JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A SURVEY ON BRAIN TUMOR DETECTION USING IMAGE PROCESSINGTECHNIQUES

ASMA PARVEEN.A [1*], Dr KAMALAKANNAN T [2*]

[1]Research Scholar,Department of computer science, VISTAS, Chennai, India.

[2] HOD, Department of Information Technology, VISTAS, Chennai, India.

ABSTRACT

Structural MRI is a powerful tool for studying the brain's intrinsic structure. A clear image of the brain's soft tissues is obtained by MRI. Radiologists are trained to identify and classify brain tumors. Anybody can get a brain tumour of any size or shape. Humans struggle to extract precise tumour regions and analyse minute variations. Clinical professionals use digital image processing techniques like preprocessing, segmentation, and classification to diagnose brain tumors. This research examines current trends in MRI-based brain tumor identification. Various state-of-the-art machine learning and deep learning methods are analysed. Dissemination data and problems This comprehensive study will aid future research in developing better decision support systems for radiologists diagnosing brain tumours.

Keywords : Brain tumour detection, image processing, machine learning, segmentation, and feature extraction.

1. OVERVIEW

A brain tumour is an abnormal growth of brain tissue. It generates pressure in the skull and disrupts normal brain function. Brain tumours can be benign or cancerous. Non-cancerous benign tumours Malignant tumours are cancerous tumours that split endlessly and spread throughout the brain. Brain tumor diagnosis and categorization into benign or malignant is critical for patient survival and therapy. Brain tumours are detected using medical imaging modalities such as CT, PET, and MRI. MRI employs a magnetic field and radiofrequency pulses to visualise the inside of the body structure. T1-weighted, T2-weighted, and FLAIR (Fluid Attenuated Inversion Recovery) MRI sequences are used to diagnose brain tumours. Figure 1: MRI sequences

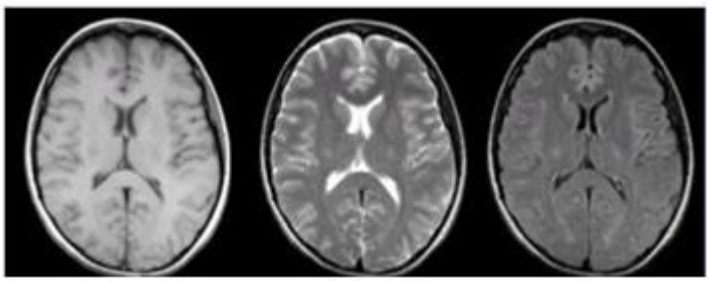

Fig 1: 2D and 3D FLAIR MRI pictures

The task of detecting tumours in the brain with MRI is essential. Experts study medical pictures to find tumour indications and locations. The human eye cannot detect minute variations in MRI due to its complexity. Various authors have recently created CAD tools to help radiologists diagnose more accurately.

This research examines the strengths and weaknesses of various automatic brain tumor categorization algorithms. Comparative analysis can be used to improve brain tumor segmentation and categorization.

2. TWO TUMOR DETECTION METHODS

These include pre-processing, segmentation, feature extraction, and classification.

2.1. Pre-processing

In medicine, precise images are required to diagnose disease. The quality of medical images depends on the artefact acquisition method (MRI, PET, CT). MRI scans can have a lot of unnecessary and irrelevant elements. Rician noise affects MRI. [33] Signal dependent Ricardian noise is difficult to eliminate. Filtering, contrast augmentation, and skull stripping are employed to preserve the original image qualities.

2.2. SEGMENTATION

Digital images are segmented to derive Regions of Interest (ROI). It's critical to distinguish tumors from brain MRI. Techniques for segmentation include thresholding, soft computing, atlas-based clustering, and neural networks. adaptive, global, Otsu's, histogram-based thresholding. Unsupervised clustering using K-means and Fuzzy C-means It segments brain MRI into gray matter, white matter, and cerebrospinal fluid (CSF). Particle swarm algorithms are used for segmentation PSO [6], GA [14]. Deep learning architectures like CNN, Mask-RNN, and Unet outperform classical methods in segmentation [21].

2.3. FEATURE EXTRACTION

MRI properties including form, texture, wavelet, and Gabor are retrieved. Most researchers employ GLCM (Gray-Level Co-occurrence Matrix). An energy, correlation, and contrast-based statistical approach. [5]. Discrete The Wavelet Transform extracts wavelet features (DWT). It takes a raw image and extracts the approximation coefficients as a feature vector. [19] These results show good performance of handcrafted and automatic features utilising deep learning models like CNN and ResNet. [1], [4]. PCA, GA reduces feature size. [6], [15].

