Raza, A., Ayub, H., Khan, J. A., Ahmad, I., S. Salama, A., Daradkeh, Y. I., ... &Hamam, H. (2022). A hybrid deep learning-based approach for brain tumour classification. Electronics, 11(7), 1146.
13. Ng, S., Fomekong, F., Delabar, V., Jacquesson, T., Enachescu, C., Raverot, G., ... &Jouanneau, E. (2020). Current status and treatment modalities in metastases to the pituitary: a systematic review. Journal of Neuro-Oncology, 146(2), 219-227.
14. Al-Rashed, M., Foshay, K., &Abedalthagafi, M. (2020). Recent advances in meningioma immunogenetics. *Frontiers in Oncology*, *9*, 1472.
15. Fujita, H. (2020). AI-based computer-aided diagnosis (AI-CAD): the latest review to read first. *Radiological physics and technology*, *13*(1), 6-19.
16. Bagchi, S., Tay, K. G., Huong, A., & Debnath, S. K. (2020). Image processing and machine learning techniques used in computer-aided detection system for mammogram screening-A review. *International Journal of Electrical and Computer Engineering*, *10*(3), 2336.
17. Brain Tumour Informatics| Home. [(accessed on 10 December 2021)]. Available online: https://braintumour.org/brain-tumour-information
18. Elshaikh, B. G., Omer, H., Garelnabi, M. E. M., Sulieman, A., Abdella, N., Algadi, S., &Toufig, H. (2021). Incidence, Diagnosis and Treatment of Brain Tumours. *Journal of Research in Medical and Dental Science*, *9*(6), 340-347.
19. Tandel, G. S., Biswas, M., Kakde, O. G., Tiwari, A., Suri, H. S., Turk, M., ... & Suri, J. S. (2019). A review on a deep learning perspective in brain cancer classification. *Cancers*, *11*(1), 111.
20. Tang, W., He, F., Liu, Y., &Duan, Y. (2022). MATR: Multimodal Medical Image Fusion via Multiscale Adaptive Transformer. *IEEE Transactions on Image Processing*, *31*, 5134-5149.
21. Nalepa, J., Marcinkiewicz, M., &Kawulok, M. (2019). Data augmentation for brain-tumour segmentation: a review. *Frontiers in computational neuroscience*, *13*, 83.
22. Yazdani, S., Yusof, R., Karimian, A., Pashna, M., &Hematian, A. (2015). Image segmentation methods and applications in MRI brain images. IETE Technical Review, 32(6), 413-427.
23. Irmak, E. (2021). Multi-classification of brain tumour MRI images using deep convolutional neural network with fully optimized framework. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *45*(3), 1015-1036.
24. Biratu, E. S., Schwenker, F., Ayano, Y. M., &Debelee, T. G. (2021). A survey of brain tumour segmentation and classification algorithms. *Journal of Imaging*, *7*(9), 179.
25. Gering, D., Sun, K., Avery, A., Chylla, R., Vivekanandan, A., Kohli, L., ... & Mackie, T. (2018, September). Semi-automatic brain tumour segmentation by drawing long axes on multi-plane reformat. In *International MICCAI Brainlesion Workshop* (pp. 441-455). Springer, Cham
26. Isensee, F., Jäger, P. F., Full, P. M., Vollmuth, P., & Maier-Hein, K. H. (2021). nnU-Net for brain tumour segmentation. In *International MICCAI Brainlesion Workshop* (pp. 118-132). Springer, Cham.
27. Panda, B., & Panda, C. S. (2019). A review on brain tumour classification methodologies. *International Journal of Scientific Research in Science and Technology*, 346-359.
28. L. Lefkovits, S. Lefkovits, M. F. Vaida, S. Emerich, and R. Măluţan, ''Comparison of classifiers for brain tumour segmentation,'' in Proc. Int. Conf. Adv. Med. Health Care Through Technol. Cham, Switzerland: Springer, 2017, pp. 195–200.
29. A. R. Abdulraqeb, W. A. Al-Haidri, L. T. Sushkova, M. M. Abounassif, P. J. Parameaswari, and M. A. Muteb, ''An automated method for segmenting brain tumours on MRI images,'' Biomed. Eng., vol. 51, no. 2, pp. 97–101, 2017.
30. M. Soltaninejad et al., ''Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI,'' Int. J. Comput. Assist. Radiol. Surg., vol. 12, no. 2, pp. 183–203, 2017.
31. Virupakshappa and B. Amarapur, ''Cognition-based MRI brain tumour segmentation technique using modified level set method,'' Cogn., Technol. Work, vol. 20, no. 79, pp. 1–13, 2018.
