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Brain Tumor Classification into High Grade and Low Grade Gliomas using Adaboost

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ABSTRACT

Brain is recognized as one of the complex organ of the human body. Abnormal formation of cells may affect the normal functioning of the brain. These abnormal cells may belong to category of benign cells resulting in low grade glioma or malignant cells resulting in high grade glioma. The treatment plans vary according to grade of glioma detected. This results in need of precise glioma grading. As per World Health Organization, biopsy is considered to be gold standard in glioma grading. Biopsy is an invasive procedure which may contains sampling errors. Biopsy may also contain subjectivity errors. This motivated the clinician to look for other methods which may overcome the limitations of biopsy reports. Machine learning and deep learning approaches using MRI is considered to be most promising alternative approach reported by scientist in literature. The presented work were based on the concept of AdaBoost approach which is an ensemble learning approach. The developed model was optimized w.r.t to two hyper parameters i.e. no. of estimators and learning rate keeping the base model fixed. The decision tree was us ed as a base model. The proposed developed model was trained and validated on BraTS 2018 dataset. The developed optimized model achieves reasonable accuracy in carrying out classification task i.e. high grade glioma vs. low grade glioma.

Keywords : High grade glioma, low grade glioma, AdaBoost, Texture Features, Feature Selection

I. INTRODUCTION

Brain is considered to be one of the complex organ of the body. If occurrence of uncontrolled division of cell takes place within the brain due to which abnormal formation of group of cells results in brain tumor. Tumor is considered to be life threatening disease. This abnormal growth of the cell may affects the normal functioning (figure-1).

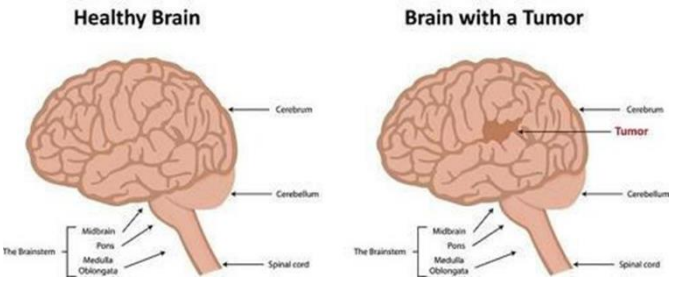

Fig 1. Figure showing healthy brain and brain with tumor [19]

Brain tumors were majorly classified in low grade tumor and high grade tumor. Grade I and Grade II tumors are considered to be low grade tumors and

Grade III and Grade IV tumors are considered to be high grade tumor [4]. Low grade tumor are considered to be non-cancerous or in other words less aggressive in comparison to high grade tumor. Exact causes of brain tumors are unknown till date and researchers are conducting research to know the causes of brain tumor [5-7, 16, 17]. Some of the symptoms of brain tumor includes: headache, difficulty in speaking, loss of movement etc. Interesting thing about brain tumor is that sometimes it does not shows the above mentioned symptoms and can discovered accidently.

Inorder to detect the tumor doctor may conduct investigations which may include imaging scans or biopsy or combination of both. Once tumor presence is confirmed, doctor may plan treatment and follow-required in process.

Magnetic resonance imaging is considered to be one of the favorite choice of investigation [1-15]. Figure below shows the some of the conventional MRI sequences such as T2, FLAIR and T1 CE respectively with tumor.

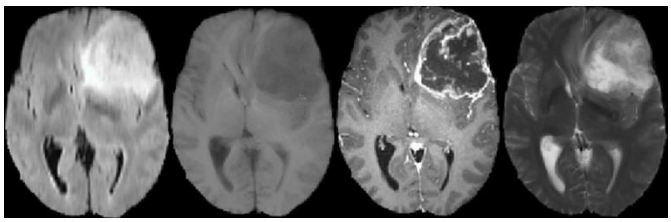

Fig 2. Row-1 show MRI images (FLAIR)(a), T1-weighted (b) Post-contrast T1-weighted (c)and T2-weighted (d) brain with tumor [1-3].

