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Brain tumor detection using transfer learning

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Abstract

In recent times, brain tumours are considering the most threatening disease for human health and life. The mortality rate of brain tumor amongst all cancerous diseases is 7%, which is quite high. The medical image analysis becomes more challenging due to complex architecture of the numerous brain tumours; which are irregular in shape and size. Their overlapping tissues with healthy brain tissues further make it extremely difficult to identify their presence. Similarly determining their type and size further expedite the complexity of analysis procedure. Traditional machines learning methods involving human intervention are not adequately producing the optimal results, time consuming and rely on human experts. Deep learning models provide fully automated models and overcome the limitation of traditional procedure. Deep learning models provide adequate mechanism to identify tumor, its type and size adequately. Our proposed R-CNN along with the transfer learning mechanism between Random Forest and Support Vector Machine (SVM) yields competitive results. The experiment is performed over MRI modalities using python open CV libraries. Deep learning fully automated analysis provide adequate and timely statistics about tumor, that helps medical expert to timely initiate the adequate treatment, which is a significant towards saving human life [1].

Keywords: Brain tumor identification; R-CNN; Transfer Learning; Random Forest and SVM; Hybrid model

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Related Work

In order to determine the type of tumor being benign or malignant features extraction performed and then analysis applied; selection of classifier is another crucial area for the success of the overall model to obtain authentic and correct type of the tumor. Various unsupervised methods like GLCM, GLDM, Haar wavelet transforms, and Markov models etc along with human intervention show poor robustness. Therefore, a fully automated deep learning model like CNN (Ketkar N., 2017), RCNN, and Faster RCNN etc showed good result comparatively [1, 2].

Rundo et al. proposed a fusion of fully automatic technique using deep learning and an unsupervised FCM clustering known as next for identification and detection of necrotic ROI for Gross Tumor Volume (GTV). (Rundo et al., 2018)

Rundo proposed another MRI enhancement based schemes for the quality improvement of the MR imagery. The scheme utilized the concept of adaptive histogram equalization. Genetic algorithm used to optimize the threshold parameters. Superior result achieved over existing enhancement schemes. (Rundo et al.,2019b). Huang et al. utilized fusion of deep learning models like differential feature neural network (DFNN) and along with data augmentation to form an automatic screening tumor system. A new differential feature map (DFM) block was introduced to ensure enhancement ROIs, that act as an input to the extended squeeze-and-excitation (SE) blocks. (Huang et al., 2020)

Havaei et al. introduced deeper convolutional neural network based brain tumor automatic segmentation technique. Various models and their performance investigated during their experimental work. (Havaei et al.,2017). Oliveira et al. introduced brain tumor segmentation model comprising genetic algorithm and AdaBoost classifier and achieved promising results. They performed their experiment using FLAIR MRI modalities. (Oliveira et al., 2018)

Sharif introduced multimodal brain tumor classification based decision support system using Densenet 201 Pre-trained deep learning model. A fusion Entropy-Kurtosis-based high feature Selection with modified genetic algorithm and SVM cubic classifier. Promising results achieved over existing neural nets models. (Sharif et al., 2021)

A. Yang et.al utilize also Convolution Neural Network (CNN) as Xception and Dense Net for extreme features extraction to sift out the imagery surface information using local binary pattern (LBP). (A. Yang et al., 2019)

Z. Ullah et al. utilized ANN to determine the tumor's type as benign or malignant by extracting feature using Haar Wavelet transform. (Z. Ullah et al., 2017)

M. Mittal et al. Introduced an efficient scheme on MRI Image modalities for segmenting unhealthy brain tissue by employing deep learning concepts [3, 4]. The fully automatic segmentation achieved as a combination of Stationary Wavelet Transform and Growing Convolution Neural Network. The proposed hybrid approach showed more accurate and optimal result in comparison with standalone automation procedure. The validation and evaluation procedure showed that the proposed strategy incorporating deep learning outperforms the existing schemes. (M. Mittal et al., 2019)