32. K. P. Raghubar, E. M. Mahone, K. O. Yeates, and M. D. Ris, ''Performancebased and parent ratings of attention in children treated for a brain tumour: The significance of radiation therapy and tumour location on outcome,'' Child Neuropsychol., vol. 24, no. 3, pp. 413–425, 2018.
33. M. Drozdzal et al., ''Learning normalized inputs for iterative estimation in medical image segmentation,'' Med. Image Anal., vol. 44, pp. 1–13, Feb. 2018
34. Simonyan, K.; Zisserman, A. Very Deep Convolutional Networks for Large Scale Image Recognition. Comput. Sci. 2014, 6, 1556.

ISSN: 2366-1313

35. Szegedy, C.; Liu, Y. Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2015; pp. 1–9.
36. He, K.W.; Zhang, X.; Ren, S.; Sun, J. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
37. 86. Zhou, T.; Huo, B.Q.; Lu, H.L. Research on Residual Neural Network and Its Application in Medical Image Processing. Chin. J. Electron. 2020, 48, 1436–1447.
38. Ioffe, S., &Szegedy, C. (2015, June). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning* (pp. 448-456). PMLR.
39. S. Deepak, P.M. Ameer, "Brain tumour classification using deep CNN features via transfer learning". Computers in biology and medicine, 2019, 111: 103345.
40. J. Amin, M. Sharif, M. Yasmin, T. Saba, M. A. Anjum, S.L. Fernandes, "A new approach for brain tumour segmentation and classification based on score level fusion using transfer learning". Med. Syst., 43 (11) (2019), p. 326.
41. A. Rehman, S. Naz, M.I. Razzak, F. Akram, M. Lmran, "A deep learning-based framework for automatic brain tumours classification using transfer learning". Circuits, Systems, and Signal Processing, 2020, 39(2): 757-775.
42. R. Chelghoum, A. Ikhlef, A. Hameurlaine, S. Jacquir, "Transfer learning using convolutional neural network architectures for brain tumour classification from MRI images"//IFIP International Conference on Artificial Intelligence Applications and Innovations. Springer, Cham, 2020: 189-200
43. S.M. Kulkarni, G. Sundari, "Comparative analysis of performance of deep cnn based framework for brain mri classification using transfer learning". Journal of Engineering Science and Technology, 2021, 16(4): 2901-2917.
44. S. Anjum, L. Hussain, M. Ali, M.H. Alkinani, W. Aziz, S. Gheller, A. A. Abbasi, A.R. Marchal, H. Suresh, T.Q. Duong, "Detecting brain tumours using deep learning convolutional neural network with transfer learning approach". International Journal of Imaging Systems and Technology, 2022, 32(1): 307-323.
45. K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image recognition". arXiv preprint arXiv:1409.1556, 2014
46. A. Cruz-Roa, J. Arévalo, A. Judkins, A. Madabhushi, F. González, "A method for medulloblastoma tumour differentiation based on convolutional neural networks and transfer learning"//11th International Symposium on Medical Information Processing and Analysis. SPIE, 2015, 9681: 8-15.
47. L. Chato, S. Latifi, "Machine learning and deep learning techniques to predict overall survival of brain tumour patients using MRI images". 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE), IEEE, Washington, DC, USA (2017), pp. 9-14.
48. Z.N.K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali, S. Ahmed, J.F. Lu, "Brain tumour classification for MR images using transfer learning and fine-tuning". Computerized Medical Imaging and Graphics, 2019, 75: 34-46.
49. S. Ahuja, B.K. Panigrahi, T. Gandhi, "Transfer learning based brain tumour detection and segmentation using superpixel technique" [C]//2020 International Conference on Contemporary Computing and Applications (IC3A). IEEE, 2020: 244-249
50. P. Kora, S. Mohammed, MJS Teja, C.U. Kumari, K. Swaraja, K. Meenakshi, "Brain Tumour Detection with Transfer Learning" [C]//2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). IEEE, 2021: 443-446
51. K. He, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition" [C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 770-778
52. S. Divya, L.P. Suresh, A.John, "A Deep Transfer Learning framework for Multi Class Brain Tumour Classification using MRI"[C]//2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN). IEEE, 2020: 283-290
53. Ö. Polat, C. Güngen, "Classification of brain tumours from MR images using deep transfer learning". The Journal of Supercomputing, 2021, 77(7): 7236-7252.
54. A. Alnemer, J. Rasheed, "An Efficient Transfer Learning-based Model for Classification of Brain Tumour" [C]//2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT). IEEE, 2021: 478-482.
55. K.S.A. Kumar, A.Y. Prasad, J. Metan, "A hybrid deep CNN-Cov-19-Res-Net Transfer learning architype for an enhanced Brain tumour Detection and Classification scheme in medical image processing". Biomedical Signal Processing and Control, 2022, 76: 103631.