Once tumor presence is confirmed in the MRI, clinician may plan biopsy to know the type and grade of the tumor. Sometimes repeated biopsies may be performed by the clinicians when tumor tissues were not enough to define the type or grade of tumor or if there was any confusions. Biopsy is an invasive procedure and may involve subjective and sampling errors. Errors in investigation procedure may affects the clinical treatment planning and follow-ups [1-9].

Researchers were worked and still are working in the direction to address on questions like: can invasive biopsies be replaced, can sampling errors may be reduced etc. Clinicians, scientist and engineers from cross disciplinary areas are working in this direction. MRI investigations is considered to be non-invasive procedure [7-10]. Quantitative features which were extracted from MRI, were investigated as it is or with the help of machine leaning or deep leaning or transfer learning or any other procedure to identify the type and grade of glioma. Positive results which were obtained with the help of machine learning or deep learning motivates the researcher to further investigate and improve the results in this direction. Some of the challenges which were mentioned by researchers in their findings were: limited data set, class imbalance error, subjectivity involve in tumor segmentation, cost & time etc.

In the proposed work, a hypothesis was presented which tries to differentiate the low grade gliomas from high grade glioma using the conventional MRI sequences using the texture features. AdaBoost algorithm was used to perform this classification task. Pearson correlation coefficient was used to select the features that will contribute in the classification task. Finally a 10-Folds cross validation was used to validate the trained model. Developed model is tested against the out of sample errors for recording the accuracy.

The rest of the paper was organized as follows: section II discusses related work. Section III discusses the proposed classification approach. Section IV discusses the obtained results on MatLab 2020b platform and section V concludes the paper.

II. Related Work

This section describes the available literature work in the area of gliomas classification i.e. HGG vs LGG.Fatenet al . in their work used advanced sequences i.e. diffusion tensor, perfusion etc. along with convention imaging in making differentiation between LGG vas HGG [7]. Authors in their work [8] used the conventional MRI sequences along with advanced MRI sequences such as diffusion weighted

imaging in classifying gliomas into LGG vs HGG. The reported accuracy in their findings were 94.5%. Shoaib et al. in their work carried out the similar task and reported the accuracy equal to 80.65% [9]. A Vamvakas et al. in their studies reported the classification accuracy equal to 95.5% [10]. They have used MRI conventional sequences, advanced sequences plus spectroscopy findings in their carried out study. Y. Yang et al. in their study used the concept of transfer learning in carrying out the classification task. They used MRI conventional sequences in their study. Their reported accuracy was 86.7% [11].

W. Chen et al. in their study investigated the role of radiomics in classification task i.e. LGG vs HGG [12]. Zurfi et al. [13] in their studies used 3D texture analysis in gliomas grading task with the help of machine learning. Authors [14, 15] in their work used the radiomics features which when fed as input to machine leaning algorithms to carry or gliomas grading task.

Although several authors worked in this area and still research is going on. The major challenges mentioned by these authors in their manuscript were: small data set, reproducibility of results, globalized medical data, different acquisition protocols across different vendors, cost, subjectivity error etc. To address some of these issues, a globally publically available BraTS 2018 data set has been used [1- 3]. To reduce the cost in acquisition of advanced sequences, only conventional MRI sequences were used to carry out the desired classification task.

III. Proposed Work

This section explains the proposed work. BraTS 2018 dataset was used for carrying out the classification task. The dataset contains 210 high grade glioma cases and 75 low grade glioma cases. For every case, the data set contains T1, post contrast T1, T2, Fluid Attenuated Inversion recovery (FLAIR) sequences. The dataset belongs to 19 different centers. The dataset was annotated into four labels: Label-0 otherwise.