2.4.CLASSIFICATION

Brain tumours can be benign or cancerous. Glioma, meningioma, and pituitary are malignant tumours. As illustrated in Fig. 2, glioma is classified into four classes by the WHO.

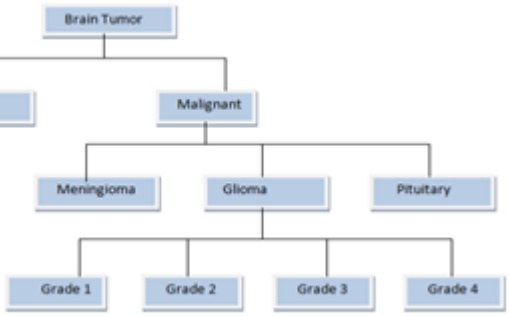

Fig 2: Brain Tumor Types

2.4.1. DEEP LEARNING TOOLS

Convolutional neural networks (CNN) are used for deep learning. They have input, output, hidden layers, and hyper parameters. It's a supervised classification method that uses kernel convolution to create feature maps. DL is effective for feature extraction and segmentation. The complexity of the designs, the adjustment of hyper parameters, the vast amount of data required for training, the increased training time and cost are some of its drawbacks. For example, rotation, cropping, scaling, and transformation are employed to enrich data. Pre-trained neural networks are used on application-specific datasets to extract similar features [11]. A variety of transfer learning models are employed to detect brain tumours. Figure 3 displays the LetNet5 architecture.

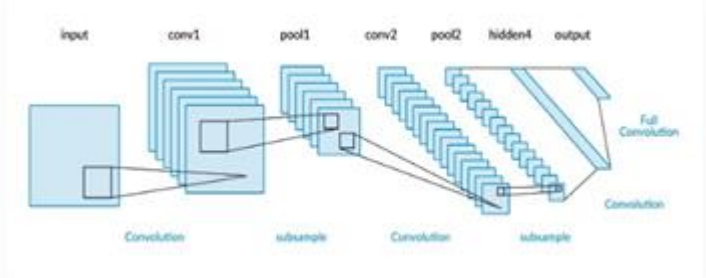

Fig 3: CNET5 Architecture **[34]**

2.4.2. SOURCE DATASETS

CAD methods for automatic brain tumour classification are tested using public databases. The McConnell Brain Imaging Centre provides the BrainWeb simulated brain MRI database. The Cancer Imaging Archive provides the REMBRANDT Repository, which contains pre-surgical multisequence MRI scans of 130 patients (TCIA). The Medical Image Computing and Computer Assisted Intervention (MICCAI) challenge database comes from the University of Pennsylvania's Center for Biomedical Image Computing and Analytics (CBICA). Brain Tumor Segmentation (BraTS) dataset

Dataset Name	Provided by	Image modalities	MRI Type	URL
BrainWeb	McConnell Brain Imaging Centre	T1, T2, proton-density weighted.	Normal, Multiple sclerosis	https://brainweb.bic.mni.mcgill.ca/brainweb/
REMBRANDT	TCIA	Multisequence	Normal, Glioma	https://wiki.cancerimagingarchive.net/display/Public/REMBRANDT
BRATS 2015	MICCAI 2015 challenge	T1,T2 weighted, FLAIR	GBM,HGG,LGG	https://www.smir.ch/BRATS/Start2015
BRATS 2017	MICCAI 2017 challenge	T1,T2 weighted, FLAIR	GBM,HGG,LGG	https://www.med.upenn.edu/sbia/brats2017/data.html
BRATS 2018	MICCAI 2018 challenge	T1,T2 weighted, FLAIR	GBM,HGG, LGG	https://www.med.upenn.edu/sbia/brats2018.html
AANLIB	Harvard Medical School	T1,T2 weighted	Normal, cerebrovascular, neo plastic, degenerative and infectious diseases	http://www.med.harvard.edu/AANLIB/
RIDER	TCIA	T1,T2 weighted	Tumor	https://wiki.cancerimagingarchive.net/display/Public/RIDER+NEURO+MRI
CE-MRI	School of Biomedical Engineering, China	T1 weighted	Glioma, Meningioma and Pituitary	https://figshare.com/articles/brain_tumor_dataset/1512427

Table 1: MRI datasets available

Harvard Medical School provides AANLIB. Infectious disorders, neoplastic, degenerative, and cerebrovascular diseases are included. TCIA provides the RIDER Image Database to evaluate therapy response. It has 19 patients' MRI data. The School of Biomedical Engineering, China provides CE-MRI data for glioma, meningioma, and pituitary cancers. Table 1 summarises publicly accessible MRI databases.

