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Brain Tumor Image Classification Using Artificial Intelligence

Abstract: Introduction: Many artificial intelligence-based steps are taken in the detection and classification of brain tumors. This paper addresses and analyzes different tumor classification algorithms in terms of accuracy, specificity, and sensitivity. **Methods:** This review will cover three original papers. Each of them used different artificial intelligence approach, however, they all have some results parameters in common. These papers were reached after searching for new technologies that used machine learning or deep learning to classify brain tumors into types, and according to normality and abnormality. **Results:** In our findings, three classification methods in three papers were found and were compared to each other taking the utilized algorithm and dataset into consideration. One paper applied a CNN module to perform the first classification type, which only classifies the tumor into normal or abnormal. The other two papers classified the tumor types by using an SVM and a deep learning classifier respectively. The CNN module had a 100% accuracy with 0% results of false positive and false negative. The SVM algorithm had also an error rate of 6.9%, more than 90% classification sensitivity and more than 97% specificity. The deep semi-supervised learning classifier managed to achieve high performance on two datasets. **Conclusion:** We concluded that artificial intelligence techniques proved to be helpful in brain tumor classification and reduced the amount of time and effort needed to identify a tumor for a medical practitioner.

Keywords: Brain tumor, MRI, CNN, K-means, Augmentation, D-SEG, Classification.

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1 Introduction

There are two types of brain tumor: benign and malignant. The first one is harmless, while the other one is life-threatening [4]. Considering the origin of the tumor, brain tumors are divided into two catagories: tumors formed in the brain from brain nerves, and from other parts of the body metastasized to the brain [2].

Magnetic resonance imaging (MRI) is very common in neurology and is used to excite the target tissue under the influence of magnetic field to produce an image of its interior [2]. Imaging techniques can give details about the size, shape, and the location of the tumor, which would help doctors to provide better treatment [2].

Computer vision -based medical applications and artificial intelligence have become important in clinics and hospitals as they assist doctors to better treat and diagnose patients [6]. Convolutional neural networks (CNNs) and support vector machines are very common classification methods and helped in automating the diagnosis process. It seems that CNN modules are more used in prediction, and support vector machines in classification [6].

The classification process usually includes feature extraction first, and then classification. It can be said that brain tumors classification has two types: classification of whether there is a tumor or not, normal or abnormal, and classification that can specify tumor types [6].

The second type of classification could be more challenging since there are more data and the cancer type must be specified [6]. Artificial intelligence and deep learning algorithms are widely used to extract features, which would make the system more efficient, and they do not require a professional knowledge in the medical field. Segmentation is also used to determine the infected region of brain tissue from an MR image [5].

This review will address different methods of brain tumor classification based on machine learning and deep learning. It will explore the results of other works that used these methods. This review is going to analyse and compare the results, utilized datasets and the methods of different algorithms.

2 Methods

2.1 Literature search

In order to evaluate brain tumor classification methods, a literature search has been conducted on PubMed to find different techniques. When searching the string "(brain) AND (tumor) AND (image) AND (classification) AND ((image segmentation) OR (neural network))", there were 399 articles. We used the filter full free text which gave us 188 results. Setting the date from 2015 to 2021 reduced the number of articles to 157. Further we used filters language only English and journal only Medline giving us 99 results. Each of them processed the acquired data in various ways. This review is focusing on articles that use machine learning approaches in classifying brain tumors, such as support vector machine, K-means clustering and regression.

We excluded review articles N = 3 articles and three original research were selected for review: Jones et al. [3], Ge et al. [1] and Khan et al. [4]. These articles were selected after considering their methods that are based on artificial intelligence and machine learning. Figure 1. shows the process used in this literature search.

2.2 Data analysis

The hardware and the computer analysis methods used were recorded, and so were the results like accuracy, specificity, sensitivity.

The datasets, pre and post processing done for the dataset used in each paper and the scope of the type of tumor classified using the models were recorded.

The result parameters in all the papers were used to evaluate the performance for each classification model.

3 Results

Khan et al., [4] suggested a CNN approach with data Augmentation and image processing to classify input images into cancerous and non-cancerous. Afterwards, the author used a transfer learning approach to compare the proposed method with previous works.

The author's dataset was small, and only 253 images were used. The image dataset quantity and complexity were increased using data augmentation techniques, such as flipping, rotating and brightness changes in the 253 images.The images were randomly split into training, validation and testing data. Each model used different number of filters, layers and parameters.

