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ANALYSIS OF RECENT BRAIN TUMOR DETECTION TECHNIQUES

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Abstract: The uncontrolled growth of cells inside the brain or skull causes a brain tumour, which is a life-threatening neurological disorder. People with this disease are dying at an alarmingly high rate. Early detection of malignant tumours is crucial for patient treatment, because early detection increases the patient's chances of survival. If a patient is not properly treated, their chances of survival are usually very low. If a brain tumour is not detected early enough, it will almost certainly result in death. As a result, the use of an automated technology is required for early diagnosis of brain cancers. A major challenge is the segmentation, identification, and isolation of contaminated tumour regions from magnetic resonance (MR) images. However, radiologists or clinical specialists must go through a difficult and time-consuming process, and their performance is totally dependent on their competence. The employment of computer-assisted approaches becomes crucial to overcome these constraints.

IndexTerms— Brain Tumor, Image Segmentation, Deep Network, Machine Learning, MRI

I. INTRODUCTION

A brain tumor is a mass formed by a cluster of abnormal cells in the brain [1]. A hard skull protects the human brain. Any expansion in such a small area will trigger severe issues. There are two types of brain tumors: malignant and non-cancerous. As benign or malignant tumors grow, the pressure inside the skull will increase. This can cause lifelong brain damage and possibly death. Figure 1 (A) shows an MRI image of a healthy brain, while Figure 1 (B) shows an MRI image of a brain with a tumor. As a result, scientists and researchers have been attempting to create advanced procedures and strategies for detecting brain cancers. Although MRI and Computer Tomography (CT) are the two modalities widely used for marking the abnormalities in terms of shape, size, or location of brain tissues which in turn help in detecting the tumors, MRI is preferred more by doctors. As a result, scientists and researchers have become more interested in MRI. While identifying brain tumors from MRI images, conventional inspection by physicians is mostly used. However, automated approaches mainly implemented by computer-aided medical image processing techniques are increasingly aiding physicians in detecting brain tumors.[11]

The objectives of this research are, firstly, to explore how various image processing techniques are applied on MRI images for the detection of brain tumors. Secondly, to compare the performance of existing image processing techniques applied on MRI images for the detection of brain tumors. Finally, to propose which technique is the most efficient for the detection of brain tumors using MRI images through machine learning approaches. As a result, this research will provide the expected outcome i.e., efficient image processing technique to detect brain tumors using MRI images through machine learning approach which will assist pathology experts to provide proper treatment.

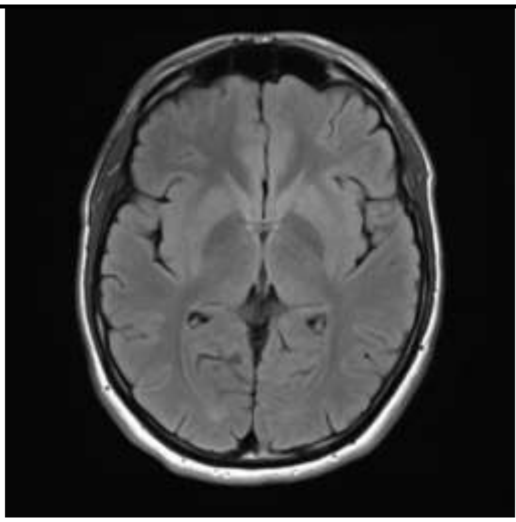

Figure 1 (A): MRI image of a healthy brain

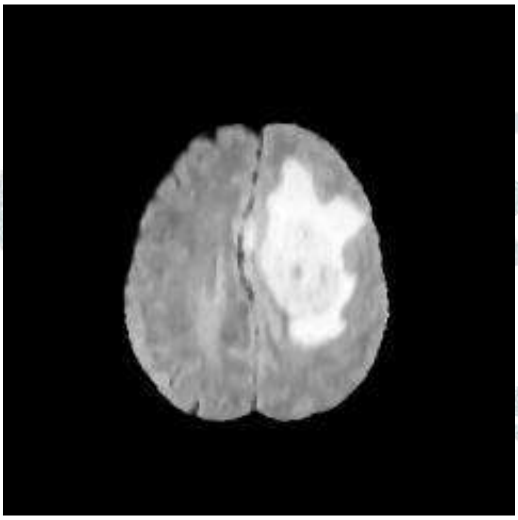

Figure 1 (B): MRI image of a brain with a tumor

II. DETECTION OF BRAIN TUMOR

Magnetic fields are used in an MRI to provide detailed images of the body and can also be used to detect tumor's size. Before the scan, a specific dye called a contrast medium is administered to create a clearer image. This dye can be injected directly into a patient's vein or taken as a tablet or drink. MRIs are used for diagnosing brain tumors because they produce more detailed images than CT scans as CT scans are just X-ray of the body from 3 different angles which are later combined by the computer into a detailed 3-dimensional image that portrays any abnormalities or tumors.[12]

There are several different path which could and are being explored for the purpose of detecting brain tumor from the MRI one being using Machine Learning and another being various non Machine learning image segmentation algorithms one of the popular being thresholding and watershed algorithms [1] However it has been proven that the Deep learning and machine learning methods combined with the predictive power of artificial intelligence has a much superior accuracy.

