A SURVEY ON DIFFERENT METHODS FOR BRAIN TUMOR DETECTION

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Abstract

The International Agency for Research on Cancer (IARC) reports that 76% of deaths are attributable to brain tumours. To prevent any potentially deadly circumstances, it is necessary to identify brain tumours as soon as possible and to give the patient the necessary therapy. Thanks to recent technological advancements, a computer-aided design can now automatically identify tumours from image graphs, including Magnetic Resonance Imaging (MRI). The use of machine learning (ML) techniques has grown in importance among medical researchers. This review examines brain tumour classifications methods and provides comparisons between their outcomes. The difficulties that researchers have had in the past while attempting to identify tumours have been explored, as well as the potential directions that they may choose to pursue in their future study.

Keywords: Brain tumors, Magnetic Resonance Imaging, Comparative analysis and Machine learning.

1. Introduction

WHO estimates that 251,329 people worldwide lose their lives to brain tumours each year, demonstrating the alarming rate at which these tumours are killing people. Brain tumour deaths have tripled in low- and middle-income nations according to National Brain Tumour

Foundation (NBTF). Brain tumours are among the most severe disorders that may affect both adults and children. Brain tumours account for 85% to 90% of cancers classed as "the primary Central Nervous System (CNS)". Every year, around 11,700 patients are diagnosed with brain tumours [1, 2].

Patients with malignant brain or central nervous system tumours have of 34% in males and 36% in women in a five year period with apt diagnostics and therapies. Brain tumours can be found most effectively via MRI . A sample of both normal and abnormal magnetic resonance imaging is shown in Figure 1. Early detection and diagnosis are critical to reducing the issue of brain tumours. Artificial intelligence (AI) in computer vision focuses on development of software and hardware that mimics human behavior[3,4,5].

Artificially intelligent computer programmes may perform a variety of tasks, including learning, planning, and problem-solving. AI has several advantages[6,7,8]. These include aiding professionals in carrying out difficult tasks, making the right decisions, and providing accurate Brain Tumour in imagegraphs. They also include lowering the risk of composite handlings, improving computer assistance identification, and increasing Brain Tumour understanding about individual behaviour. Research on AI and ML (ML) focuses on low-cost, quick, and non-invasive methods for accurately detecting brain tumours utilising sophisticated performance measures including sensitivity, recall, accuracy, F1-score, precision, and specificity[9].

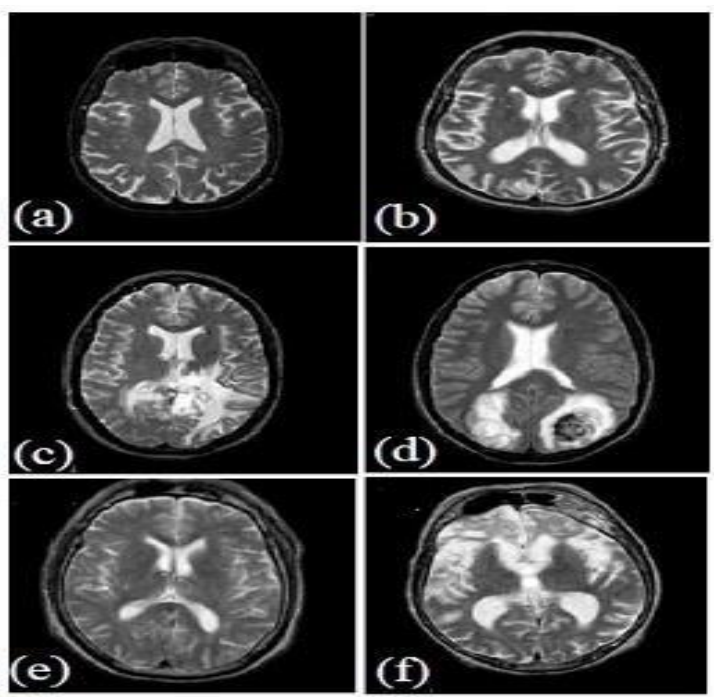

Figure 1.Samples of the brain tumor: a) Normal (b-f) Abnormal

This review examines methods proposed for brain tumour classifications, with a complete comparison analysis presented on the basis of the findings. The difficulties that researchers have had in the past while attempting to identify tumours have been explored, as well as the potential directions that they may choose to pursue in their future study.

Section I is an analysis of brain tumor identification while Section II provides the review on the traditional approaches that are used for tumor identification with comparisons of research strategies along with their benefits and drawbacks, Section III discusses the inference from the recent research about brain tumor identification, Section IV produces the solution for future development in the brain tumor identification area and section V concludes this work with future scope discussed in Section VI.