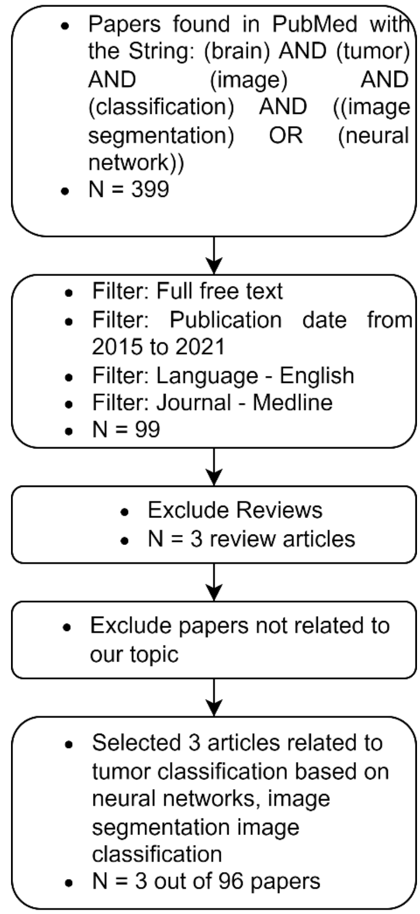

Figure 1: Flowchart of the literature search procedure.

The filter's sizes were also not the same. The proposed model by the author was able to reach 100% accuracy when classifying unknown data. Figure 4. shows the proposed methodology used.

Jones et al., [3] suggested a Diffusion Tensor Imaging (DTI) Segmentation (D- SEG) method to delineate tumor volumes of interest (VOIs). The DTIs scans were obtained using 2 different types of scanners from 95 patients with different types of tumors and 29 healthy subjects. The D-SEG technique uses K-means clustering to segment regions with similar diffusion characteristics [3]. The flood filling algorithm was used to extract tumor VOIs. The classification of tumor type was done using a support vector machine (SVM). The accuracy of SVM classification reached 94.7% with a low balanced error rate of 6.9%. Figure 2. illustrates the VOI extraction methods used in the proposed model. Row A shows Conventional fluid attenuated inversion recovery. Row B shows the tumor core, cystic and edematous regions. Row C shows the tumor cases, and row D represents the extracted VOI.

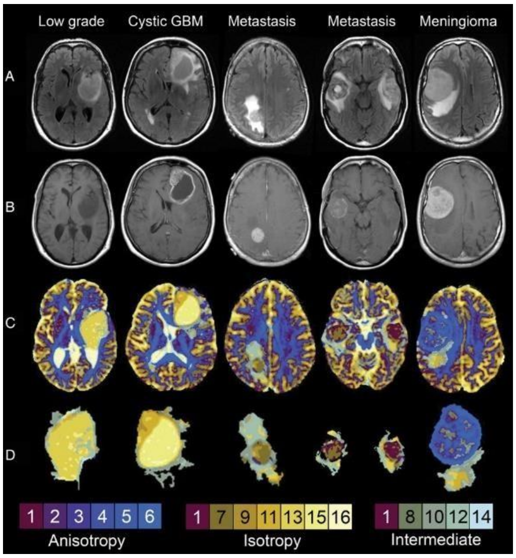

Figure 2. Individual patient images. Published by Jones et al., [3]. [The data is reproduced with no permission of the Author & publisher]

Ge et al., [1] used a deep semi-supervised learning classifier to classify different types of gliomas specifically [1]. Two datasets were used: the TCGA (The Cancer Genome Atlas) dataset for glioma subtype classification, and MICCAI (Medical Image Computing and Computer Assisted Intervention) for glioma grading. Ge et al., [1] used labelled and unlabelled training datasets, in addition to the testing data for glioma classification. The accuracy of the proposed method reached 86.53% on TCGA dataset and 90.70% when using MICCAI dataset.

Figure 3. shows the classification accuracy, sensitivity and specificity on the TCGA dataset. where the results were obtained from the test set averaged over 5 runs. Left: performance where GAN augmented data was added in the training set; Right: performance where no GAN augmented data was used in the training set. Red: from the proposed semi-supervised scheme; Black: from baseline-1 method; Blue: from baseline-2 method.

Khan et al., [4], Jones et al., [3] and Ge et al., [1] used different approaches to the classification problem. Accuracy was the common result attribute which helped them evaluate the performance of their model. Table 1 shows the information about each classification model used.