5. LITERATURE REVIEW

5.1. BRAIN TUMOUR DETECTION WITH ADVANCED MACHINE LEARNING ALGORITHMS

MRI brain tumour segmentation and classification using machine learning approaches is documented. Hasan et al. presented deep and custom picture characteristics for MRI brain scan classification [1]. used to extract statistical features from preprocessed MRI. CNN extracts features automatically. Based on 600 axial MRI data points, SVM classification was 99.30 percent accurate. When comparing the suggested method to other transfer learning networks like AlexNet and GoogleNet, the proposed method outperforms them. This system uses threshold-based maximum entropy segmentation [3]. The system was tested on 114 MRIs from REMBRANDT. The suggested approach has the benefit of detecting tumours in all brain regions, including the temporal lobe. [4] proposes a new brain tumour detection method based on maximum fuzzy entropy segmentation and CNN. MRI uses Single Image Super Resolution to boost resolution. Pre-trained ResNet architecture features extracted 99.5% accuracy in SVM Binary classification. Brain tumour classification using Edge Adaptive Total Variation [5] uses mean shift clustering for segmentation. Unlike K-mean and fuzzy c-mean, the suggested approach preserves edges while denoising the image. A PSO with fusion characteristics for brain tumour identification combines a local binary pattern and a fine-tuned capsule network [6].

On the BRATS2018 and RIDER datasets, SVM classification accuracy is 98.3% and 97.9%. The proposed design combines handcrafted and deep features well. The accuracy of pre-trained GoogleNet for deep feature extraction is tested on the CE-MRI dataset for 3 class classifications into Glioma, Meningioma, and Pituitary cancers using SVM and KNN classifiers [7]. The multinomial logistic regression model accurately classified all 48 photos in the BRATS 2017 dataset. The system's performance needs to be tested on larger datasets [8]. Keerthana et al. [13] propose an intelligent method for early brain tumor identification. This is followed by threshold-based segmentation. SVM uses GLCM texture information to classify normal, benign, and malignant tumours. The GA-SVM classifier performs well. Brain tumor categorization using GA for tumor segmentation. SVM receives GLCM texture features with 91.23% accuracy [14]. To classify HGG and LGG brain tumours using k-means segmentation [15], PCA selects 10 relevant wavelet features. SVM classifies images as normal or abnormal. An SVM classifier is used to classify HGG and LGG cancers. However, the proposed approach has to be tested on a larger dataset with more relevant properties. A wavelet transform method for brain tumour identification uses morphological operations with threshold-based segmentation [19].

Amin et al. proposed a new MRI brain tumour detection [23]. MRI noise is removed using skull stripping and Gaussian filtering. After K-means segmentation, GLCM texture features extraction Evaluation on 3 datasets: local, AANLIB, and RIDER with linear, RBF and cubic SVM kernels. The linear kernel with 5 fold cross validation achieved 98 percent accuracy. [25] proposes an Otsu thresholding CAD system for brain tumour detection. A customised Otsu approach is used on pre-processed MRI to find normal and pathological tissue thresholds. LBP, Gabor, Zeneka moments, form characteristics. The proposed method has the advantage of high accuracy due to the fusion of diverse aspects. A decision support system for glioma identification using brain MRI leverages DSR-AD [26]. Texture features are retrieved using the RLCP approach. It keeps textural qualities and can identify directional biassing of textual pattern. Its classification accuracy is 96% using 10 fold cross validation. Please note that arithmetic equations may need to be re-formatted due to page layout issues. This may include making some in-line equations display equations to improve paragraph flow. The display equations will be reformatted if they do not fit in two columns. Authors should ensure that equations fit inside the column width. Using wavelet characteristics for brain MRI tumour classification was proposed by Kumar S. et al. PCA selects meaningful feature sets. SVM has 90% classification accuracy. Minz et al. discuss Adaboost classifier for brain tumour classification [29].

Then comes threshold-based segmentation. The system proposes GLCM-based texture categorization. Using SVM with RBF kernel and CSO, a 99 percent accurate brain tumour diagnostic approach was achieved [30]. Iris MRI images are segmented using global thresholding. The CSO optimization algorithm is used to optimise SVM parameters. In terms of accuracy, robustness, and execution speed, CSO outperforms PO. [31] proposes Gustafson-Kessel fuzzy clustering for brain tumour classification. Histogram-based segmentation of Wiener-filtered pictures. G-K fuzzy approach uses GLCM texture features for 95% accurate binary classification. Table 2 summarises many state-of-the-art approaches.