Joans and Sandhiya introduced a genetic Algorithm based feature selection scheme for the classification of MRI imagery. In order to accomplish this strategy 2nd order features have been utilized. The proposed scheme showed higher accuracy in comparison with existing schemes. (Joans and Sandhiya., 2017)

Fields et al. proposed decision classifier based on machine learning using 3D MRI radiomics metrics features to distinguish among benign and malignant brain tissues. A bulk of features up to 1708 features extracted from each ROI [5]. The proposed models works equally well with restricted datasets like T2FS and STIR showing promising results thus eliminating complex analysis required for co-registration and increased the applicability in clinical practice.(Fields et al., 2021)

Introduction

Brain tumor mortality rate is increasing rapidly as time passes, from 2005 to 2015 there was a 1.4% incidents of brain tumor amongst all tumor cases and in 2018 there were 6-8% people were effected as reported by WHO report.

The diagnosis and analysis of tumor region is challenging task due to its complex structure. (Zheng et al.,2019). MRI due to its longitudinal and contrast provide a flexibility to visualize soft brain tissues thus making it suitable choice for tumor analysis. (Y.Q. Li. et al.,2019).Various ML schemes including Content base retrieval, threshold, region growing and clustering based techniques were introduced in the form of an automatic and semiautomatic schemes for classification and segmentation of brain tumor.

Ukil and Quinlan and J.R narrated that The key success of a model depends on not only to detect the presence of the tumor but to determine its type to be benign or malignant as well; however miss classifying the type would pose a serious threat to the patient. Support Vector Machine, Decision Trees and Random forest were use as major classifier for image classification and segmentation as well.

Zhao et al. works narrated that Neural Network in its various variations played a significant role for obtaining result that is more promising for classification and segmentation of digital imagery [6].

We have organized our work in this experimental study by arranging the sections as follows: Section 2 explains the existing proposed deep learning models, hybrid fusion schemes, random forest and SVM based schemes foe classification over MRI modalities to distinguish benign and malignant soft brain tissues. Section 3 explains the in details the proposed strategy and their combination that ultimately forms the framework. All three models are explained separately and how they related to each other and interfaced at an abstract level. Section 4 contains Data sets and evaluation criteria utilized for the proposed study. Section 5 explains the results and analysis about results obtain and their mutual comparison with existing schemes. Finally, the conclusion and future scope of work elaborated.

Discussion

CNN-RF-SVM transfer learning model

Data pre-processing: For an adequate performance, a lot of data is required to build a CNN. The aim is to cover all possible sample space with as much distinct and unique samples with voluminous data set. However, as a ground reality it is hard to find such samples pertaining to brain tumor. Therefore, an amplification of the available data set is inevitable, using micro-variable replica of the existing data set, incorporating the rules of data production, eventually to get more similar data of sample space. The amplified data is close to the real sample space, covering and exploiting the characteristics of the real sample space. We have use cropping, zooming and flip rotation to amplify our data, we have also utilize any publically available synthesize data as well [7].

CNN configurations: We have adopted classical CNN model that includes, dual convolution and dual pooling layers, followed by a fully connected layers, ReLU activation function utilized; for fast convergence and gradient diffusion reduction. Softmax is utilized at outer layer. With the aim to get maximum features, we have introduced all possible MRI modalities including Flair, T1, T2 and TIC. We have introduced two CNN with different configuration to extract maximum and versatile feature, the depiction of each given.

Random Forest and SVM transfer learning: We are utilizing the power of RF and SVM, as former utilize weak predictor's aggregation to have an optimal result by exploring entire solution space and resistant to over fitting as well, while later provide an ease of linear separation in high dimensional space [8].

Random Forest Classifier: It's an ensemble method in the form of closest neighbour predictor. RF starts as a weak predictor as a decision tree, from top to bottom the idea is to transform the input in the form of traversal get grouped into smaller and smaller group.

