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Detection of Gliomas in Spinal Cord Using U-Net++ Segmentation with Xg Boost Classification

Oshin Dhiman
Information Technology Programmer Analyst,
LaSalle College, Montreal
oshin.dhiman@gmail.com

Dr. Anand Sharma
Asst. Prof., Department of CSE,
Mody University of Science and Technology, Lakshmangarh
https://orcid.org/0000-0002-9995-6226
anand_glee@yahoo.co.in

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Abstract

The most prevalent primary brain tumours are gliomas. According to recommendations of the World Health Organization (WHO), they are divided into 4 classes (Grade I-II-III-IV). This paper proposes novel technique in early detection of Gliomas in spinal cord based on segmentation and classification techniques by DL methods. Here input image has been pre-processed for noise removal, image resizing and smoothening of image. Then this processed image has been segmented utilizing U-Net++ architecture in which the skull or vertebral column parts has been segmented and classified using XG_Boost architecture. Our method's effectiveness on a dataset of 3064 MRI image slices from 233 patients that is publically available is compared with previously published classical ML as well as DL techniques. In comparison, our methodology remarkably outperformed the other methods utilising the same database, with a tumour classification accuracy of 0.965.
Keywords: Gliomas, brain tumors, segmentation, classification, deep learning.

1. Introduction:

Primary malignant tumours called gliomas, which are frequently found in the brain and have a high mortality rate and relapse rate. The American Cancer Society reports that 23,880 people received diagnoses for malignant brain and spinal cord tumours in 2018, and 70% of those people passed away [1] [2]. Meningiomas, gliomas, and hypoyphosis tumours are some of the primary brain tumours [3] [4]. The information needed to diagnose cancers (tumour kind, shape, size, location, etc.) can be obtained using a variety of medical imaging modalities [5]. Hundreds of 2D image slices with strong soft tissue contrast are produced during acquisition phase of an MRI scan without use of ionising radiation. T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted contrast-enhanced MRI (T1-CE), and Fluid Attenuated Inversion Recovery are 4 MRI models utilised in diagnosis (FLAIR). The remaining paper is arranged as follows: Exhibits in Section 2 discuss a literature review on crops. A suggested gliomas detection design is presented in Section 3. Findings of experiment are shown in Section 4. Future application is covered in Section 5 of the study.

2. Related works:

Recently, many imaging modalities, particularly those acquired using MRI, have been utilised to detect and grade brain cancers using ML as well as DL methods. Work [7] suggests a system that combines deep learning (DL) methods and discrete wavelet transform (DWT) features. According to the findings, they are able to attain a sensitivity of 97.0% and an accuracy rate of 96.97%. A brain tumour classification method based on characteristics from CNN and Gray Level Co-occurrence Matrix (GLCM) research was described in [8]. For automated brain tumour detection as well as grading, author [9] suggested a deep CNN-based system. The outcomes demonstrated that the method has a 97.5% accuracy rate. On the other hand, study [10] used fine ring-form partition and region of interest (ROI) augmentation to enhance effectiveness of brain tumour classification procedure. Experimental findings shown that for the intensity histogram, GLCM, and BoW, respectively, the accuracy increased from 71.39% to 78.18%, 83.54% to 87.54%, and 89.72% to 91.28%.

3. Materials and Methods:

In this research, we applied a U-Net++ method network for tumor segmentation and XG_Boost architecture based classification. We initially used a single U-Net++ and sent all training dataset to that network for segmentation and classification. All dataset images are grayscale and the foreground of the images are located at the center. Images are captured from different views of the skull; hence the size and position of the tumors vary in different angles. These differences in the size of the tumors make the diagnosis of the tumor hard. In practice, the expert physician knows the direction that the MR image is captured. Since the learning process in deep networks is similar to the human learning process, we decided to create the same situation for the deep neural networks. We found out using a single network for identification of tumors in all images does not produce accurate results. The overall proposed architecture is shown in figure-1.