Table 2: ML detection of brain tumours

Ref	Preprocessing, Segmentation	Features	Classification	Dataset	Accuracy
[1]	Image resizing and enhancement	GLCM,CNN	SVM	Local-Iraqi center of research.	99.30%
[3]	Morphological operation, pixel subtraction, Maximum entropy threshold segmentation	Morphological ,Intensity	Naive Bayes	REMBRANDT	94%
[4]	Single Image Super Resolution for image enhancement Segmentation-Maximum fuzzy entropy (MFE)	ResNet deep features	SVM	TCIA	95%
[7]	Min-max normalization, Resize 224*224	GoogleNet deep features	SVM,KNN	CE-MRI	SVM-97.8% KNN-

					98%
[14]	Median filter GA segmentation	GLCM	SVM	Harvard Medical Dataset	91.23%
[15]	OTSU Binarization K-means clustering	DWT	SVM	BRATS 2013,BRATS 2017,Midas	99%
[23]	Skull stripping-BSE Gaussian filtering, K-Means segmentation	GLCM, Intensity, shape	SVM	Local ,AANLIB and RIDER	98%
[25]	Image enhancement-DSR-AD ,OTSU segmentation	Tamura, LBP, GLCM, Gabor, Shape	SVM	Local	98%
[26]	Image enhancement-DSR-AD ,Global adaptive segmentation	RLCP	Naive Bayes	Local-JMCD,BRATS	96%
[29]	Median filter noise removal, Threshold based segmentation	GLCM	Adaboost	Public dataset	89.90%
[31]	Wiener filtering Histogram based segmentation	GLCM	G-K Fuzzy system	-	95%

5.2. DEEP LEARNING FOR BRAIN TUMOUR DETECTION:

A deep learning programme can detect brain tumours. Researchers employ deep learning architectures to automatically segment and classify brain cancers. Gumaei et al. proposed Regularized Extreme Learning with hybrid features [2]. The spatial feature extractor is a Hybrid PCA-NGIST. Normalized feature descriptor used to tackle image lighting and shadowing issues. RELM is an input-output feedforward neural network with one hidden layer. Using 5 fold cross-validation, the suggested technique accurately classified Meningioma, Glioma, and Pituitary tumours in the CE-MRI dataset. [9] uses a LinkNet lite deep neural network architecture to classify brain tumours. On a publicly available UCI repository dataset, binary classification was 91% accurate. [10] Mallick et al. demonstrated deep wavelet autoencoder based deep neural network for brain MRI cancer diagnosis. Deep wavelet autoencoder is fed DICOM pictures from Rider dataset.

MLP classification has 96 percent accuracy and 0.65 Kappa statistics. However, future DNN/other Denoising and sparse autoencoding techniques could be assessed. [11] proposes a transfer learning brain tumour categorization system. Resized MRI images to fit VGG19 model. Weights are updated by fine tweaking factors including learning rate, scheduling rate, and momentum. 94.82 percent accuracy on CE-MRI dataset. The system's downside is that fine tweaking parameters block by block takes 20-30 minutes. MLP uses statistical and wavelet properties to classify brain tumours [12]. The system is tested using both statistical and DWT features. The combined feature set performed well with 96.73 percent accuracy. The system performs well on a 40,300 picture dataset. ANFIS glioma detection uses Non-Sub Sampled Contourlet Transform image enhancement [16]. ANFIS classifies BRATS 2015 data into normal and Glioma brain tumours. Traditional classification methods like SVM and CNN generate classification errors for low intensity Glioma images, while ANFIS works well for both. Tested on 66 MRI pictures, Deep Neural Networks Classify Brain Tumors AANLIB data set MRI segmentation uses fuzzy C-mean clustering. PCA selects relevant DWT features. To classify tumours into four categories, DNN uses a 7-layer DNN architecture [17]. Raju et al. proposed utilising Bayesian fuzzy clustering and HSC based multi SVN to classify brain tumours [18].

An information theoretic, scatter, and wavelet feature vector. Multi SVNN classification with 4 levels proposed. Toxins are classified into four categories: normal, abnormal, and advanced. Weights in SVNN are optimised using the HCS method, which combines Harmony and Crow search. This method has the advantage of reduced complexity and faster global optimal convergence than Harmony search. CAD system for brain tumour detection utilising ANN [20]. The AANLIB dataset contains 239 photos with 99 percent accuracy utilising Haarlick texture features. [21] proposes a multigrade CNN brain categorization method. Tumor segmentation using InputCascadeCNN. Data samples are augmented by rotating, flipping, and embossing them. 94.58 percent accuracy on CE-MRI dataset using VGG19 architecture. The proposed

approach overcomes the lack of MRI image availability by enhancing data. It is possible to construct a CAD system for brain tumour grade classification utilising a lightweight CNN architecture. [22] suggests utilising CNN and GA to grade MRI-based brain tumours. 3 forms of tumours: Glioma, Meningioma and Pituitary. Using 6 convolution layers and 2 fully connected layers to classify Gliomas. The number of convolution layers, maximum pooling layers, number of filters, size of filters, activation function, and learning rate are all determined by GA. Based on the BRATS dataset, a novel neuro fuzzy feature selection method for brain tumour classification 10 hazy rules