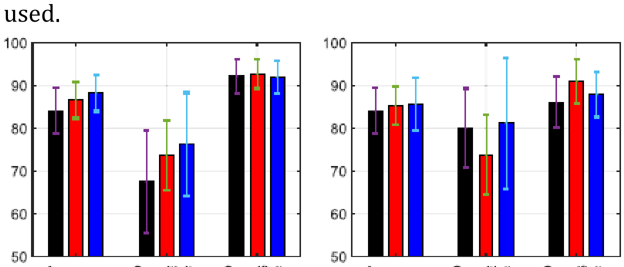

Figure 3. Performance on the TCGA dataset, published by Ge et al., [1], [The data is reproduced with no permission of the author & publisher]

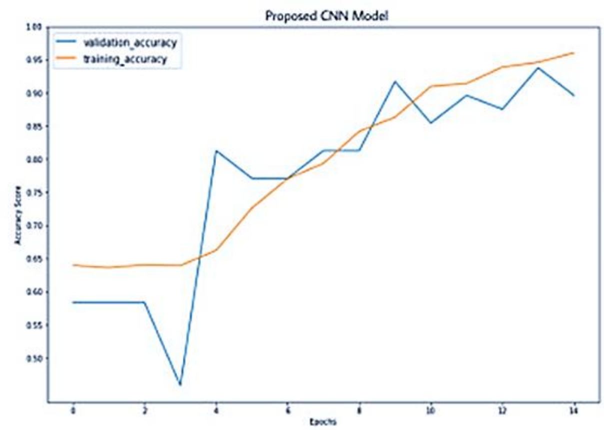

Figure 4: The accuracy graph of the proposed CNN Model. Published by Khan et al., [4]. [The data is reproduced with no permission of author & publisher]

4 Discussion

In this paper, a review was conducted on different methods used to classify types of brain tumors. In the first paper, Khan et al., [4] only considered whether the tumor was malignant or benign without specifying the tumor type. The author had a 100% true classification, where true negative (TN) and true positive (TP) are correct classification. TP indicates that there is an abnormal tumor, and TN shows that the brain is normal. False negative (FN) and false positive (FP) are incorrect classification.

Jones et al., [3], on the other hand, classified the tumor type using SVM that depended on training data set for each type. The method was able to classify glioma, metastases, and meningioma. Therefore, in this method, the system also needs to classify the type, not only if it is cancerous or not. Jones et al., [3] achieved more than 90% sensitivity and 97% specificity. The parameters to investigate in this paper would be accuracy, error rate, sensitivity, and specificity. It can be said that Jones et al. [3] method included more parameters than Khan et al. [4] and is, therefore, wider and addresses more aspects like types, healthy tumors, tumors size.

Ge et al., [1] also had the same parameters as Jones et al., [3], and classified specifically different types of gliomas. The proposed method, however, used two datasets. The first dataset included 3D brain scans for training while the other dataset included glioma types. The parameters to consider are also the same as in Jones et al., [3], but there are 2 datasets and thus, 2 different results for them.

Ge et al., [1] considered some factors when retrieving the results. For example, average results were shown, in addition to other results that took data augmentation and dataset into consideration. The methods used by Ge et al., [1], Jones et al., [3] and Khan et al., [4] show promising results but had a very small dataset to train the model.

Table 1: Information each classification model

Article	Classification algorithm	Dataset used	accuracy	specificity	sensitivity
Khan *et al.*, 2020 [4]	CNN model	155 images of malignant cancer and 98 of benign tumor	100%	True Negative:100%	True Positive:100%
Jones *et al.*, 2015 [3]	Support vector machine	95 tumor images and 29 healthy subjects images	94.70%	>97%	>90%
Ge *et al.*, 2020 [1]	Semi- supervised learning classifier	TCGA	86.53%	92.73%	73.75%
		MICCAI	90.70%	93.01%	84.35%

Future work could include other types of models and more realistic data in a variety of complexities as well as quantity to address the need to classify brain tumors. Moreover, this review can be expanded to include more brain classification-related papers with different classification techniques which would help in forming a bigger dataset that enables the solution to be generalized.

5 Conclusion

We conclude that implementing artificial intelligence techniques proved to be helpful in brain tumor classification and reduced the amount of time and effort needed to identify a tumor for a medical practitioner. Our results showed that convolutional neural network with pretrained models showed the highest accuracy in detecting the cancerous tumor.

The obtained results from these papers would be the first step to develop our own brain tumor classification model. Other relevant approches will be searched to have a clear understanding about the problem which would lead to a model with better results.

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