56. Zhou, T., Canu, S., Vera, P., &Ruan, S. (2021). Feature-enhanced generation and multi-modality fusion based deep neural network for brain tumour segmentation with missing MR modalities. Neurocomputing, 466, 102-112.
57. Hussain, S.; Anwar, S.M. Segmentation of Glioma Tumours in Brain Using Deep Convolutional Neural Network. Neuro Comput. 2018, 282, 248–261
58. Saouli, R.; Akil, M.; Kachouri, R. Fully Automatic Brain Tumour Segmentation Using End-to-end Incremental Deep Neural Networks in MRI Images. Comput. Methods Programs Biomed. 2018, 166, 39–49
59. Zhao, X.; Wu, Y.; Song, G.; Li, Z.; Zhang, Y.; Fan, Y. A Deep Learning Model Integrating FCNNs and CRFs for Brain Tumour Segmentation. Med. Image Anal. 2017, 43, 98–111.
60. Cinar, N., Ozcan, A., & Kaya, M. (2022). A hybrid DenseNet121-UNet model for brain tumour segmentation from MR Images. *Biomedical Signal Processing and Control*, *76*, 103647.
61. Zhou, Z.X.; He, Z.S.; Jia, Y.Y. AFP-Net: A 3D Fully Convolutional Neural Network with Atrous-convolution Feature Pyramid for Brain Tumour Segmentation via MRI Images. Neuro Comput. 2020, 402, 03097
62. Zhou, Z.X.; He, Z.S.; Shi, M.F.; Du, J.L.; Chen, D.D. 3D Dense Connectivity Network with Atrous Convolutional Feature Pyramid for Brain Tumour Segmentation in Magnetic Resonance Imaging of Human Head. Comput. Biol. Med. 2020, 121, 103766
63. Badrinarayan, V.; Kendall, A. SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. IEEE Trans. Pattern Anal. Mach. Intell. 2017, 39, 2481–2495. [CrossRef] [PubMed]
64. Chen, S.C.; Ding, C.X.; Liu, M.F. Dual-force Convolutional Neural Networks for Accurate Brain Tumour Segmentation. Pattern Recognit. 2019, 88, 90–100.
65. Zhou, Z.W.; Siddiquee, M.R. U-Net++: A Nested U-Net Architecture for Medical Image Segmentation. International Workshop on Deep Learning in Medical Image Analysis Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support; Springer: Cham, Switzerland; Berlin/Heidelberg, Germany, 2018; pp. 3–11.
66. Alom, M.Z.; Hasan, M.; Yakopcic, C.; Taha, T.M.; Asari, K. Recurrent Residual Convolutional Neural Network Based on U-Net (R2U-Net) for Medical Image Segmentation. Comput. Vis. Pattern Recognit. 2018, 5, 06955
67. Zhang, J.; Lv, X. Ares U-Net: Attention Residual U-Net for Brain Tumour Segmentation. Symmetry 2020, 12, 721
68. Sahayam, S., Nenavath, R., Jayaraman, U., & Prakash, S. (2022). Brain tumour segmentation using a hybrid multi resolution U-Net with residual dual attention and deep supervision on MR images. *Biomedical Signal Processing and Control*, *78*, 103939.
69. Milletari, F.; Navab, N.; Ahmadi, S.A. V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation. In Proceedings of the International Conference on 3D Vision, Stanford, CA, USA, 25–28 October 2016; pp. 565–571
70. Hua, R.; Huo, Q.; Gao, Y.; Sui, H.; Zhang, B.; Sun, Y.; Mo, S.; Shi, F. Segmenting Brain Tumour Using Cascaded V-Nets in Multimodal MR Images. Front. Comput. Neurosci. 2020, 14, 9.
71. Çiçek, Ö. 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation. In Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention, Cambridge, UK, 19–22 September 1999; pp. 424–432.
72. 98. He, C.E.; Xu, H. Research on Automatic Segmentation Algorithm for Multimodal MRI Brain Tumour Images. Acta Opt. Sin. 2020, 40, 0610001.
73. Tseng, K.L.; Lin, Y.L.; Hsu, W.; Huang, C.Y. Joint Sequence Learning and Cross-modality Convolution for 3D Biomedical Segmentation. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 3739–3746.