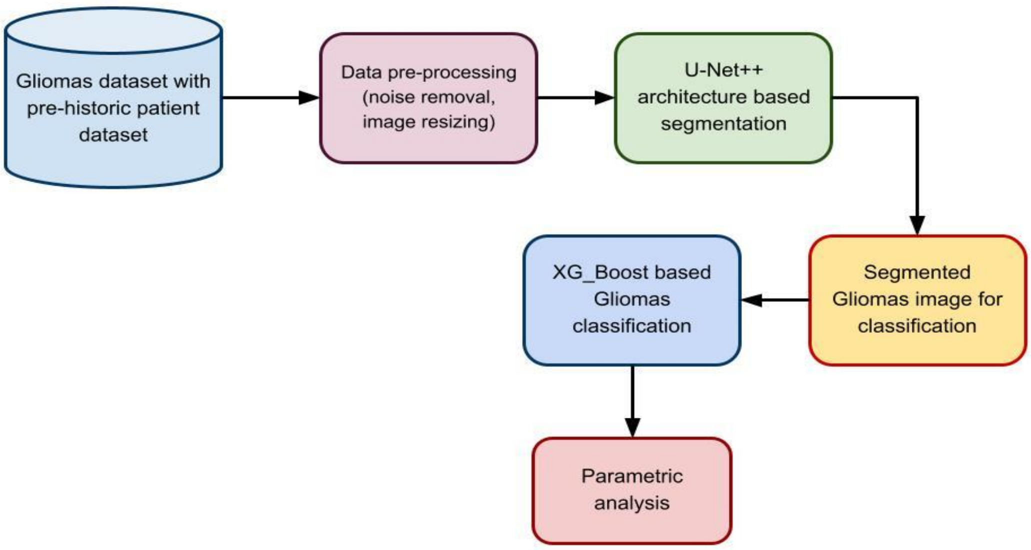

Figure-1 Overall Proposed architecture

3.1 U-Net++ based Gliomas segmentation:

No contextual information was transferred between shallow as well as deep layers in the prior basic architecture. The architecture produces images with the same dimensions as the input images, which have a resolution of 256 x256. The following are numerical representations of ReLU with the sigmoid activation function in eq. (1):

$$\mathrm{ReLU}(q) = \begin{cases} 0, & \text{if } q \leq 0 \\ q, & \text{otherwise} \end{cases}$$
$$\mathrm{Sigmoid}(q) = \frac{1}{1+\exp(-q)} \qquad (1)$$

3.2 XG-Boost based Gliomas Classification:

An effective gradient-boosted decision tree technique is XGBoost. XGB invented the technique known as gradient boosting. Since the full tree has been made, we prune the final tree in a bottom-up manner, and the user is also aware of the depth. Using 50 photos and cross-validating the results, our methodology demonstrated 100% accuracy in the classification of brain tumours. The outcomes were as we had anticipated, and computation took incredibly little time.

In order to grow a tree, the aim is to continuously add trees and split features in eq. (2).

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{T} f_k(x_i), f_k \in \mathcal{F} \qquad (2)$$

Describing function as eq. (3), (4).

$$\mathcal{F} = \{f(x) = w_{q(x)}\}(q: R^m \to T, w \in R^T) \qquad (3)$$

$$L(\phi) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1} \Omega(f_k), \text{ where } \Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \qquad (4)$$

The terms "T" and "W" stand for "Leaf Node Weight" and "N" correspondingly. In order to avoid overfitting, regulates number of leaf nodes. In study, we select XGBoost classifier as method for numerical experiments. Its maximum depth is nine, learning rate γ is 0.1, and accuracy λ is 0.3 by 10-fold cross-validation.

4. Experimental analysis:

Results of numerous experiments used to evaluate effectiveness of suggested hybrid method are presented in this section. Proposed hybrid method was evaluated using a computer that had the following features: Windows 7 operating system, NumPy, SciPy, Pandas, Keras, and Matplotlib frameworks, as well as an Intel(R) Core (TM) i5-7500 CPU with a 32-bit OS, 4 GB of RAM.

Table-1 Comparative analysis between proposed and existing technique

Parameters (%)	**CNN**	**KNN**	**SVM**	**DNN**	**U-net_VGG-19**	**U-net++_XGboost (propose)**
Accuracy	88	89	91	93	93.51	96.9
Precision	86	85	84	94.1	93.3	96.97
Recall	77	75	76	87.5	92.43	96.27
F1 - Score	79	80	81	80	92	96.56

The above table-1 shows comparative analysis between proposed and existing technique in Gliomas detection based on segmentation and classification techniques. Here the proposed technique has been compared with CNN,KNN, SVM, DNN and U-net_VGG-19. The comparative graphs has been shown below.

