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Review on Brain Tumor Classification using MRI Image

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Abstract: According official statistics, cancer is the second leading cause of human fatalities. Among the various types of cancer, brain tumor is considered the deadliest as it affects the life of both patients and their families. Treatment of brain tumor involves proper identification of the type. Humor centered diagnosis is usually error prone, resulting in the interest towards automating the process. In this paper, various techniques for brain tumor detection and classification based on MRI are discussed.

Keywords: Brain tumor, MRI, Biopsy, Neural Networks, Feature Extraction.

INTRODUCTION:

According to world health organization's statistics, cancer is considered as the second leading cause of human fatalities across the world. Among different types of cancers, brain tumor is seen as one of the deadliest, due to its aggressive nature, heterogeneous

characteristics, and low relative survival rate. Brain tumor can drastically influence the quality of life, for both patients and their families. The key factor in treating brain cancer and increasing its survivability rate is early diagnosis and correctly determining its type. Brain tumor can have different types (e.g., Meningioma, Pituitary, and Glioma) depending on several factors such as the shape, texture, and location of the tumor. Determining the correct type of brain tumor is of great importance, as it can significantly influence the choice of treatment and predicting patient's survival.

Brain tumor diagnosis usually involves Magnetic Resonance Imaging and biopsy. MRI is preferred as it non-invasive. Though in some cases, MRI alone is not enough to determine the type of tumor, requiring a biopsy. The risk associated with biopsy is high and does not guarantee accurate results. The technicians performing these procedures have a great impact on the results, introducing the problem for human-error. There is a need for computer aided systems to assist doctors to make correct decisions. In recent years there has been a lot of research in this regard using various machine learning techniques. Before the advent of deep learning, feature selection techniques like PCA, DWT and so on followed by classifiers like SVM, KNN and others are used. Now the primary focus is on utilizing neural networks to achieve more promising results.

LITERATURE REVIEW:

[1] presented a novel convolutional neural network (CNN) based multi-grade brain tumor classification system. The tumor regions are segmented using Input Cascade CNN consisting of two separate streams for extracting local features and global features. The abundant data requirement of deep learning models is satisfied by applying eight different augmentation techniques with 30 parameters overall. A pre-trained VGG-19 CNN architecture is fine-tuned for tumor grade classification. Accuracy of 87% and 90% was achieved on original and augmented data respectively indicating the impact of data augmentation.

[2] Suggest an idea of using Genetic Algorithm to evolve the CNN architecture for tumor classification. The study

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uses gadolinium enhanced T1 images that are dimensioned into 128 x 128 pixels. Simple techniques like rotation, scaling, mirroring are rotation, scaling, mirroring are applied to increase the dataset size. GA is implemented to choose parameters such as number of convolutional and max-pooling layers, number of filters and their size and so on. To decrease the variance of classification error, bagging an ensemble method is used on the best model evolved by GA. The technique resulted in architectures consisting of five convolutional and max-pooling layers as well as one fully connected layer for glioma grading and six convolutional and max-pooling layers and one fully connected layer with 384 neurons for classifying meningioma, glioma and pituitary tumor. The accuracy obtained was 90.9% and 94.2% for glioma grading and tumor classification respectively.

[3] adopt the concept of transfer learning for feature extraction in the classification system. As pre-processing the MRI images were normalized and reduced to 224 x 224 pixels. A pre-trained GoogLeNet is modified to learn features from brain MRIs. The extracted features are tested on SVM and KNN classifier models along with the softmax layer of GoogLeNet. The classification accuracy of the deep transfer learned (standalone) model, SVM and KNN are 92.3%, 97.8% and 98% respectively.

[4] study the effect of preprocessing techniques on brain tumor classification using CapsNet. Rotation and patch extraction are the preprocessing steps used. The images are resized to 28 x 28 pixels and fed to Capsule network. The architecture involves a hidden layer with convolution layer for feature extraction and capsule layer followed by a fully connected layer for classification. The CapsNet is applied on the original dataset yielding an 87% accuracy. The same architecture when applied on pre-processed data results in 92.6% accuracy showing that accuracy increases when data is pre-processed.

[5] use a pre-trained deep CNN model and propose a block-wise fine-tuning strategy based on transfer learning. The method is evaluated on T1-weighted contrast-enhanced magnetic resonance images (CE-MRI) benchmark dataset of size 512 x 512.The images are reduced to 224 x 224 and normalized. A pre-trained VGG19 architecture is divided into six blocks based on pooling layers to reduce the time for fine-tuning. Five-fold cross-validation is used to evaluate the performance. The accuracy of proposed method is 94.82%.

