NEUROLOGY INDIA
Publication of the Neurological Society of India

REVIEW ARTICLE

Year : 2023 | **Volume** : 71 | **Issue** : 4 | **Page** : 647--654

Brain Tumor Detection using Deep Learning Approach

Debendra Kumar Sahoo[1], Satyasish Mishra[1], Mihir Narayan Mohanty[2], Rajesh Kumar Behera[3], Srikant Kumar Dhar[4],

[1] Department of Electronics and Communication Engineering, Centurion University of Technology and Management, Siksha 'O' Anusandan (Deemed to be University), Bhubaneswar, Odisha, India

[2] Department of Electronics and Communication Engineering, Siksha 'O' Anusandan (Deemed to be University), Bhubaneswar, Odisha, India

[3] Department of Mechanical Engineering, Orissa Engineering College, Bhubaneswar, Odisha, India

[4] Department of Medicine, IMS and SUM Hospital, Bhubaneswar, Odisha, India

Correspondence Address:
Rajesh Kumar Behera
Department of Mechanical Engineering, Orissa Engineering College, Bhubaneswar, Odisha
India

Abstract

Early detection of brain tumor has an important role in further developing therapeutic outcomes, and hence functioning in endurance tolerance. Physically evaluating the various reversion imaging (magnetic resonance imaging [MRI]) images that are regularly distributed at the center is a problematic cycle. Along these lines, there is a significant need for PC-assisted strategies with improved accuracy for early detection of cancer. PC-backed brain cancer detection from MR images including growth location, division, and order processes. In recent years, many inquiries have turned to zero in traditional or outdated AI procedures for brain development findings. Presently, there has been an interest in using in-depth learning strategies to detect cerebral growths with an excellent accuracy and heart rate. This review presents a far-reaching audit of traditional AI strategies and in-depth study methods for diagnosing brain cancer. This research paper distinguishes three main benefits i.e. exhibition, estimation and measurements of brain tumour detection.

How to cite this article:
Sahoo DK, Mishra S, Mohanty MN, Behera RK, Dhar SK. Brain Tumor Detection using Deep Learning Approach.Neurol India 2023;71:647-654

How to cite this URL:
Sahoo DK, Mishra S, Mohanty MN, Behera RK, Dhar SK. Brain Tumor Detection using Deep Learning Approach. Neurol India [serial online] 2023 [cited 2023 Sep 10];71:647-654
Available from: https://www.neurologyindia.com/text.asp?2023/71/4/647/383858

Full Text

Cancers develop as an unmanageable and unusual expansion of cells in the parts of the body. The development of unusual growth of cells inside the brain is said to be brain tumor, which is the most common cancer of all types.[1] The study of Glioma tumor is an important area for tumor detection in brain cancer.[2] Chemotherapy and radiotherapy are some of the methods used to treat gliomas.[3] Various medical applications like computerized tomography (CT), single-photon emission computed tomography (SPECT), magnetic resonance spectroscopy (MRS), and positron emission tomography (PET) with magnetic resonance imaging (MRI) have been used.[4],[5],[6] MRI provides details about the anatomy of human tissue and is considered a common technique because of its wide accessibility with soft-tissue contrast. MRI uses powerful magnetic field of radiofrequency signals to obtain images of human brain cells.[7],[8] The detection methods are mostly employed to identify tumors from MRI image database, which has been considered as a basic and understandable method. On MRI scans, the brain tumor partitioning algorithms have been employed to localize and distinguish different tumor tissues.[9] The survey pivots on the diagnosis of brain tumors using MRI with traditional methods of machine learning (ML) and deep learning (DL) study. Though there are numerous literature reviews, special attention is paid to a specific process, such as segmentation, classification, or diagnostics.[10],[11],[12],[13] The study involves application of the classic ML and DL algorithms. A summary of the progress of the survey is presented in [Figure 1].{Figure 1}

Materials and Methods

Ground work

Unsharp masking, median filters, and Wiener filters are examples of preprocessing techniques. To safeguard the borders of an image, median filters are typically utilized in the preprocessing step.[14] As shown in [Figure 2], the general structure of the computer-aided design (CAD) system for diagnosing brain tumors using MRI images includes data acquisition, preprocessing, segmentation, feature exclusion, and feature selection. Many preprocessing approaches are used, such as unsharp masking, veneer filters, as well as median filters.[15] Fuzzy C-means (FCM) pooling, median shift, as well as expectation maximization algorithms are examples of such algorithms. The various extraction techniques such as violet transform, Gabor features, texture features, boundary feature extraction, principal component analysis (PCA), and spectroscopy are also used for segmentation of the tumor analysis as described.[16],[17],[18],[19],[20] Therefore, feature selection methods have been used in the literature to select the most important features like genetic algorithm (GA), particle swarm optimization (PSO), sequential inverse selection (SBS), PCA, and sequential forward selection (SFS).[21],[22],[23],[24],[25],[26],[27],[28],[29],[30]{Figure 2}