III. RECENT HEADWAYS IN BRAIN TUMOR DETECTION

There are different hybrid models developed for detecting brain tumors. To develop the hybrid models, the features were extracted from the second last (sixth) layer of the top-performing transfer learning model (VGG16_CNN) as it provides the second most reduced set of features. In total there were 32 features in that layer. These features were then used as input for developing four other models, such as AdaBoost, CatBoost, XGboost, and the Stacked classifier. However, due to high time and space complexity, developing these models considering all the features of the images was not feasible. Thus, the VGG16_CNN model was used as a feature selection method to gain a reduced feature set, which is representative of the whole feature set.**[2]**To evaluate the performance of each prediction model, a separate test set was used which contains a total of 90 images, where 81 images were labeled as YES, on the other hand, the rest of the images were labeled as NO. The performance of each prediction model was measured in terms of its precision, recall, and F1 scores as discussed in table 1.

Table 1: Comparison of hybrid algorithms

Model	Precision	Recall	F1 score
Stacked	0.992	0.991	0.992
AdaBoost	0.942	0.933	0.937
CatBoost	0.939	0.944	0.939
XGBoost	0.956	0.956	0.956

From table 1 we can observe that the highest precision, recall as well as F1 score was achieved by XGBoost. Although the paper furnished splendid comparison and results via hybrid model there were a few problems identified. For starters, there is no established Benchmark Dataset for comparing existing approaches for detecting brain tumours from MRI data. As a result, data sharing is now available. Benchmark datasets can be used in conjunction with the dataset provided for this study (with prior permission from the originator). Second, a substantial volume of data was unavailable, which is essential for developing deep learning models.Third, as indicated by the enhanced performance of the developed models in this study, significant hyperparameter adjustment can aid in increasing the performance of ML and DL models. Fourth, there is a trade-off between algorithmic performance and time complexity; DL techniques produce superior results, but their time complexity is extremely high, suggesting that obtaining the results on these techniques takes an extremely long time. The ML algorithms, on the other hand, have a relatively low temporal complexity. It was observed that classification performance is extremely dependent on datasets and processes utilised; different state-of-the-art approaches can produce different results on the same dataset; the same methodology can produce different results for different datasets.

Another paper with the aim of classifying brain tumours implemented different and hybrid classification algorithms that the paper claimed to be better or atleast at par with the other classification algorithms. For their method, in the pre-processing stage, the suggested method employed a median filter. The features were extracted using Discrete Wavelet Transform, and Color Moments were utilised to compress the data to an ideal set of nine features, reducing complexity and memory utilisation. These nine features were retrieved from all 70 photos used in this study, 25 of which were normal and 45 of which were aberrant and impacted by three different disorders. These feature sets for all photos were fed into supervised classifiers, with Feed Forward - ANN and hybrid classifiers Random Subspace with Random Forest and Random Subspace with Bayesian Network showing promise in separating normal and abnormal images in terms of classification accuracy. The proposed technique was investigated using several statistical techniques, and the findings were compared to previous research. The majority of researchers employed accuracy to gauge performance, according to the literature. The performance and accuracy of the proposed algorithm for hybrid classifiers and FF-ANN are shown in Table 2. The RSwithRF and RSwithBN classifiers had accuracy of 97.14 percent and 95.71 percent, respectively. During the training stage, the suggested model for the FF-ANN had a classification accuracy of 100 percent, while during the testing stage, it had a classification accuracy of 91.66 percent. On average, depending on both training and testing, 95.83 percent accuracy was observed.[3]

Hybrid classifiers are more useful and complex than individual classifiers, according to a comparison of hybrid and individual classifiers. Individual classifiers perform worse than hybrid classifiers.

Table 2: Accuracy comparison of classification algorithms

Techniques	Overall Accuracy
LK + PCA + SVM	74
QK + PCA + SVM	84
PK + PCA + SVM	76
DWT + Feed Forward Back Propagation - ANN (FP-ANN)	92
DWT + PCA + FP-ANN	97
Encoded Information + PCA + KNN	96.33
MsFCM	96.77
DWT + PCA + FP-ANN	90

PCA + SVM	85
Pearson Correlation Coefficient (PCC) + SVM	79
ICA + SVM	82
DWT + RSwithRF	**97.14**
DWT + RSwithBN	**95.71**
DWT + CMs + FF-ANN	**95.83**

Although the paper provided some great insight into the comparison of hybrid and non-hybrid models there were some notable limitations such as it only put the proposed mechanism to test against a single non-hybrid and two hybrid classifiers. It is tested against only 70 photos from a single dataset hence lacking versatility. Furthermore, only three statistical features were evaluated in this study and are not compared to the most recent deep learning studies.