Feature extraction from GLCM, GLRL, and Geometric Shape and Size. The adaptive neuro fuzzy classifier (ANFC) can classify high and low grade cancers. Useful for comprehending fuzzy linguistic factors. [28] proposes a new method for classifying brain tumours using PNN. K- means GLCM texture features follow segmentation. PNN classifies brain pictures as benign, malignant, and normal. PNN performance is compared to various neural network architectures. On the AANLIB dataset, an ANN-based strategy for brain tumour classification achieved 95% accuracy. Colour MRI images are retrieved for mean, standard deviation, and skewness [32]. Table 3 summarises various Deep Learning approaches.

Table 3: Summary of brain tumor detection using DL

Ref	Pre-processing	Classification	Dataset	Accuracy
[2]	Intensity normalization and contrast enhancement	RELM	CE-MRI	94.33%
[9]	Average filter, Pixel subtraction	CNN-LinkNet	UCI	91%
[10]	DICOM image processing, DWT-DNN features	MLP	RIDER	96%
[11]	Min-max intensity normalization	VGG19	CE-MRI	94.82%
[12]	Histogram, GLCM,DWT features	MLP	BRATS 2015	96.73%
[16]	NSCT image enhancement, GLCM texture features	ANFIS	BRATS 2015	98.5%
[17]	DWT features	DNN	AANLIB	96.97%
[18]	Bayesian fuzzy clustering segmentation, information theoretic, scatters and wavelet features.	HSC based multi SVNN	BRATS	93%
[20]	Sharpening & smoothing filters, Threshold based segmentation, SGLD features	ANN	AANLIB	99%
[21]	InputCascadeCNN segmentation, Data augmentation	VGG19	CE-MRI	94.58%
[22]	Image rescaling, Data augmentation	CNN	Brainweb, REMBRANDT,CE-MRI	96%
[24]	VOI segmentation, GLCM,GLS,GLRL,GSS features	ANFS-LH	BRATS 2012,BRATS 2013	85.83%
[32]	Median filter, Colour moments feature extraction	ANN	AANLIB	95%

6.ANALYSIS

Expert radiologists do brain tumour segmentation and classification. Machine learning and deep learning can help radiologists make better decisions. This paper summarises current strategies for automatic brain tumour detection and classification. Hetogram equalisation, median, Gaussian and Wiener filters are used to preprocess MRI images. There are six forms of segmentation: clustering, statistical, ANN, region, and threshold based [35]. K-means Researchers frequently utilise C-means clustering and adaptive global thresholding. Deep learning segmentation allows for more precise tumour extraction [21]. GLCM and DWT largely extract features. GLCM returns texture characteristics, while DWT returns approximation coefficients. Deep learning architectures ResNet and capsule network automatically extract features [4, 6]. PCA and bio-inspired algorithms like PSO are used to reduce dimensionality. Choosing the optimal features

for categorization is difficult, hence a hybrid technique integrating several features is utilised. Machine learning and deep learning algorithms classify data. Multi-kernel SVM Binary classification uses linear, RBF, and Cubic. These results are comparable to VGG19 and ResNet. ANFIS, a fuzzy-ANN hybrid, performs better for binary classification. Table 1 discusses common CAD database types. BRATS is a popular dataset of T1, T2 and FLAIR pictures. However, the database does not capture all tumour forms and grades. Or they have to obtain MRI from nearby hospitals. As a result, comparing the performance of different approaches is difficult. A common database of all tumour kinds is required for future research.

7. CONCLUSION

CAD systems for brain tumour identification using MRI images use digital image processing methods such pre-processing, segmentation, and classification. Ontology-based techniques for brain tumour identification are reviewed. Various research publications from standard journals and conferences have been researched and analysed in detail. This page describes the most common MRI datasets. However, SVM has shown good accuracy in classification using machine learning and deep learning. SVM is often used to classify brain tumours as normal or abnormal. The autonomous brain tumour detection system must be reliable, accurate, and fast. These findings can be used to develop effective diagnosis tools for additional brain-related conditions like dementia, stroke, Alzheimer's and Parkinsonism using MRI imaging modalities.

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