For certain numbers T trees the entire RF can be trained as follows:

A. From the combined ranked based high coefficient features vector N cases are randomly selected for the formation of subset, 9 N must be (60%-70% of the features vector volume)

B. From all the predictor variables 'm' predictor variables selected at each node. An optimal split obtained by an objective utility selected, to operate on each node to obtain a binary split.

C. Repeat step 2 at each node for some other m predictor variables.

Encountering an input, The RF runs it down to all trees, so as a result an average or weighted average from all trees is aggregated or using majority voting to form the strongest result. Thus achieving the strongest result from all weaker predictors.

SVM classifier and learning transfer: We have utilized our previously proposed SVM model. (Syed Afsar Ali Shah Tirmzi et al.,2021). An optimal classification technique for classifying soft tissues used in this experimentation, as brain tissues is soft in nature. Using SVM hyper plane formed in high dimensionality space, which provides delineation for pattern to be classified. To increase the optimal result determination SVM model design modelled in such a way that input data remain at most distance from its hyper plane; elaborates various components and configuration of proposed SVM.

The combined features vector from multi CNN placed in using one of our previously proposed genetic algorithm based placement strategy based on rank selection i.e. high ranked features are place from bottom up, the reduction of weaker features are dropped. Again using genetic based selection criteria the features selected for training of the RF and SVM classifier. The RF share its learning with SVM classifier and proposed region from RPN updated intermediately. The iteration procedure for transfer learning between RF and SVM finally yields the optimal tumor region. The procedure repeated until all the proposed tumor regions gets refined. This strategy takes advantage of both RF and SVM side by side, one overcoming limitations of other as well; RF segments may contains hole which are filled with RPN proposed segments and SVM learning, The entire framework is depicted.

Both CNN1 and CNN2 with varying input size are trained simultaneously, the features are extracted and place in vector V1 and V2 respectively as V1 [v11, v12... v1m] and V2= [v21, v22... v2n]. These vectors then merged into single vector containing strongest features only and weaker ones are drop to obtained optimal results. This vector is then forward to the fully connected layer.

Identification of tumor based on hybrid model with transfer learning

After getting strongest features from multiple CNNs, these features then used to train both Random Forest and SVM separately, both classifiers uses transfer learning iteratively. The proposed region generated by RPN is refined as an intermediate step during all the iterations. The SVM and RF eventually classify and get an optimal segmentation; the type of tumor classified by the SVM as either benign or malignant.

Data Set and Validation

Data Set

For our experiment, The BRATS2015 contest data is utilized. It contains 220 high and 54 low grade glioma. It also contains mixed 53 low/high glioma. It consists of T1, T2, T1C and Flair as test cases.

Evaluation Criteria

The accuracy and efficiency are crucial for devised algorithms, model or system. Some of such parameters are as follows:

1. Accuracy

2. Sensitivity

3. Specificity

Results and Discussions

Dual CNN vs. Single CNN

Our results as how that dual CNN comes up with better performance than a single CNN. It is also evident; that CNN with different configuration provide multifarious features and combining their strongest features improved the overall results of the proposed framework. Shows the classified image of benign and malignant tumor.

We have tried to take advantage of different configurations of CNN along with the combined effect of both and our results showed model is adequate to produce good results.

Identification of tumor based on hybrid model with transfer learning

After balancing malignant and benign cases in the available data sets, our proposed hybrid model incorporating RCNN, RF and SVM with transfer learning mechanism produced competitive results as compared to the existing schemes [9, 10]

Conclusion

This article explored a hybrid model using RCNN , RF and SVM employing transfer learning mechanism from RF to SVM classifier with the aim to take advantage of both the classifiers i.e. RF's ability to explore larger feature and dimensional space and SVM's high dimensional reparability to get optimal classification of the segmented ROI. Our proposed model successfully achieves competitive results for correct identification of brain tumor as either benign or malignant. Our obtain results endorsed the fact that proposed model is highly robust and accurate. It is also not prone to misclassification and class imbalance. We have also achieved good classification pertaining to benign and malignant accuracy. In future we will determine the size, location and volume of the tumor.

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