A clinical perspective on ML

ML has ignited a considerable interest in modern computers in the field of medicine. In the area of brain tumor recognition, a variety of advanced ML approaches are applied. Advanced methods are employed to identify the use of brain pictures and improve the quality of the information collected, such as image labeling, image reconstruction, skull removal, and registration.[31] The diagnosis of a semi-automated brain tumor frequently necessitates the manual intervention of radiologists and clinics to start the technology, analyze the results, and fix flaws in the procedure outcomes. Fully automated brain tumor diagnosis, on the other hand, relies on computers systems that employ previous information and human intelligence to complete tumor diagnosis procedures without the need for human interaction.[32] These findings show that ML diagnostics outperform manual diagnoses in terms of processing interval and accuracy with the efforts of radiologists. [Figure 3] displays an example of manual segmentation of a brain tumor by four separate specialists on the same MRI and in the same patient to demonstrate this point.{Figure 3}

Brain MRI

The benefits of MRI in allowing clinicians to diagnose physical problems in the brain are well established. During MR imaging, a series of 2D pictures can be used to show the brain's volume in 3D. Each MRI approach contributes to the diagnosis in a different way. The different MRI techniques utilized for the diagnosis, that is, gadolinium contrast enhancement, are presented in [Figure 4].{Figure 4}

MRI database available

The Section of Biomedical Image Analysis (SBIA) is utilized to create PC based picture examination strategies for diagnosing brain infections like schizophrenia, Alzheimer's illness, and chemical imbalance of the cerebral injury. Each strategy should be approved by contrasting a quantitative record and a reality model to gauge the effectiveness. Regularly, a reality model is made by specialists. New techniques can be assessed by radiologists and doctors by utilizing engineered pictures.

DL model

Research on DL uses a multilayer neural network (MNN) with multiple hidden layers and independent parameters to conduct research. In contrast, in the repeatedly used MNN, each MRI's input is passed via a convolutional layer, filters, fully connected (FC) layers, pooling layers, and ultimately Soft-max to get the final judgment process. However, ML and DL methodologies are subsets of Artificial intelligence (AI) techniques. All existing work on tumor grading systems (TGS) can be categorized into the above two subcategories. The fundamental difference between the ML and DL methods lies in the selection of features. Manually generated features (i.e. features designed by human experts) are typically used for ML methods, while these features are automatically extracted in DL methods during training through convolution operations. Thus, DL has many advantages over traditional ML methods.[33],[34]

As shown in [Figure 5], DL network structures come in a variety of shapes and names, including convolutional neural networks (CNNs), deep residual networks, deep feed forward networks, deep belief networks, as well as deconvolutional networks. In the realm of image processing, the CNN has become the frequently used architecture. The majority of its structure is made up of input layers, feature extraction levels, convolutional layers, and pooling layers with classification layers.{Figure 5}

DL techniques, particularly CNNs, have grown in favor of diagnosing brain imaging. As a result, DL is preferred over traditional ML methodologies. From brain MRI data, CNN learns recurring complicated properties, letting the focus to shift away from identifying and minimizing elements and onto network architecture design.

Diagnosis of a Brain Tumor

Many experts in the field of medical tomography have made tremendous progress in the identification of brain tumors in recent years with both fully automatic and semi-automatic tactics. Diagnostic strategies' clinical acceptance is determined by their ease of computation with degree of monitoring. As shown in [Figure 2], brain tumor recognition can be divided into three stages, tumor detection, differentiation, and classification, which have all been clarified in detail in this section. The additional distinctive performance was explained with the given technology.

Detection of tumor

The technique of recognizing the absence or presence of tumor from MRI database is called tumor detection. Diagnosis of brain tumor and its abnormality leads to benign and malignant which plays an essential role in medical field. Different techniques like Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Back-Propagation Neural Network (BPNN) are adopted to recognize the abnormal and normal tumors by using MRI image. The most prevalent strategies are presented in [Figure 2], and the various diagnostic methods are summarized in [Table 1]. It shows the classification model, features used, dataset, and measurement of performance. An MRI database is usually required to train the classifier and achieve optimal feature extraction using a detection approach for the best detection method.{Table 1}

Tumour identification with traditional ML process

There are several ML methods to detect brain tumors by utilizing MRIs. During the discovery phase, an artificial feedback neural network and KNN are used. Three features are extracted using wavelet entropy-based spider web plots.

Segmentation of tumors

Division is the most common way of isolating an image into Release of Information (ROI). The division showing the ROI and the allied information to facilitate the visualization. The goal of image segmentation is to make imaging easier to study the location and its extent in cancer. The objective in division of image is to make the image more prominent to study the location and extent of cancers directly. The division separates growth tissue, e.g. edematous and necrotic tissue, from normal tissue such as dark matter (GM) and white matter (WM) as shown in [Figure 6].{Figure 6}

Furthermore, tumour segmentation algorithms depend on similarities and differences of the picture intensity.

Traditional ML used in tumor segmentation

A number of ML algorithms as well as methodologies are available for partitioning of brain tumor utilizing the MRI data. In this method, a registered brain book-map is utilized to find out the malignant areas, and was performed a strong estimations on image analysis. Shape and position restriction are applied for the newly discovered tumor.

Tumor segmentation with DL technique

The use of graphics processing unit (GPU)-based standalone workstations reduces segmentation time by a significant amount. It is the most powerful computer hardware which has a high-performance registered applications for computing multilayer image processing. The authors used online GPU provided by Google colab and Jupiter notebook in the python platform.

The GPU significantly reduces the required processing time and increases the prompting options. A stacked autoencoder network captures the features from classifies and input image patches to map a binary image. Morphological filters are then utilized to partition the tumor.