Label-1 Non-enhancing tumor and necrotic region
Label-2 Edema
Label-4 Enhancing tumor

The every sequence in BraTS 2018 dataset coregistered and interpolated. Texture features were extracted from region of interest (ROI) with the help of pyradiomics using python [16, 17]. Label-1 and label 4 were combined to form ROI. A total 104 features were computed which belongs to 7 different class's i.e. shape-based (2D), Gray level matrix (Cooccurence, Run Length, dependence and Size Zone Matrix) and Neighbouring Gray Tone difference matrix. Feature selection were made with the help of Pearson correlation coefficient method. Features were normalized using the concept of z-score. Finally 49 features were selected out of 104 computed features.

AdaBoost algorithm was used for carrying out the classification task. AdaBoost algorithm combines various weak learners to form a strong learner based on ensemble concept [18]. A 10-fold cross validation were performed to finally validate the model. The mean accuracy was calculated across the ten folds by developing different models by varying the number of estimators and learning rate (0.001 to 1). Decision tree was used as base estimator.

IV. Results

Learning rate was varied from 0.001 to 1 and no of estimators were varied from 10 to 400. It was noted further increasing in number of estimates shows no improvement in accuracy and hence not shown in figure-4. From the figure-4, it was observed that model performs better when number of estimators were equal to 150. From figure-5, it was observed model performs well when learning rate was equal to 0.1. Final model was developed keeping the hyper parameters i.e. learning rate equals to 0.1 and no of estimators equals to 150. Developed model achieves the accuracy equals

to 86.3% in classifying the tumor into high grade vs. low grade.

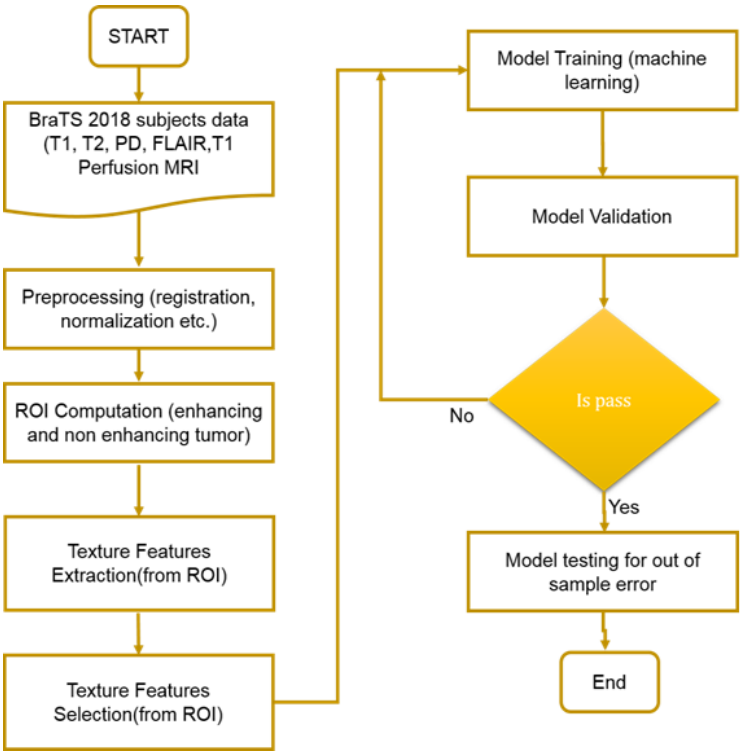

Fig 3. Figures shows the systematic diagarm of proposed concept (classification model development)

Table-1 Showing the optimized classifier performance

Base Classifier	No. of Estimator	Learning rate	Accuracy	Sensitivity	Specificity
Decision Tree	150	0.1	86.3	84.2	90.1