[6] attempt to identify the optimal CNN architecture for brain tumor classification. 5 CNN architectures with varying number of convolution layers and fully connected layers are studied. The CNN architecture consisting of 2 layers of convolution of 32 filters, activation (ReLu), and maxpool followed by one fully connected layer of 64 neurons is found to be the optimal with 84.19% validation accuracy. Two variations of this architecture having 64 and 128 filters in the convolution layer are considered. The validation accuracy of architecture with 32 filters is the highest among the other variations.

[7] propose a cod system for detection and classification of HGG and LGG tumors. Otsu binarization is applied to convert the images into binary. The segmented images are then subjected to feature extraction using Discrete Wavelet Transform, that not only extracts feature but also reduces noise. As the number of features extracted is huge, Principal Component Analysis is used for feature reduction. SVM then classifies the images as HGG and LGG. The accuracy of this system tested on 100 images is 99%.

[8] considered a Deep Neural Network for classifying a dataset of 66 brain MRIs into 4 classes. Fuzzy C-means technique is used for segmenting the image into five sections. Discrete Wavelet Transform extracts features from the segmented tumor region. Feature reduction is carried out by Principal Component Analysis. The classifiers used are DNN with 7

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hidden layers, KNN with k=1 and k=3, Linear discriminant analysis (LDA) and SMO-SVM. DNN gives the highest accuracy 98.4% among all techniques.

[9] proposed a brain tumor classification system using normalized histogram and segmentation using K-means clustering algorithm. Various noise removal techniques like Median filter, Adaptive filter, Gaussian filter, Averaging filter and Un-sharped masking filter are comparatively studied. Median filter is chosen for use as it provided the highest Peak Signal to Noise Ratio. After histogram normalization, the images are classified into tumor images and non-tumor images using Naïve Bayes classifier and SVM. SVM was found to be more efficient at 91.49% compared to Naïve Bayes at 87.23%. The images in which tumor was detected were subjected to segmentation using K-Means algorithm.

[10] propose a CapsNet architecture for brain tumor classification. The input MRI images fed to the network are down sampled to 128 x 128 from 512 x 512. The second layer is convolution layer. Following two layers are capsule layers with the last one containing one capsule for each tumor type. The tumor boundary concatenated with the vector obtained goes through two fully connected layers with different number of neurons. Finally, the softmax layer returns the probability for each class of tumor present. Accuracy of 90.89% is given by the proposed architecture.

Below table 1 show the summary of different techniques used in brain tumor classification.

Table 1. summary of classification techniques.

No	Author Name	Methods	Accuracy
1	Muhammad Sjjad, et.al	InputCascadeCNN, Pre – trained VGG – 19 CNN	90%
2	Amin Kabir ,et.al	Genetic Algorithm, CNN	94.2%
3	Deepak, et.al	SVM, KNN, GoogleNet	92.3%, 97.8%, 98%
4	R. Vimal Kurup, et.al	CapsNet	92.6%
5	Zar Nawab Khan Swati, et,al	Pre – trained deep CNN, Pre – trained VGG - 19	94.82%
6	Nyoman Abiwinanda, et.al	CNN	84.19%
7	F. P. Polly, et.al	Otsu binarization, Discrete Wavelet Transform, SVM	99%
8	Heba Mohsen, et.al	Fuzzy C Means, Discrete Wavelet Transform, Principal Component Analysis, Deep Neural Network	98.4%
9	Garima Singh, et.al	K – Means, Median filter, Adaptive filter, Gaussian filter, Averaging filter and Un-sharped masking filter, Naïve Bayes classifier, SVM.	87.23%, 91.49%
10	Parnian Afshar, et.al	CapsNet	90.89%

CONCLUSION:

Owing to the deadly nature of brain tumors, lot of research has been carried to automate its detection and classification. With the advancement in machine learning, neural networks have become the primary focus of interest in developing models for brain tumor diagnosis. Transfer learning techniques can be applied to these models and hence used for other similar diagnosis. This paper attempts to summarize few techniques designed for brain tumor classification. There is still a need for further research and enhancement of techniques in this regard to ensure that the developed systems can be deployed for use by doctors as second opinion to diagnose tumor.

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