2. Literature Review

Nandpuru et al [2014][10] suggested automatic classifications to address image categorizations. Brain tumours are a primary cause of death in humans. If the cancer is detected early enough, it may be able to survive. The human brain is investigated via magnetic resonance imaging (MRI). This paper develops and uses Support Vector Machine (SVM)-based classification methods to the challenge of categorising brain images. In this study, grayscale, symmetry, and texture characteristics will be employed to extract features from MRI images.This paper's primary goal is to provide a good result (i.e., a lower error rate and a better accuracy rate) for the SVM-based MRI brain cancer classification.

Giraddi and Vaishnavi [2017][11] suggested a method for dividing the images into two categories: benign and malignant. The proposed approach is built on second-order texture features and SVM classifiers. The system is built with a number of second-order qualities, including energy, entropy, homogeneity, and correlation. Preprocessing, which includes feature extraction, is followed by training the images on an SVM classifier utilising the collected features, and then testing on an SVM classifier with multiple kernels. The linear kernel achieves maximum sensitivity, specificity, and accuracy at 80%, 90%, and 80%, respectively. The work's output allows one to categorise a tumour in an image as benign or malignant. The outcomes show how reliable the approach is in detecting and categorising brain tumours.

Zhang,et al [2018][12] suggested automated classification pipelines based on random forests to discriminate WHO Grade III and Grade IV gliomas by retrieving discriminative properties from 3D patches. Their proposed pipeline used three key components in training and testing phases. Firstly, we take many 3D patches in and around the MR image's tumour locations. This has the potential to suppress the normal region's intensity data, which is unimportant for the categorization procedure. To improve the efficacy of malignant tumour classification, we extract characteristics based on patch-wise and subject-wise clinical information. Third, the classification forest is utilised to train and test the classifier. We tested the proposed framework on 96 people who had malignant brain tumours, including Grade III (N = 38) and Grade IV (N = 58) gliomas. Their results of trials indicated that their suggested framework was true for categorizing high-grade gliomas, which could potentially assist alleviation of dismal prognosis of these tumours.

Usman and Rajpoot[2017][13] suggested a technique for classifying and segmenting brain tumours using multi-modal magnetic resonance imaging data. The Multi-Modal Brain Tumour Segmentation Challenge (MICCAI BraTS 2013) co-registered and skull-stripped data are used, with histogram matching performed on a high contrast reference volume. The preprocessed images are then used to extract the intensity, intensity differences, local neighbourhood, and wavelet texture. Following that, the random forest classifier gets the integrated characteristics and predicts five classes: background, necrosis, edoema, enhancing tumour, and non-enhancing tumour. These class names are then used to create three unique areas in a hierarchical order (full tumour, active tumour, and enhancing tumour). Compared to the Dice overlap recorded in the MICCAI BraTS challenge, Srudy's leave-one-out cross-validation produced superior results: 88% for the total tumour region, 75% for the core tumour region, and 95% for the augmenting tumour region.

Habib et al [2022][14] sought to use the watershed method and threshold segmentation to separate brain tumours from MRI images, and then use several classifiers to categorise the tumours based on the characteristics that were retrieved (MSER, FAST, Harlick, etc.). Their recommended technique included the following steps: segmentations, pre-processes, feature extractions, and image acquisitions. To accurately categorise brain tumours from the datasets used, a variety of classifiers are utilised. The findings show that by reaching more than 90% accuracy, the suggested mechanism improves brain tumour image identification over the current methods.

Zhou et al [2015][15] presented a computer-assisted diagnosis technique based on the wavelet-entropy of the feature space approach (in this work, a 2D-discrete wavelet transform was used to extract more information) and a Naive Bayes (NB) classifier classification method for improving the accuracy of brain diagnosis using NMR images. The wavelet entropy, which is used to train a NB classifier, is selected as the most important image feature. Based on 64 photos, the results show that the classifier has a maximum sensitivity of 94.50%, specificity of 91.70%, and total accuracy of 92.60%. The findings clearly reveal that the proposed classifier can detect aberrant brains from normal controls with high accuracy, beating even the most modern approaches in use.