Classification of tumors

The way of allocating different input information elements into various groups is classification. Selected highlight extraction has become crucial in classification, especially in cerebral growth classification, which requires the collection of many MRI scans from different databases. The primary goal of brain tumor categorization is to establish whether a tumor is benign or malignant, as well as its grade, utilizing MRI. Brain tumors can also be classified using supervised techniques like SVM, KNN, and ANN, as well as unsupervised techniques like Fuzzy C-means clustering (FCM) and Self Organizing Map (SOM). The most often used strategies are summarized in [Figure 2]. Brain tumors can be classified in a variety of ways using MRI.

Tumor classification using traditional ML

For brain tumor classification using MRI scans, a variety of ML approaches and methodologies are available.[20] In MRI scans, a software approach is used to distinguish between metastatic and basic brain cancers.[27] The authors used a nonlinear Linear Solitary fibrous tumor (LSFT) in conjunction with a probabilistic neural network classifier Message Passing Neural Networks (MPNN) that has been modified. To improve the contour of the tumor zone, the distance and the greatest probability measurements are used.

Tumor categorization with DL

A DL method for brain tumor classification is a very young field of study, with little contributions to date. A DL-based brain tumor categorization strategy was suggested by different researchers. A CNN's performance is compared to that of a back propagation neural network in terms of sensitivity and specificity. According to the findings, utilizing the CNN enhanced the outcomes by 18%–20%.

Results

In the domain of medical imaging, brain tumors are still a popular issue. This research gives a thorough summary of the most up-to-date technology for diagnosing brain tumors. Tumor detection involves detecting the absence or presence of brain tumors by applying MRI scans. Multiple pictures require further examination using tumor segmentation and classification approaches. Tumor classification involves using High grade (HG) or Low grade (LG) or tissue analysis to determine whether a tumor is malignant or a specific type of malignant tumor. The majority of the methods considered are for semi-automated and automated tumor diagnosis. Furthermore, a majority of the approaches involves pre-processing, extraction of feature, feature reduction, segmentation, and classification. Pathology and diffusion tensor imaging (DTI) are used to create an artificial foundation for MR images of tumor tissues and edema. [Table 1] shows the best results with respect to tumor detection versus efficacy. The best tumor detection versus efficacy scores were employed by standard ML techniques to achieve excellent tumor segmentation results. In-depth study technique, as shown in [Table 2] and [Table 3], had the best classification results for brain tumors, with 100% classification accuracy. In comparison to the preceding methods, this one suffers from a lack of uniform datasets, particularly for tumor recognition and classification, and a single application structure.{Table 2}{Table 3}

The DL models have recently been shown to be effective in the interpretation of medical images, particularly in the identification of brain cancers. DL networks have outperformed traditional ML methods in terms of accuracy. Furthermore, DL networks outperform classical ML methods with sophisticated algorithms when dealing with massive amounts of data. Traditional ML methods require sophisticated feature extraction and reduction techniques, whereas DL methods do not need them.

Discussion

The primary goal of this analysis was to identify the most significant advances in brain tumor diagnosis to date in terms of tumor detection, differentiation, and categorization. DL algorithm is a type of ML process that has more sophisticated potentialities than the typical approaches to ML. DL is a novel and crucial research tool that was identified to increase the performance of classic ML approaches. An in-depth examination of MR images and their features is possible, thanks to several layers of representation and abstraction. The current study discovered a scarcity of in-depth tumor detection studies, tumor classification approaches, and in-depth tumour segmentation training applications. This issue is also depicted in [Figure 1]. This review shows how the correctness of certain scientists in characterizing the dataset, tumor type, and functional parameters of the algorithm, as well as measurements of accuracy, specificity, and sensitivity may be extrapolated in the tables provided. Many databases are listed in [Table 1], which contain multiple sorts of photos (normal and abnormal), while others contain only images. Now a day, building a competition for the best tools and technologies for brain tumor detection requires a large database.

Conclusion

When compared to manual procedures, these technologies give enhanced accuracy, volume reduction, and speed. As a result, these techniques have been thoroughly investigated in comparison to classic ML applications and DL methodologies. Tumors are separated and classified using standard databases. Traditional ML approaches are being employed to detect cancers; however, incorporating DL technologies into these processes is expected to produce favorable results, as seen below.

The current study of DL techniques has been applied to tumor detection and has achieved a maximum Dice score of 96.8%. Therefore, to increase the DL assessments in tumor detection and classification, there is a need to compile all three processes (detection, classification, and segmentation) into one fully automated system for brain tumor diagnosis.[1]DL algorithms should not be evaluated with glasses at this time. To classify tumors, researchers used both traditional ML and DL methods; however, both studies achieved 100% accuracy.ML deployments are generally preferred over DL deployments.In order to broaden advanced tumor detection and classification studies, standard tumor detection and classification databases are required.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

