Recent Advancement in Brain Tumor Detection Using Machine Learning Algorithm: Systematic Survey, Comparisons and Challenges

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| Article Info	Abstract
	Brain tumors and cancers are fatal diseases that are often caused by the accumulation of genetic diseases and various pathological changes. Cancer cells are abnormal areas that often grow in any life-threatening part of the human body. Cancer, also called a tumor, needs to be identified quickly and accurately in its early stages to see what benefits its cure. Even if modalities have different considerations. Complicated medical history, inadequate diagnosis and treatment, leading causes of death. The purpose of this study is to analyze, review, classify, and address current developments in brain tumor detection using machine learning techniques and supervised, unsupervised, and deep-his learning techniques. Multiple state-of-the-art techniques are grouped into the same cluster, and the results are compared to benchmark datasets for accuracy, sensitivity, specificity, and false-positive metrics. Finally, challenges for future work are also identified.

1.0. Introduction

The brain is the most complex organ in the human body. Morphological cell behavior in the human brain is affected by inappropriate mechanisms of mitosis. During this procedure, cancer cells with multiple morphological features, i.e. Size and Strength. Brain tumors mainly he has two grades. Low grade and high grade. Low-grade tumors grow slowly, while high-grade tumors are more aggressive and disrupt the blood brain supply. Therefore, most malignant brain tumors are called neuroepithelial tumors. Glioblastoma is a common type of brain tumor, with a 5% rate of this type of tumor and a patient survival rate of less than 5 years [1]. Most cancer cells have low contrast compared to neighboring cells. Accurate detection of brain tumors is therefore an important challenge. MRI modalities are most commonly used to detect brain tumors. This is a painless procedure that helps analyze tumors from multiple viewpoints and views. Analysis of MR images is therefore the best method among other methods for detecting brain tumors [2].

Various types of machine-assisted cancer detection and classification have opened a new research area in cancer screening and demonstrated the ability to reduce the interference of manual systems. This review includes several sections on state- of-the-art techniques, analyzes, and comparisons of benchmark brain tumor datasets in terms of F value, sensitivity, specificity, precision, and precision. A visual representation of this study is shown in Figure 1.

2.1 Benchmark Datasets

This section describes benchmark datasets commonly used for experimentation, analysis, and comparison of state-of-the-art cancer detection and classification techniques. This section further discusses sources, training sets, test sets, performance measures related to cancer detection, segmentation, and classification.
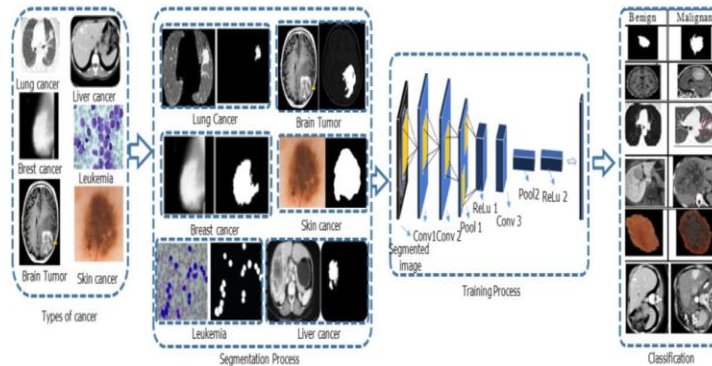
Fig. 1. Machine assisted system for cancer detection

2.2. BRATS 2015 dataset

This data set was developed by the Perelman School of the Pennsylvania College of Medicine and includes 192 training cases (154 HGG and 38 LGG) and 82 test cases (66 HGG and 16 LGG) for a total of 274 data sets. It has been constructed. The training images contain high- and low-grade gliomas and ground truth. The ground truth is labeled with five labels, such as 1 for necrosis, 2 for edema, 3 for non-enhanced tumors, 4 for enhanced tumors, and 0 for all others [3-12].