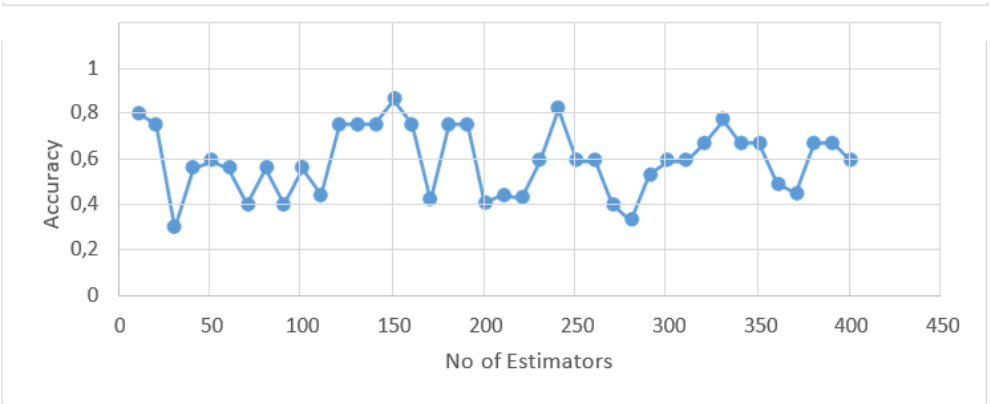

Fig 4. Shows the accuracy achieved by models by varying the no. of estimators keeping the base model fixed.

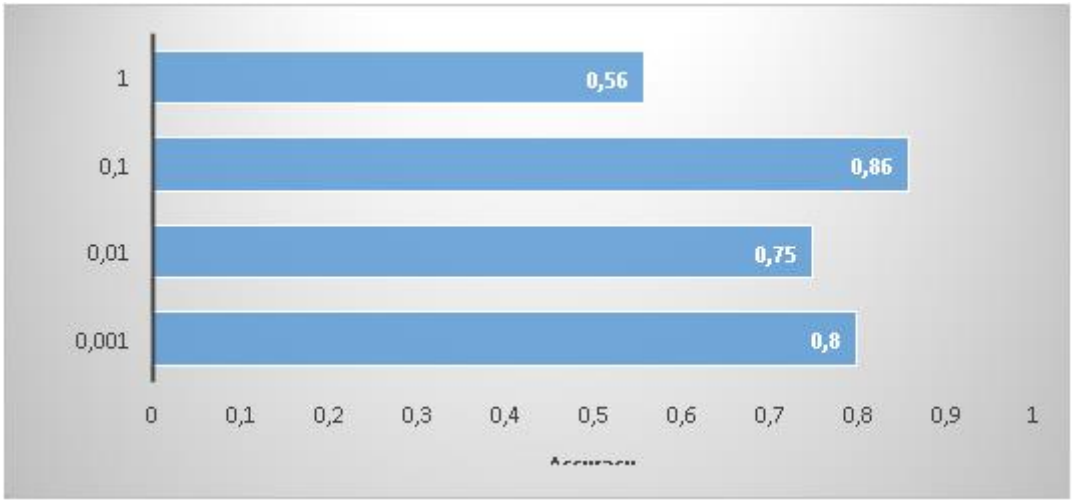

Fig 5. Shows the accuracy achieved by models by varying the learning rate keeping the base model fixed.

V. CONCLUSION

The whole paper was organized in four major sections: introduction, related work, and proposed work and simulation results. Introduction section briefly explains the need of brain tumor diagnosis. This section also explains the limitation of biopsy procedure and hence establishes need of precise glioma classification. The section II i.e. related work discusses the some of the recent work carried out by clinician and scientist in the area of glioma classification. In section III proposed work has been discussed. AdaBoost was used as an underlying concept to develop the model to carry out the designated task. Hyper parameters were optimized and cross validated. Finally model was developed over these optimized hyper parameters keeping the base estimator same. In result section, only the final optimized model accuracy were reported along with sensitivity and specificity. The results shows the model achieved the reasonable accuracy in classifying high grade glioma from low grade glioma. Hence concludes the presented paper.

VI. ACKNOWLEDGMENT

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