The next paper approached Multimodal magnetic Resonance Image Brain Tumor segmentation using ACU-Net Network. To overcome the problem of network computation efficiency, an ACU-Net network based on the U-Net architecture was proposed, with a deep separable convolution layer replacing the conventional convolution layer in the model.[4]
The full-scale jump connection approach is used to realise flexible feature fusion and enhance the speed of deep network convergence in the ACU-Net network using the Dense Residual block.[5] The active contour model was inserted into the ACU-Net to ensure that the inside and outside of the boundary were well-fitting, improving segmentation accuracy.
However the proposed model still has less scalability and poor adaptability.

Experimental results in table 3 show that ACU-Net has high segmentation accuracy for brain tumor images. Compared with other algorithms, Dice, Recall, and Precision have respectively increased by 13.65%, 8.82%, and 6.38%.

Table 3: Dice,Precision and recall of all the compared algorithms

WT/Models	FCN8s	FCN16s	FCN32s	U-Net	H-DenseUNet	UNet++	Proposed Method
Dice	0.8375	0.8106	0.7385	0.7457	0.8402	0.8383	**0.9273**
Recall	0.8446	0.7979	0.7316	0.7565	**0.8894**	0.8784	0.8119
Precision	0.8557	0.8512	0.7955	0.9026	0.8538	0.8617	**0.9054**
95% HD	2.7443	2.9843	3.285	2.6623	2.6275	2.6428	**1.3565**

Another approach involved using deep networks to segment the brain tumor. It states that Ensembling is frequently used for brain tumour segmentation, and it has the benefit of increasing both results and performance. It presented a lightweight ensemble made up of as few as two networks, each of which was trained on the training set selectively. These networks produce a segmentation map that differs in terms of tumour sub-regions segmented. After that, the segmentation maps are blended to get the final prediction.[6]
Network 1 (3D CNN)
The ensemble's first model is a 3D CNN, which was first built by Chen et al. To obtain feature representation at several scales for volumetric segmentation, it employs a multifiber unit (an array of 3D) with weighted dilated

convolutions. During the BraTS 2018 Challenge, the network performed admirably. They developed the model for better segmentation by building on their work.

Network 2 (3D U-Net)

The ensemble's second model is a 3D U-Net variation that differs from the conventional U-Net architecture in that the ReLU activation function is replaced with leaky ReLUs, and instance normalisation is used instead of batch normalisation. On the medical segmentation benchmark, the Medical Segmentation Decathlon, and the BraTS 2018 Challenge, the network produced comparable results. The model is built from the ground up on the dataset and has the same architecture.

Table 4 shows the results of an ensemble of two networks, U-Net and CNN variations, that were trained on the BraTS 2019 training set (n = 335) and tested on the BraTS 2019 validation set (n = 125). Instead of just averaging, we intelligently blend the segmentation maps from different models to produce a final prediction for tumour tissue type. The ensemble (proposed) achieved dice scores of 0.750 for augmenting tumour, 0.906 for total tumour, and 0.846 for tumour core.

Both models' segmentation maps are generated individually, and then the final merged output is displayed. The patient's dice scores for augmenting tumour, total tumour, and tumour core were 0.930, 0.949, and 0.927, respectively.

Table 4.1: Observed scores

Strategy	ET	WT	TC
Simple Averaging	0.740	0.903	0.805
Proposed Ensembling	0.750	0.906	0.846

Table 4.2: Observed scores of specific algorithms

Authors	ET	WT	TC
FCN	0.766	0.896	0.790
Residual Inception Dense Networks	0.779	0.898	0.784
U-Net	0.787	0.896	0.800
3D Multi-Encoder/Decoder Network	0.75	0.90	0.83
CNN	0.800	0.894	0.834
Proposed Method	0.750	0.906	0.846

Further analysis was done on different ensemble techniques to identify if there is any discrepancy between the methods and which of the two results is the most accurate of segmentations. The suggested ensembling methodology outperforms simple averaging, as evidenced by comparisons with several state-of-the-art methods (also validated on the BraTS 2019 dataset). During training, none of the other frameworks used any new data. The suggested ensemble, with the exception of the enhancing tumour, produces better segmentations than the other available networks for both the overall tumour and the tumour core, as indicated by the results of the dice The encouraging performance of their simple U-Net and CNN ensemble demonstrates its efficiency and potential usability in achieving comparable and often superior segmentation accuracy than competitors.[7] Although the method was accurate there were some noted limitations such as Only the official validation set of the challenge is used to test the proposed segmentation ensemble. Validity of the approach can be confirmed by comparing it to different clinical MRI data.[8]

Second, they did not pre-process the data and post-process the results thoroughly enough. Several reported models use intensity normalisation and bias correction procedures to prepare their imaging data in order to reduce variability and make data identical and comparable.[9] The use of conditional random fields and other post-processing approaches has also been shown to improve segmentation accuracy.[10]

IV. CONCLUSION

The existing methods have enhanced the possibility of detection of brain tumor from the MRI and therefore increased the accuracy of detection and moreover eased the job of doctors. Using different kinds of Machine learning and deep learning algorithms and hybrid networks have opened new doors to discover more and develop more accurate and better solutions to add on to the existing methods.A thorough examination of existing methodologies will aid researchers in identifying their flaws. and find out more efficient solutions to them, which will help the doctors and increase the efficiency and accuracy of detection of this deadly problem.

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