Reddy,et al [2019][16] created precise segmentations and classifications with automated identifications of pancreatic cancers and brain tumours. The proposed k-NN classifier contains three phases: (a) image preprocessing using a median filtering model; (b) accurate image segmentation using a fuzzy C-segmentation model; and (c) feature selection using a grey level co-occurrence matrix (GLCM). The k-NN classifier then takes the enhanced features as input. Finding the k value plainly frees up the classes. The recommended classifier performs tests on data from the Cancer Imaging Archive repositories and the Harvard Medical School database. To compute experimental data, criteria such as precision, accuracy, specificity, and recall are used. The outcomes demonstrate how much better our suggested classifier performs than the SVM, Naïve Bayes, and Probability Neural Network classifiers from earlier research.

Ahmed et al [2019][17] proposed a hybrid system to categorise MRI brain images as benign or malignant where Radial Basis Function (RBF) kernels and Grey Wolf Optimizer (GWO) were combined in executions. To improve generalisation, 5-fold cross validation was applied.Their hybrid system achieved a classification accuracy of 98.75%.

Latif, et al [2018][18] offered a refined technique that combines wavelet and hybrid statistical characteristics to classify glioma MR images. The suggested technique produces 152 features overall by extracting 52 characteristics using the discrete wavelet transform and 1st and 2nd order statistical features from MRI including Flairs, T1, T1c, and T2. Multilayer perceptron (MLP) classifier is used with the retrieved features applied. The MLP findings were contrasted with those of other well-known classifiers. The MICCAI BraTS 2015 dataset, a common dataset used in research, was utilised to evaluate the methodology. In comparison to previous research, the suggested hybrid statistical and wavelet characteristics yielded 96.72% accuracy for high-grade gliomas and 96.04% accuracy for low-grade gliomas.

Nayak and KengeriAnjanappa[2023][19] suggested usage of hybrid naive-bayes classifier to differentiate MRI brain images. Using a hybrid naive-based classifier in MRI brain images, it is feasible to successfully discriminate between normal and abnormal images associated with illnesses and injuries, thereby enhancing classification accuracy and image quality of human body components, including the brain. The suggested model is used to accomplish feature extraction, noise reduction, and image pre-processing. Four stages comprise the processing of the proposed model: pre-processing of the images, feature extractions, and reductions using NB . A hybrid method efficiently uses the median filter to eliminate noise like scalp and skull. A vast number of sample images have been gathered in order to conduct the performance analysis and effectively use the suggested technique to distinguish between normal and aberrant images. The suggested technique has been compared to other approaches, such as Feed Forward-ANN (FF-ANN), Random subspace with Bayesian Network (RS with BN), and Random subspace with Random Forest (RS with RF). The recommended hybrid NB classifier provides a 35-65% splitting ratio for training and splitting. The samples show 2%, 3%, and 2.5% increases in normal and abnormal image classification using the approaches feed forward-ANN (FF-ANN), RS with BN, and RS with RF, respectively.

Amarapur[2017][20] created a tumour segmentation model that is effective by utilising artificial neural network classifiers, Gabor Wavelets for multiple feature extraction, and Fuzzy-C-Mean (FCM) clustering. Their recommended system's performance was assessed using 40 trained images from 60 tested MRI-scanned medical datasets. The accuracy of the proposed system's performance is evaluated in respect to the confusion matrix. the study achieved the required system accuracy level of 85%.

Machhale et al [2015][21] suggested a clever categorization scheme to distinguish between aberrant and normal MRI brain images. These days, radiological appearance and symptoms are the main factors used to diagnose and treat brain tumours. MRI is a crucial controlled method for determining the anatomical location of brain tumours. Different methods were employed in this experiment to categorise brain cancer. These methods enable the successful execution of image preprocessing, image feature extraction, and subsequent brain cancer classification. The results revealed that their Hybrid classifier, SVM-KNN, had the highest classification accuracy rate of 98% when 50 images were categorised using three different ML techniques: SVM, K-Nearest Neighbour (KNN), and Hybrid Classifier. The major goal of this study is to demonstrate an excellent MRI brain cancer classification rate using SVM-KNN.

Deepa and Sam Emmanuel[2019][22] proposed firefly backpropagation neural networks with fused features that achieved high classification accuracies through preprocesses, feature extractions/selections/fusions. Vverage filters in preprocessing stages reduced image intensity fluctuations. Gabor wavelet feature extractions provided textural information for categorizations by extracting tumour image's locations, orientations, and frequencies. To reduce duplications and increase feature relevances, limited collection of features were selected using kernel principal component analysis (KPCA). Gaussian radial basis function (GRBF) for feature fusions provided diverse information from different feature sets. Finally, utilising fused data, their proposed technique correctly classified tumours with high levels of accuracy. Their simulations in MATLAB showed that their recommended strategy improved tumour classification values of accuracy, sensitivity, and specificity.