References

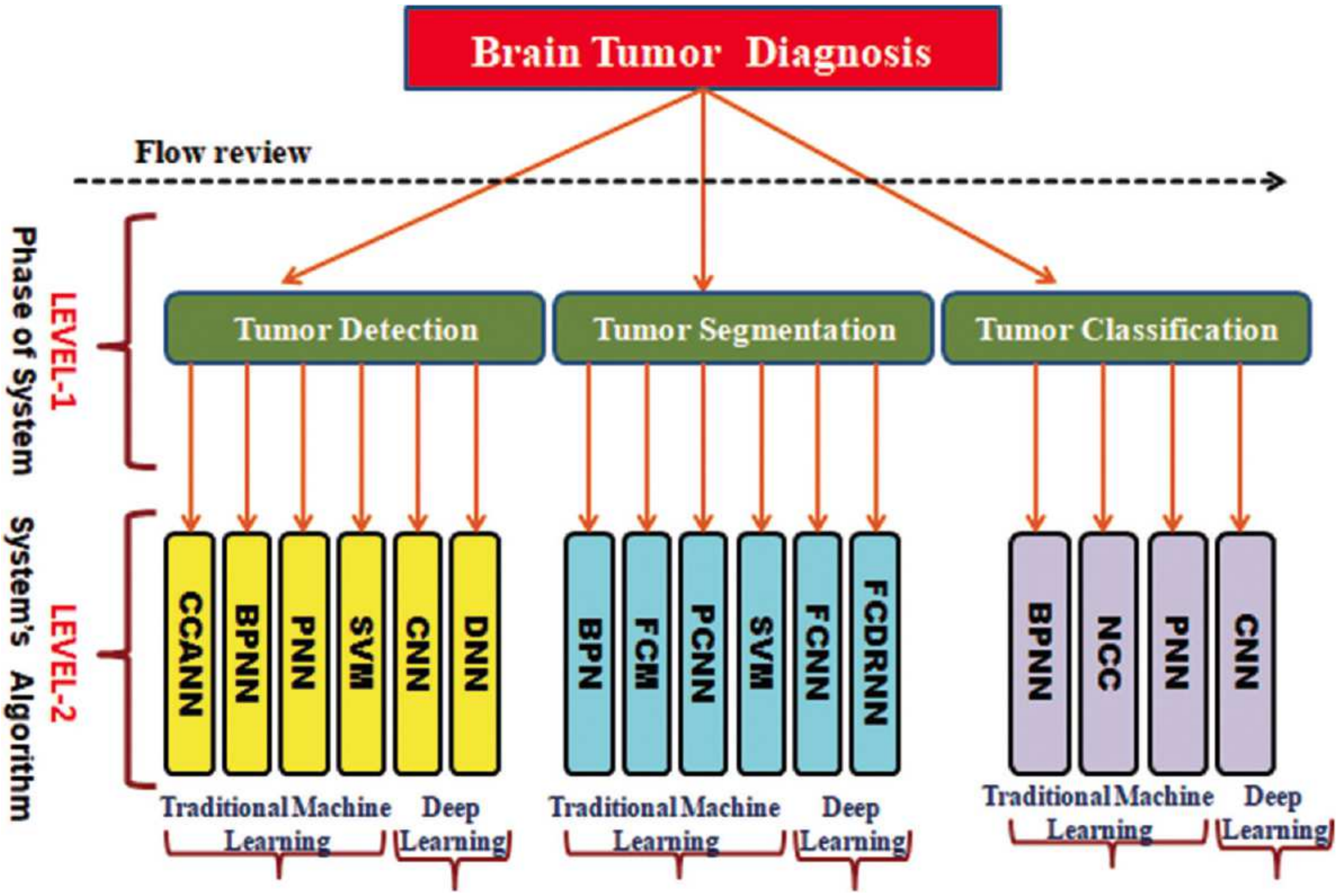
1 Abd-Ellah MK, Awad AI, Khalaf AAM, Hamed HFA. Classification of brain tumor MRIs using a kernel support vector machine. Building Sustainable Health Ecosystems: 6th International Conference on Well-Being in the Information Society, WIS 2016, Tampere, Finland, September 16-18, 2016, CCIS 2016;636:151-60.
2 Neelum N, Sellapan P, Abdul Q, Iftikhar A, Muhammad I, Muhammad S. A deep learning model based on concatenation approach for the diagnosis of brain tumor. IEEE Access 2020;8:55135-44.
3 Nema S, Dudhane A, Subrahmanyam M, Srivatsava N. Rescue Net: An unpaired GAN for brain tumor segmentation. Biomedical Signal Processing and Control 2020;55:101641–52.
4 Ghahfarrokhi S, Sepehr Hamed K. Human brain tumor diagnosis using the combination of the complexity measures and texture features through magnetic resonance image. Biomedical Signal Processing and Control 2020;61:102025–9.
5 Rai HM, Chatterjee K, Dashkevich S. Automatic and accurate abnormality detection from brain MR images using a novel hybrid UnetResNext-50 deep CNN model. Biomedical Signal Processing and Control 2021;66:102477.
6 Aghalari M, Aghagolzadeh A, Ezoji M. Brain tumor image segmentation via asymmetric/symmetric UNet based on two-pathway-residual blocks. Biomedical Signal Processing and Control 2021;69:102841. doi: 10.1016/j.bspc. 2021.102841.
7 Gordillo N, Montseny E, Sobrevilla P. State of the art survey on MRI brain tumor segmentation. Magn Reson Imaging 2013;31:1426–38.
8 Jayadevappa D, Kumar SS, Murty DS. Medical image segmentation algorithms using deformable models: A review. IETE Tech Rev 2011;28:248–55.
9 Yazdani S, Yusof R, Karimian A, Pashna M, Hematian A. Image segmentation methods and applications in MRI brain images. IETE Tech Rev 2015;32:413–27.
10 Liu J, Li M, Wang J, Wu F, Liu T. A survey of MRI-based brain tumor segmentation methods. Tsinghua Sci Technol 2014;19:578–95.
11 Bauer S, Wiest R, Nolte LP, Reyes M. A survey of MRI-based medical image analysis for brain tumor studies. Phys Med Biol 2013;58:R97.
12 Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60–88.
13 Hu J, Zhou J, Wu X. Non-local MRI denoising using random sampling. Magn Reson Imaging 2016;34:990–9.
14 Huang J, Chen C, Axel L. Fast multi-contrast MRI reconstruction. Magn Reson Imaging 2014;32:1344–52.
15 Qu X, Guo D, Ning B, Hou Y, Lin Y, Cai S. Undersampled MRI reconstruction with patch-based directional wavelets. Magn Reson Imaging 2012;30:964–77.
16 Kayvanrad MH, McLeod AJ, Baxter JS, McKenzie CA, Peters TM. Stationary wavelet transform for under-sampled MRI reconstruction. Magn Reson Imaging 2014;32:1353–64.
17 Xing XX, Zhou YL, Adelstein JS, Zuo X-N. PDE-based spatial smoothing: A practical demonstration of impacts on MRI brain extraction, tissue segmentation and registration. Magn Reson Imaging 2011;29:731–8.
18 Maier A, Syben C, Lasser T, Riess C. A gentle introduction to deep learning in medical image processing. Z Med Phys 2019;29:86–101.
19 El-Dahshan ESA, Hosny T, Salem ABM. Hybrid intelligent techniques for MRI brain images classification. Digit Signal Process 2010;20:433–41.
20 Saritha M, Joseph KP, Mathew AT. Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural net-work. Pattern Recogn Lett 2013;34:2151–6.
21 Mohsen H, El-Dahshan ESA, El-Horbaty ESM, Salem ABM. Classification using deep learning neural networks for brain tumors. Future Comput Inf J 2018;3:68–71.
22 Abdel-Maksoud E, Elmogy M, Al-Awadi R. Brain tumor segmentation based on a hybrid clustering technique. Egypt Inf J 2015;16:71–81.