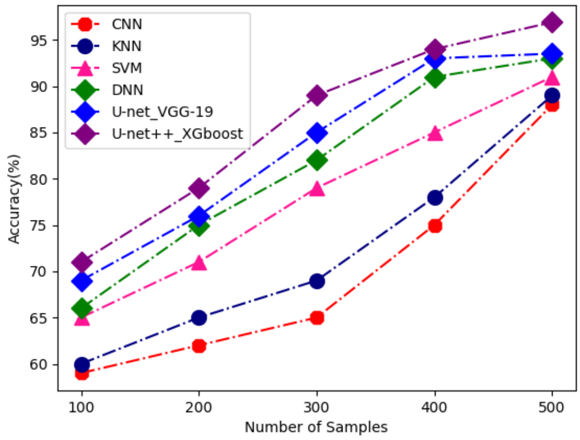

Figure-3 Comparative analysis of Accuracy

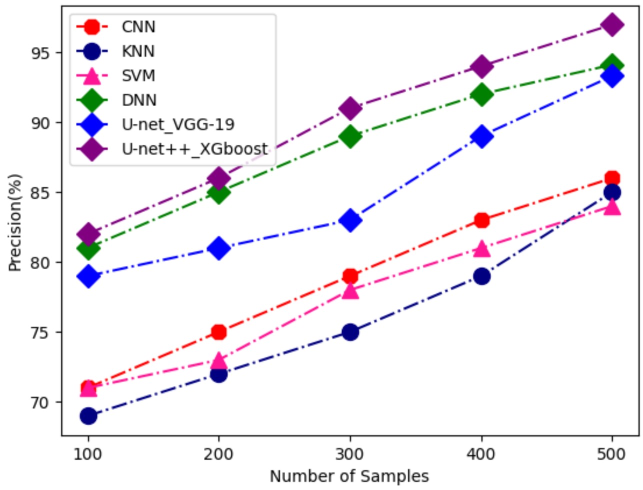

Figure-4 Comparative analysis of Precision

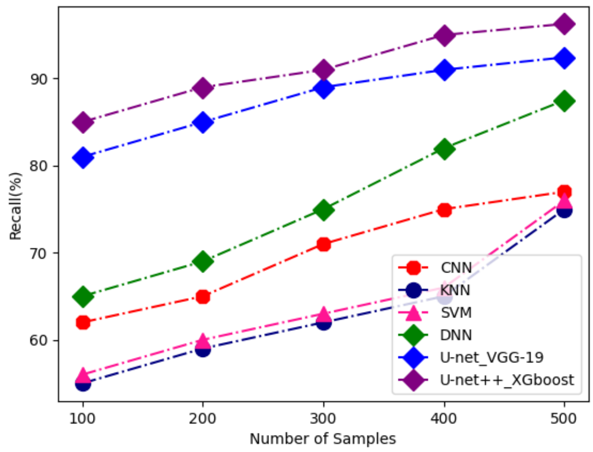

Figure-5 Comparative analysis of Recall

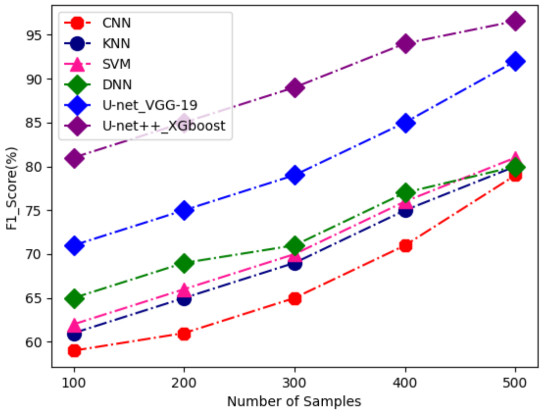

Figure-5 Comparative analysis of F-1 score

Above figure 2-5 shows the comparative analysis based on proposed and existing techniques in Gliomas detection. Here the proposed technique obtained optimal results in terms of accuracy, precision, recall and F-1 score. Proposed technique U-net++_XGboost obtained accuracy of 96.9%, precision of 96.97%, recall of 96.27% and F-1 score of 96.56%. when compared with existing accuracy in detecting tumor is enhanced with minimal computational time.

5. Conclusion:

This paper proposed novel technique in early detection of Gliomas using deep learning based segmentation and classification. Here We assessed its performance utilizing a dataset of T1-weighted, contrast-enhanced MRI images that is available to the general public. We have added two new building pieces to the U-Net++ architecture: wide context (WC) and residual extended skip (RES). The cost function, which includes number of leaf nodes in tree as well as score sum of squares on every leaf node, is then added with regular terms to manage the complexity of the model using an XG Boost based classifier. We contrasted our findings with those of seven additional brain tumour classification methods that made use of the same dataset. With a score of 0.965, our approach produced the highest tumour classification accuracy.

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