2.3 Record of BRATS2016
19 teams participated in his BRATS 2016, as BRATS 2016 uses the same training dataset as his BRATS 2015. The training data set is the same as the BRATS15 training data set. BRATS12 and BRATS13 test records and 191 hidden records from TCIA. The image size is 155x240x240. A total of 431 sets, including 285 training cases (210 HGG and 75 LGG) and 146 HGG and LGG test cases

2.4 BRATS 2018 record

The dataset has been updated with clinically acquired more routine multimodal 3T MRI scans and all ground truth labels have been manually revised by expert panel-certified neuroradiologists. A total of 476 sets, of which 285 training cases (210 HGG and 75 LGG), and 191 HGG and LGG test cases)

2.5 LIDCIDRI

The Lung Image Database Consortium Image Collection and Image Database Resource Initiative (LIDC-IDRI) is an open-source database consisting of images of nodule contours and subjective nodule characterization. This database was developed to support the study of pulmonary nodules and contains 244,617 images.

2.6 ISIC record

ISIC has developed a benchmark dataset of publicly available dermoscopy skin lesion images. We discuss the main challenges, lesion segmentation problems, clinical diagnostic pattern recognition, lesion classification, and describe his CC-0 licensed images and metadata of approximately 3000 high-resolution, human-validated training and test sets. The size of the image is not fixed as we continuously acquire different types of visual sensors.

Atlas or Dermnet is an open source dataset of over 23,000 images collected and tagged by the Dermnet Skin Disease Atlas. This dataset provides diagnostics for 23 super classes of disease taxonomically divided into 642 subclasses.

2.7 PH2 record

A dataset of skin lesions named PH2 was developed for benchmarking and research purposes to enable comparative studies of classification and segmentation algorithms for dermoscopy images. The Dermatology Department at Pedro Hispano Hospital recorded a similar situation using the Tuebinger Mole Analyzer system at 20x magnification. It is an 8-bit RGB color image with a resolution of 768 x 560. The dataset consists of 200 images, 80 of which belong to benign lesions, another 80 to suspicious lesions and the remaining 40 to malignant [12-64].

2.8 Brain Tumor

Brain tumors are collections of abnormal cells with four grades. Grade 1 and 2 brain tumors tend to grow slowly, while grade 3 and 4 tumors are malignant (cancerous), grow faster and are more difficult to treat [50,58-63]. Tumor detection has several basic steps, and a preprocessing phase is performed to remove noise and non-brain tissue from the input image to improve accuracy [65]. The brain surface extractor (BSE) technique is used to remove organs other than the brain. Fast Nonlocal Mean (FNLM), Partial Differential Diffusion Filter (PDDF), and Wiener Filter are used to suppress noise, and contrast stretching is used to enhance contrast. The most common brain tumor segmentation techniques are fuzzy c-means, k-means clustering, and Otsu thresholding. Similarly, the U-Net architecture is also his one of the famous CNN architectures used for brain tumor segmentation. After the segmentation process, handcrafted features are extracted and the segmented image is converted into a mathematical description. More robust feature extraction techniques are currently in use and used for classification. Well-known feature extraction techniques include Histogram Oriented Gradients (HOG), Gabor Wavelet Transform (GWT), Local Binary Patterns (LBP), and shape-based features. Additionally, various feature selection and reduction techniques such as genetic algorithms (GA) and principal component analysis (PCA) are used for optimal feature selection. CNN architecture is now also recognized as a powerful brain tumor detection technology. Figure 2 shows the process of preprocessing, segmentation, deep learning training and final tumor prediction.