23 Tustison NJ, Shrinidhi KL, Wintermark M, Durst CR, Kandel BM, Gee JC. Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation (simplified) with ANTsR. Neuroinformatics 2015;13:209–25.
24 Nabizadeh N, Kubat M. Brain tumors detection and segmentation in MR images: Gabor Waveletvs. Statistical features. Comput Electr Eng 2015;(Suppl C 45):286–301.
25 Huang M, Yang W, Wu Y, Jiang J, Chen W, Feng Q. Brain tumor segmentation based on local independent projection-based classification. IEEE Trans. Biomed Eng 2014;61:2633–45.
26 Khayati R, Vafadust M, Towhidkhah F, Nabavi SM. A novel method for automatic determination of different stages of multiples clerosis lesions in brain MRFLAIR images. Comput Med Imaging Graph 2008;32:124–33.
27 Akram MU, Usman A. Computer aided system for brain tumor detection and segmentation. International Conference on Computer Networks and information Technology 2011;299-302. doi. 10.1109/ICCNIT.2011.6020885.
28 Rajendran A, Dhanasekaran R. Enhanced possibilistic fuzzy means algorithm for normal and pathological brain tissue segmentation on magnetic resonance brain image. Arab J Sci Eng 2013;38:2375–88.
29 Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Transactions on Medical Imaging 2016;35:1240–51.
30 Prastaw M, Bullitt E, Gerig G. Simulation of brain tumors in MR images for evaluation of segmentation efficacy. Med Image Anal 2009;13:297-311.
31 Sanaullah, Javid SMA, Buzdar SA. A novel computer aided diagnostic system for quantification of metabolites in brain cancer 2021;66: 102401.https://doi.org/10.1016/j.bspc.2020.102401.
32 Cassani R, Falk TH. Alzheimer's disease diagnosis and severity le vel detection based on electro encephalography modulation spectral “Patch” features. IEEE Journal of Biomedical and Health Informatics 2020;24:1982-93.
33 Lundervold AS, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Zeit Med Phys 2019;29:102–27.
34 Razzak MI, Naz S, Zaib A. Deep learning for medical image processing: Overview, challenges and the future. Classification in BioApps : Automation of Decision Making 2018;5686:323–50. https://doi.org /10.1007/978-3-319-65981-7_12.