Dixit and Nanda[2019][23] suggested a model that uses pertinent characteristics, an SVM classifier, and segmentation based on Particle Swarm Optimisation (PSO) to distinguish between brain tumours and non-tumors. Using Discrete Wavelet Transform (DWT) based features, PSO retrieved thirteen distinct features and precisely located the tumour from the images. These characteristics trained SVM classifier using two distinct kernel functions for distinguishing brain tumours from non-tumors in MR images. A collection of 50 brain MR images is used to validate the suggested model.

Hassan et al [2021][24] offered a sophisticated segmentation and classification method for brain MR images that assisted medical professionals in making diagnoses. Nonetheless, the strategy will be divided into 4 stages. The MRI image will be enhanced through pre-processing, which will be followed by segmentation using binary thresholding and morphology operations. Local Binary Pattern (LBP), Grey Level Co-Occurrence Matrix Occurrence Matrix (GLCM), and Connected Regions feature extraction fusion will then be carried out. SVM in conjunction with Modified Binary Cat Swarm Optimisation (BCSO) is used for feature selections and classifications. The module outperforms artificial fish swarms and SVM alone in achieving the required accuracy. The obtained outcome demonstrates that using a binary cat swarm to tackle the extracted feature optimisation problem is feasible.

Table 1.Comparsion of existing methods for brain tumor detection

Author name	**Methods**	**Merits**	**Demerits**
Nandpuru et al [2014]	SVM	Give an excellent outcome	Increases the error rate
Giraddi and Vaishnavi [2017]	SVM	Highest sensitivity, specificity and accuracy obtained are 80%, 90% and 80% respectively	Does not perform well with high volume data
Zhang, et al [2018]	Random forest	Improves the classification accuracy	Increases the false positive rate
Habib et al [2022]	Different classifiers	Achieving more than 90% accuracy	Time consuming nature
Zhou et al [2015]	NB	Overall accuracy is 92.60%	Multi-disease classification is not focused in this wok
Reddy, et al [2019]	K-NN	Outperforms better than prior classifiers	Need to reduce the image modalities
Ahmed et al [2019]	Hybrid SVM with Radial Basis Function	Accuracy of classifications were greater than 98.750%	Need to use deep neural network

Latif, et al [2018]	MLP	produced results with a high-grade glioma accuracy of 96.72% and a low-grade glioma accuracy of 96.04%.	Need to use deep learning for feature extraction
Nayak and KengeriAnjanappa [2023]	Hybrid naive-bayes	Produces better accuracy	Increases the false positive rate
Amarapur [2017]	Fuzzy-C-Mean (FCM) clustering	Obtains accuracy level upto 85%	Apriori specification of the number of clusters
Machhale et al [2015]	SVM-KNN	Give an excellent outcome	Does not implemented for other diseases
Deepa and Sam Emmanuel[2019]	Fused feature adaptive firefly back propagation neural network	Achieves high accuracy	Computational complexity is very high
Dixit and Nanda[2019]	SVM	Provides better results	Very expensive
Hassan et al [2021]	Support Vector Machine	Feasible and efficient	Increases the error rate

3. Inferences from the existing works

Current methods employ laborious manual segmentations and handcrafted feature extractions before categorizations which are prone to errors. These strategies often need assistances of specialists who select most effective features and segmentation algorithms for successful tumour diagnostics. Consequently, these systems exhibit inconsistent performance while handling bigger datasets. Deep learning models currently in use have several limitations.

Deep learning approaches based on CNN demand large amounts of data, making the process intricate and costly. Accurate tumour identification and segmentation require large feature sets.

4. Solution

Improving classifiers for brain tumour identification and classification is the main goal of future research in this field. Additionally, several preprocessing operations are carried out at the beginning to improve the image quality, such as noise reduction and data augmentation.The brain area will be segmented using enhanced deep learning. A better deep learning technique will be used to detect brain tumours..

5. Conclusion and future work

Detecting brain tumours is one of the most difficult challenges in medical image processing. Because brain tumours may take on a range of shapes and textures, detecting them is difficult owing to their visual diversity. Brain tumours are caused by several types of cells, which might reveal information about the tumor's origin, severity, and rarity. Tumours may appear anywhere, and their location might reveal information about the kind of cells that are creating them, which can help with additional diagnostics. A review of research publications on the identification of brain tumours using MRI images was offered in this study. After examining those approaches, it was shown that deep learning techniques are superior for the identification and segmentation of brain tumours from MRI images, suggesting that future research should concentrate on this area.

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