Vaishnavee and Amshakala [66] used SVM and self-organizing map (SOM) strategies to address the problem of brain tumor segmentation. Histogram equalization was performed in the preprocessing phase. Four characteristics were determined for classification: mean, severity, number of incidents, and variance. They used his SOM clustering to identify irregular brain clusters and segmented them in a second stage. In addition, his MR images of the brain were classified into various intratumoral groups. To perform this characterization of the subtumor-level gray-level

coexisting texture matrix (GLCM), we used principal component analysis (PCA) to measure these texture properties as a dimensionality reduction step. However, the authors did not compare prior art results and there was no justification for using SVM and SOM.
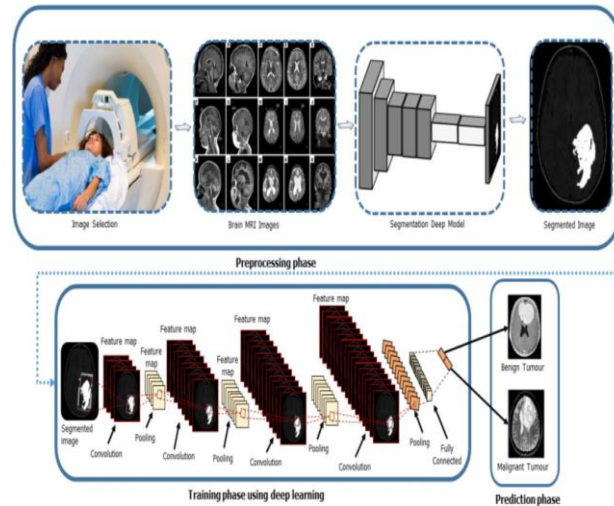

Fig. 2. Generalized framework for deep learning-based brain tumor classification

Nie et al. [68] reported a fully automated 3D CNN brain tumor segmentation system using both T1, MR test (MRI) and diffusion tensor imaging (DTI). Different preprocessing strategies have been applied to enhance the MR modalities using T1, DTI tensors and fMRI-specific BLD dispersion rates (blood oxygen dependent). H. Standardization of intensity.
The extraction function was 3D-CNN and the final prediction was performed by SVM with 89.9% (accuracy), 92.19% (sensitivity) and 88.22% (specificity).

However, the proposed system is computationally intensive and not suitable for large datasets. Arican et al. [76] proposed a semi-automated joint seed selection-based her SVM approach for brain tumor fragmentation. They used an anisotropic diffusion filter on the MR images in the preprocessing stage to remove noise. A random seed for SVM classification is then selected from the previously processed MR images. The freely accessible BRATS 2015 data set was used to assess success. To test the results of the new procedure, they selected four patients from the MICCIA BRATS 2015 data collection. Their solution achieved an average cube similarity (DS) of about 81% compared to terrestrial reality. Elwar et al. [67] proposed a fully automated segmentation approach for MRI-based brain tumors using iterative random trees.

We iteratively improved patient accuracy using specific details of the dataset used for random forest classification. This technique was tested in BRATS-2016. The selection requirement for the person with the strongest knowledge leads to positive results. However, no rationale for selection requirements was given and no accuracy results were reported.

Abbasi and Tajeripour [71] proposed his automated 3D interface for brain tumor detection and segmentation in the BRATS 2013 dataset. Separated from FLAIR image context for preprocessing, bias field correction, histogram communication, and ROI (region of interest). In the learning task, the HOG and LBP features were input into a random forest classifier. However, they used synthetic data in their experiments and reported 93% accuracy.

Mehmood et al. [73] proposed an effective system for brain imaging and simulation using MR images. It started with an immersive, semi-automatic 3D segmentation technique, essentially

separating the brain and tumor regions from the MR part, using an SVM of 95.53-accuracy, 99.49% sensitivity, 99.0% accuracy, and a mean squared error of 0.09. increase. However, the experiments were performed on self-generated datasets. Das et al. [74] used texture-based features to recognize normal and abnormal tissue samples. Eighty abnormal and normal tissue images obtained from GMCH, Guwahati Hospital were used. Features were extracted from images by fusion of five descriptors (LBP, Tamura, HOG, GRLN, and GLCM) to formulate a set of 172 feature vectors.

In addition, six classifiers, SVM, K-NN, logistic regression, quadratic discriminant, linear discriminant. Used to evaluate the performance of each characteristic set both within groups and individually.
Experimental results show 100% accuracy using the full function set versus the individual function set, improving the average classification accuracy to 98.6%. They concluded that childhood brain lesions are so important that computerized systems may lead to better diagnoses. be computationally intensive.