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

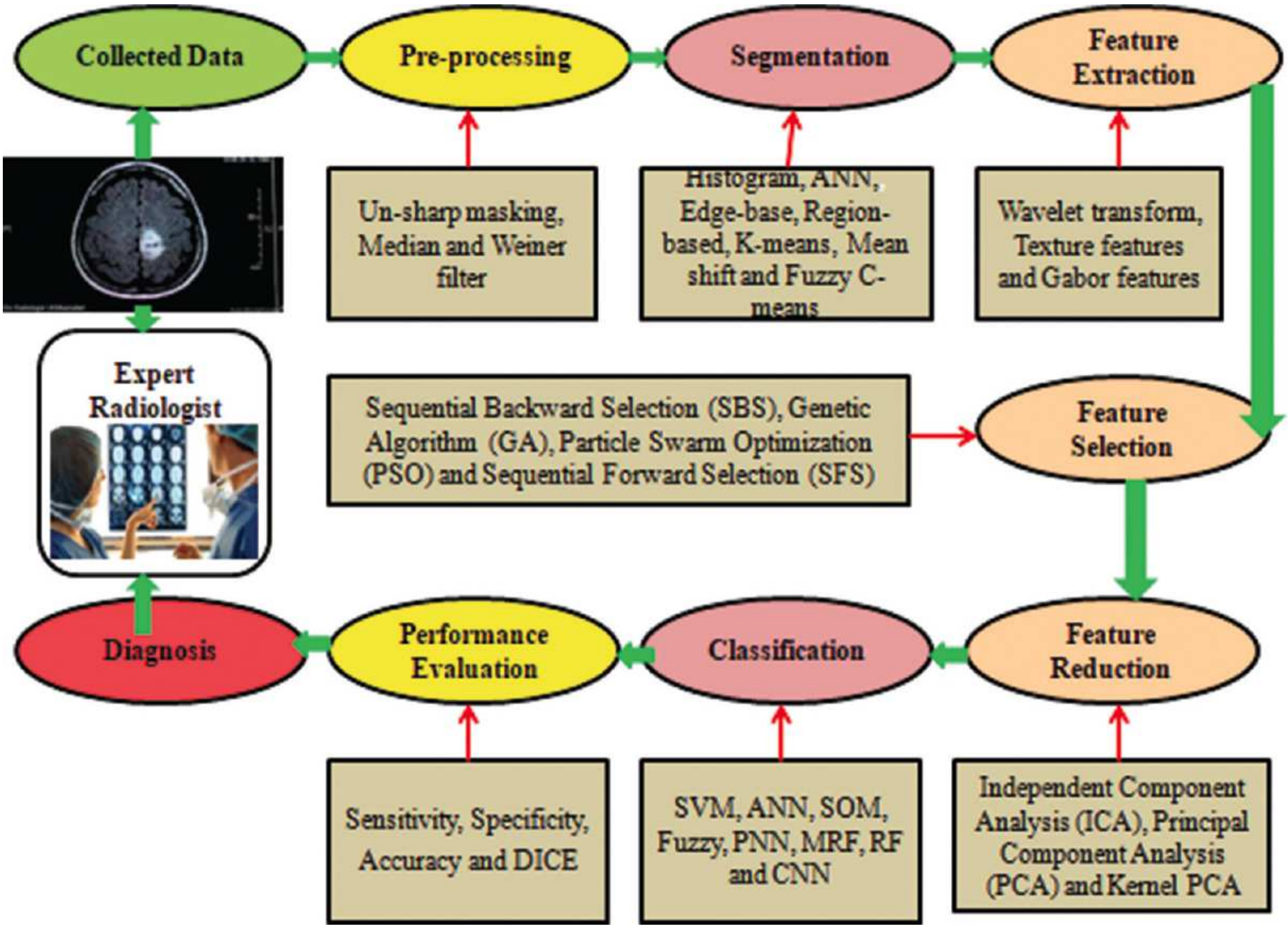
Figure 1: Tumor detection, division, and information of level classification processes. CNN = convolutional neural network



NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

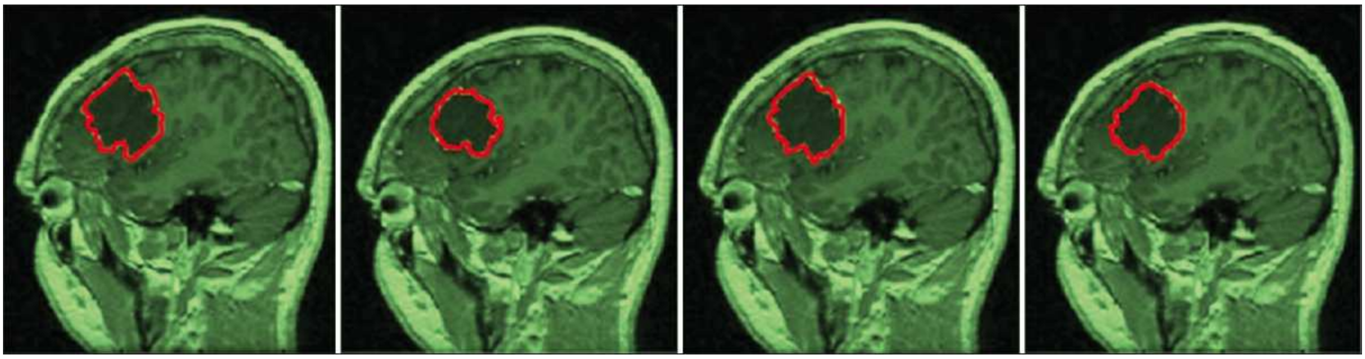
Figure 2: Flowchart of a CAD system for brain tumors. CAD = computer-aided diagnosis, CNN = convolutional neural network



NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Figure 3: Four independent technicians manually segmented glioma on MRI scans. MRI = magnetic resonance imaging