74. Isensee, F.; Wick, W.; Kickingereder, P.; Bendszus, M.; Maier, H.K. Brain Tumour Segmentation and Radio Mics Survival Prediction: Contribution to the BRATS 2017 Challenge. In Proceedings of the 3rd International Brain lesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries, Quebec City, QC, Canada, 10–14 September 2017; Springer: Berlin/Heidelberg, Germany, 2018; pp. 287–297
75. Kang, J., Ullah, Z., &Gwak, J. (2021). Mri-based brain tumour classification using ensemble of deep features and machine learning classifiers. Sensors, 21(6), 2222.
76. Xu, L., Gao, Q., &Yousefi, N. (2020). Brain tumour diagnosis based on discrete wavelet transform, gray-level co-occurrence matrix, and optimal deep belief network. *Simulation*, *96*(11), 867-879.
77. Hussain, L., Malibari, A. A., Alzahrani, J. S., Alamgeer, M., Obayya, M., Al-Wesabi, F. N., ... & Hamza, M. A. (2022). Bayesian dynamic profiling and optimization of important ranked energy from gray level co-occurrence (GLCM) features for empirical analysis of brain MRI. *Scientific Reports*, *12*(1), 1-19.

ISSN: 2366-1313

78. Kang, J., Ullah, Z., &Gwak, J. (2021). Mri-based brain tumour classification using ensemble of deep features and machine learning classifiers. *Sensors*, *21*(6), 2222.
79. Raza, A., Ayub, H., Khan, J. A., Ahmad, I., S. Salama, A., Daradkeh, Y. I., ... &Hamam, H. (2022). A hybrid deep learning-based approach for brain tumour classification. Electronics, 11(7), 1146.
80. Kumar, R. L., Kakarla, J., Isunuri, B. V., & Singh, M. (2021). Multi-class brain tumour classification using residual network and global average pooling. Multimedia Tools and Applications, 80(9), 13429-13438.
81. Kokkalla, S., Kakarla, J., Venkateswarlu, I. B., & Singh, M. (2021). Three-class brain tumour classification using deep dense inception residual network. Soft Computing, 25(13), 8721-8729.
82. Bodapati, J. D., Shaik, N. S., Naralasetti, V., &Mundukur, N. B. (2021). Joint training of two-channel deep neural network for brain tumour classification. *Signal, Image and Video Processing*, *15*(4), 753-760.
83. Sasank, V. V. S., &Venkateswarlu, S. (2021). Brain tumour classification using modified kernel based softplus extreme learning machine. Multimedia Tools and Applications, 80(9), 13513-13534
84. Saxena, P.; Maheshwari, A.; Maheshwari, S. Predictive modeling of brain tumour: A Deep learning approach. arXiv 2019, arXiv:1911.02265
85. Xuesong, Y.; Yong, F. Feature extraction using convolutional neural networks for multi-atlas based image segmentation. Med. Imaging Image Process. 2018, 10574, 1057439.
86. Francisco, J.P.; Mario, Z.M.; Miriam, R.A. A Deep Learning Approach for Brain Tumour Classification and Segmentation Using a Multiscale Convolutional Neural Network. Healthcare 2021, 9, 153.
87. Demir, F. (2022). Deep autoencoder-based automated brain tumour detection from MRI data. In *Artificial Intelligence-Based Brain-Computer Interface* (pp. 317-351). Academic Press.
88. Neelima, G., Chigurukota, D. R., Maram, B., &Girirajan, B. (2022). Optimal DeepMRSeg based tumour segmentation with GAN for brain tumour classification. *Biomedical Signal Processing and Control*, *74*, 103537.
89. Das, S. (2022). Optimizing prediction of MGMT promoter methylation from MRI scans using adversarial learning. *arXiv preprint arXiv:2201.04416*.
90. Khan, A. H., Abbas, S., Khan, M. A., Farooq, U., Khan, W. A., Siddiqui, S. Y., & Ahmad, A. (2022). Intelligent model for brain tumour identification using deep learning. *Applied Computational Intelligence and Soft Computing*, *2022*.
91. Islam, M. K., Ali, M. S., Miah, M. S., Rahman, M. M., Alam, M. S., & Hossain, M. A. (2021). Brain tumour detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm. *Machine Learning with Applications*, *5*, 100044.
92. Almadhoun, H. R., & Abu-Naser, S. S. (2022). Detection of Brain Tumour Using Deep Learning. *International Journal of Academic Engineering Research (IJAER)*, *6*(3).
93. Rinesh, S., Maheswari, K., Arthi, B., Sherubha, P., Vijay, A., Sridhar, S., ... &Waji, Y. A. (2022). Investigations on brain tumour classification using hybrid machine learning algorithms. *Journal of Healthcare Engineering*, *2022*.
94. Kaur, T., & Gandhi, T. K. (2020). Deep convolutional neural networks with transfer learning for automated brain image classification. *Machine Vision and Applications*, *31*(3), 20.