Iqbal et al. [72] proposed a deep learning model for reliably delineating brain tumors from medical benchmarks using short-term memory (LSTM) and co-evolutionary neural networks (ConvNet). Two different models, ConvNet and LSTM, have the same data set and form groups to maximize performance. Two separate models are merged. For this reason, a data collection consisting of his MRI images of four modalities T1, T2, T1c and FLAIR has been published. MICCAI BRATS 2015 is accessible. Several variations have been developed to improve image sharpness, adding output variations that are best suited for preprocessing approaches such as noise reduction, histogram equalization, and edge enhancement. Current models use class weighting to address the issue of class inequality. Validation details from the same image collection are checked against the trained model and the results of each experiment are recorded. The ConvNet is 75% single-valued (accuracy), 80% is generated by LSTM-based networks, and the overall fusion is 82.29%.

Although the proposed grab-cut approach [75] has been implemented to specifically segment the actual symptoms of loss, it has been perfected into the Visual Geometry Transfer Learning System "VGG-19" feature and continuously assembled. (shape and texture). Such techniques are developed by Entropy to reliably and easily identify fusion vectors and send them to the classification unit. The models described are tested on his MICCAI challenge database, including Multimodal Brain Tumor Segmentation (BRATS) 2015, 2016, and 2017, respectively, using high-quality scientific image processing and computational interventions. Studies using cube similarity coefficients (DSC) reached 0.99 for BRATS 2015, 1.00 for BRATS 2016, and 0.99 for BRATS 2017.

However, they did not use other classifiers or their fusions to confirm the viability of the technique. Recently, Ramzan et al. [78] To enable effective end-to-end mapping between MRI volumes and brain segments at the voxel level, his 3DCNN with residual learning and extensive convolution was used to map multiple brain regions. segmented. Mean cube scores of 0.879 and 0.914 were obtained for 3 and 9 brain regions using data from 3 different sources. By comparison, for the eight brain regions using MRBrains18 data acquisition, the mean cube value of 0.903 is higher than the 0.876 obtained in the last study. Similarly, Nayak et al. [61] proposed a CNN model consisting of 5 layers (4 convolutional layers and 1 fully connected layer) with learnable parameters. His two benchmark MRI datasets for multiple brain classes, namely MD-1 and MD-2, were used to confirm the viability of their model. The authors claimed classification accuracies of 100% and 97.50% for the MD-1 and MD-2 datasets, respectively.

Lu et al. [59] proposed a deep learning CNN ResNet based on pyramid unfolding convolution for

glioma classification. The experiment was performed on a local clinical dataset and achieved an accuracy of 80.11% in glioma classification. However, we did not use an experimental benchmark data set, an overview of existing brain tumor detection methods, adopted methods, datasets and results.

3. Summary

The last few decades have seen a revolution in the use of machines to detect and treat cancer. Therefore, this paper provided a systematic review of current techniques for diagnosing and treating multiple cancers that severely affect the human body. The focus of this article is to identify, analyze and classify methodologies for different types of cancer and to clarify existing limitations. The main purpose of this study is to provide an intellectual background to new researchers wishing to initiate research activities in this field.

3.1 Challenges

The major challenges in the cancer detection and cure process are redesigning research pipelines, understanding cancer growth phenomena, developing preclinical models, accurately handling complex cancers, providing early treatment, and clinical trials. is an innovative method for designing and implementing, and improving accuracy. This helps doctors as a second and initial opinion.

4. Conclusion

Finally, we systematically review the latest machine-assisted cancer detection technologies and their strengths and weaknesses. However, the accuracy of each cancer category is still immature. Most researchers either did not use a benchmark data set or used a small set to test the proposed method. To this end, we use a benchmark data set to compare current state-of-the-art technology and to demonstrate the limitations of existing technology.

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