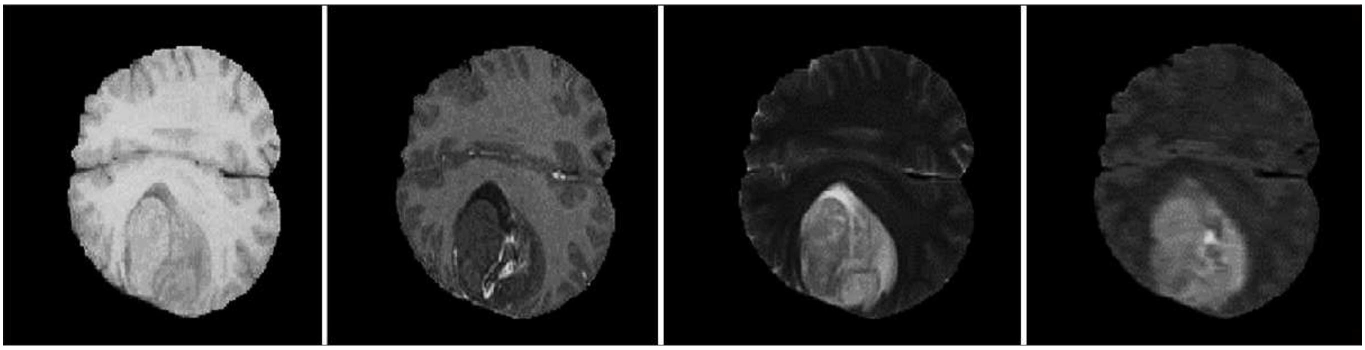


Impostazioni cookie

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Figure 4: Various MRI-modalities registered for HG glioma: T1 MRI, T1-Gd MRI, T2 MRI, and Fluid attenuated inversion recovery (FLAIR) MRI

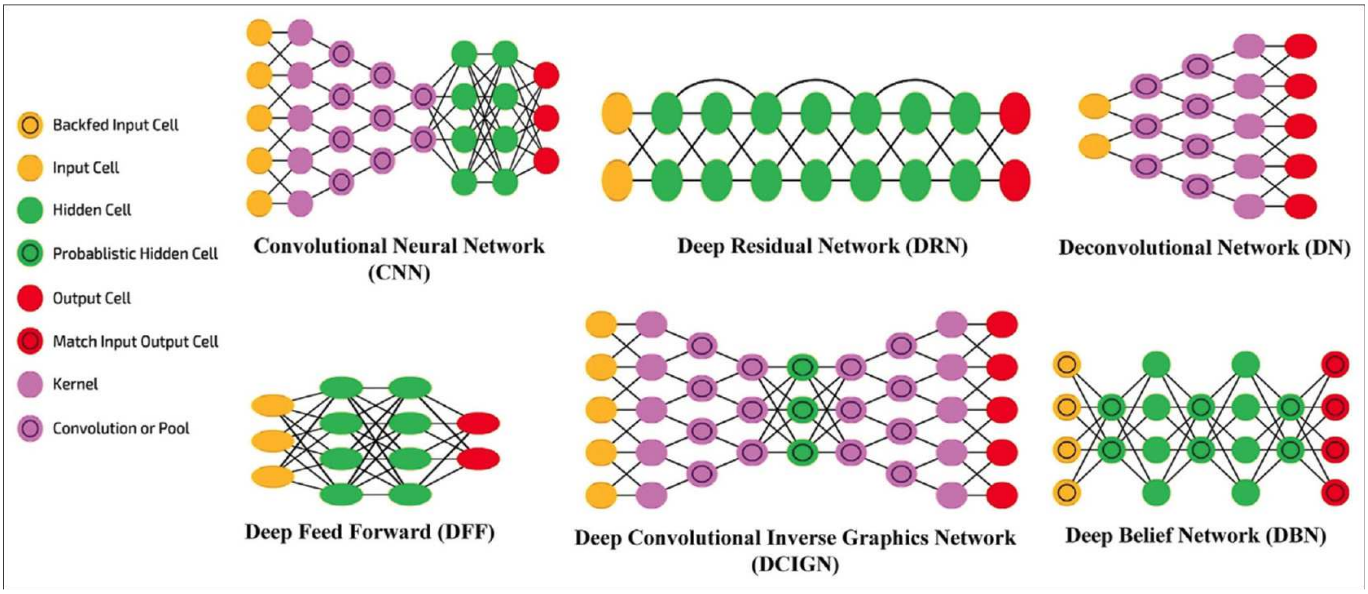


Impostazioni cookie

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Figure 5: Neural network common charts

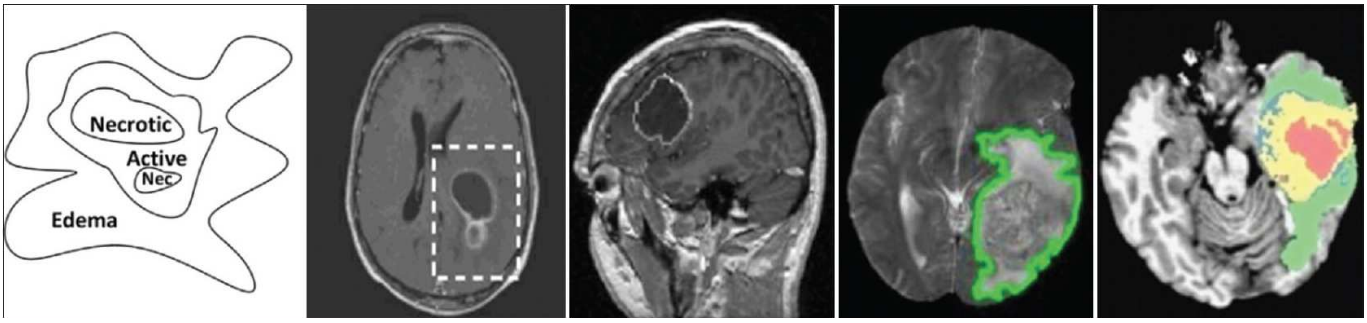


Impostazioni cookie

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Figure 6: MRI modalities were segmented using several strategies. MRI = magnetic resonance imaging



NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Table 1: MRI brain tumor detection using machine learning techniques

Reference	Review extraction	Methods of detection	Used data	Limitations
[1]	DWT	FPANN and KNN	AAN LIB	New training sets are required
[2,3]	2D-DWT	PNN	AANLIB	With each database modification, a new training set is necessary
[4]	2D-DWT	SVM	AANLIB	Other features are ignored in favor of computing the wavelet energy feature
[5,6]	SCICA and ICA	ICA, SC-ICA, and SVM	MNI	Over-clustering is caused by a low threshold, which raises the cost of feature extraction
[7]	DWT features	SVM	AMDI	The classification error is increased by a large feature vector
[8,9]	Grayscale, symmetry, and texture feature	SVM, KNN, and SVM-KNN	Brain Web	Due to changes in the dataset, a new training set is necessary; feature extraction is hard
[10]	Texture feature	ANN, KNN	AANLIB	There is no mention of the algorithm employed in the feature extraction stage
[11,12,13]	DWTS GLDM	GASVM	AANLIB	Because the system is a complex one, it takes longer to compute
[14,15]	Texture feature	BPN and RBFN	PSGIMS	Due to the minimal database size, performance is poor
[16,17]	DWT	KSVM	Randomly selected	Some characteristics are not discussed at all
[18,19]	DTDAUB-4	SVM	AMDI, in Malaysia	Feature vectors were decreased without mentioning the features that were chosen or why they were chosen
[20,21,22]	GLRLM	SVM, FCM	Different medical centers	The system is applied in a nonstandard database and is complex due to the skull stripping stage; the testing dataset is smaller than the training dataset, which improves accuracy
[23,24]	Energy, homogeneity, correlation	Neuro-fuzzy	Brain Web	The database is quite modest
[25,26]	GLCM	SMO	PSGIMS, Coimbatore	It is a small dataset
[27,28]	GLCM	LVQ, SOM, MLP, and RBF classifier	UKM Medical	Due to the intricacy of the system, it takes a long time to compute
[29,30,31]	ICA	SOM neural network	Randomly selected	A smaller dataset may yield better results
[32,33,34]	DWT	KNN, Parzen window, and ANN	AANLIB and LONI	The method can only be used on T2 pictures and has a high level of classification difficulty

MRI=Magnetic resonance imaging, DWT=Discrete wavelet transform

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Table 2: Different MRI approaches for segmenting brain tumors

Reference	Review extraction	Methods of detection	Used data	Limitations
[7]	GLCM	Neuro-fuzzy logy	Radiology Department (Tata Memorial)	For entire photos, dynamic change cannot be enhanced.
[8]	DCT	PNN	-	Only a few pictures were used to train and test the network. Due to the use of three approaches for feature extraction.
[9]	Gabor texture features	SVM	-	
[10]	Grayscale, LoG and texture features	ANN	PGIMER	Performance measured with respect to individual class-accuracy.
[11]	DWT	KSVM	Non standard database	A conventional database is not used in this method.
[12]	Centralized moment calculations	NCC	AANLIB	There are only a few photos utilized.
[13]	Binary-feature extraction	BP-ANN	Medical-City of Martyr GhaziAl-hariri	There is no explanation for FS.
[14]	Supervised FS	SLPANN	INTERPRET	The accuracy of SLPs was improved by training them with the entire dataset.
[15]	CNN	CNN	BRATS2014	Classification by grade.

MRI=Magnetic resonance imaging

NEUROLOGY INDIA
Publication of the Neurological Society of India

Close

Table 3: Brain tumour classification techniques using MRI

Reference	Review extraction	Methods for detection	Used data	Limitations
[7]	ROI histogram, co-occurrence matrices, and run-length matrices	LSFTPNN	Hellenic Air-Force Hospital	The method of external-cross validation has a lo- discriminatory accuracy.
[16]	Thresholding methods	Approximate reasoning- method	-	Computational-cost, complexities and optimization are very high.
[19]	Boot strap sampling	Shelf classifier	INTERPRET	Various diseases and pathological groupings are involved in a number of concerns.
[23]	GLCM	Neuro-fuzzy logy	Department of Radiology (Tata Memorial)	For entire photos, dynamic change cannot be enhanced.
[25]	DCT	PNN	-	Only a few pictures were used to train and to test the net-work.
[27]	Gabor texture-features	SVM	-	Due to the use of three approaches for feature extraction, the system complexity has increased. The process of extracting and selecting features is not discussed.
[28]	7 texture features	MK-SVM	CHU de Caen	The use of FDCT to dis-sect the in-put image adds to the complexities because the data set is nonstandard
[30]	GLCM	PNN-RBF	-	
[32]	CNN	CNN	BRATS2014	

MRI=Magnetic resonance imaging

Impostazioni cookie