International Journal of Humanities and Social Science Invention (IJHSSI)
ISSN (Online): 2319 – 7722, ISSN (Print): 2319 – 7714
www.ijhssi.org ||Volume 11 Issue 4 Ser. II || April, 2022 || PP. 12-17

Model for Prediction of Brain Tumour Status Using MRI Image Data

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ABSTRACT

Radiology is a broad subject that needs more knowledge and understanding of medical science to identify tumors accurately. The need for a tumor detection program, thus, overcomes the lack of qualified radiologists. Using magnetic resonance imaging, biomedical image processing makes it easier to detect and locate brain tumors. In this study, a segmentation and detection method for brain tumors was developed using images from the MRI sequence as an input image to identify the tumor area. This process is difficult due to the wide variety of tumor tissues in the presence of different patients, and, in most cases, the similarity within normal tissues makes the task difficult. The main goal is to classify the brain in the presence of a brain tumor or a healthy brain. The proposed system has been researched based on Berkeley's wavelet transformation (BWT) and deep learning classifier to improve performance and simplify the process of medical image segmentation. Significant features are extracted from each segmented tissue using the gray-level-co-occurrence matrix (GLCM) method, followed by a feature optimization using a genetic algorithm. The innovative final result of the approach implemented was assessed based on accuracy, sensitivity, specificity, and coefficient.

Date of Submission: 04-04-2022 Date of Acceptance: 19-04-2022

I. INTRODUCTION

A brain tumor is a mass or growth of abnormal cells in the brain which might be cancerous (malignant) or noncancerous (benign). The early, comprehensive diagnosis and proper treatments are essential for a patient's survival in brain tumor management. During the past decades, more than 120 types of brain tumors were discovered by medical scientists. These brain tumors can be broadly categorized into two main groups, namely, primary brain tumors, which originate in the brain itself and secondary deposits in the brain, where the primary tumor is elsewhere in the body [1]. Typically, noninvasive medical imaging techniques such as Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) are favoured as brain tumor identification tools at the initial stages, over incursion invasive procedures like tissue biopsies [2, 3]. The authors in [4] found that CT, MRI, and Positron Emission Tomography (PET) usage has increased by 7.8%, 10%, and 57%, respectively, during the period of 1996–2010. Furthermore, as of healthcare resource statistics of the EU for 2020 [5], the EU Member States have shown a widespread increase in the availability of medical imaging technology and equipment for diagnosis in the recent decades. Moreover, according to [6], the overall employment of radiologic and MRI technologists grows faster than the average for all occupations in the USA. All these findings confirm that medical image-based diagnosis is favoured in the modern healthcare system.

Medical image classification and segmentation is a field, where deep learning can make a huge impact with promising results. It facilitates the automation of noninvasive imaging-based diagnosis. Interestingly, computer-aided brain tumor diagnosis has effectively utilized the advances in medical image processing in the past and has opened up many promising research activities in the domain of deep learning, with the expectation of developing entirely computerized automatic accurate diagnostic systems for physicians. Each year, the dataset is updated and the overall performance of the proposed algorithms has shown a tremendous improvement over time. On the whole, the accuracy of the algorithms proposed using the BRATS dataset falls around 90% [8–10]. Some of these algorithms were developed using classical CNN architecture whereas some are developed using improved CNN algorithms like U-net [11] and superpixel-based extremely randomized trees [12].

Another popular and publicly available brain tumour dataset is the Figshare MRI dataset [13, 14] which is the dataset employed in this paper. Due to the easy accessibility and the ready availability, the Figshare MRI brain tumour dataset also has been used in many brain tumor classification and segmentation related research

[15–18]. The dataset, which was initiated in 2015 and last updated in 2017 [13, 16], carries an average classification accuracy in the range of 90–95% [14, 16, 19, 20]. The authors in [16] achieved a classification average of 95% accuracy by using a modified CNN architecture while the authors in [15] achieved around 96% accuracy with an automatic content-based image retrieval (CBIR) system. A deep network was enhanced by employing cross channel normalization (CCN) and parametric rectified linear unit (PRELU) in [18] for brain tumor segmentation.

II. PROBLEM DESCRIPTION

In the previous work by the authors, a region proposal algorithm is proposed to address the problem of selecting a random number of objects in a single region [21, 22]. In the proposed method, instead of searching the entire image for the number of objects, the algorithm searches for objects in several selective areas of the image, while treating each subregion as an independent subimage. In [21], a fully autonomous learning algorithm was constructed using Region-based Faster Convolutional Neural Network (Faster R-CNN) to localize the meningioma tumor regions in MRI. Once the tumor is localized, Prewitt and Sobel edge detection algorithms are applied to the localization output, with the expectation of detecting the exact tumor boundary. Both of these techniques compute an approximate tumor boundary using the gradient intensity function of the image [23]. As MRIs on the whole consist of Rician noise and edges are not defined only by gradient, these algorithms underperform in this task. In practice, the effectiveness of the developed deep learning models to make informed decisions are evaluated through accuracy and system loss. Going beyond simple accuracy, standard mathematical objective parameters such as precision, recall, and Dice Score are utilized to choose the best model for the given problem. Furthermore, graphical representations such as confusion matrix and receiver operation characteristic (ROC) too are utilized to evaluate the performance of the deep learning model. A confusion matrix is a two-dimensional matrix which summarises the performance of the classification algorithm. One dimension of the matrix represents the true classes of an object while the other represents the class that the classifier predicts [24, 25]. The ROC curve is also a two-dimensional plot which illustrates how well a classifier system works as a discrimination cut-off value is changed over the range of predictor variable [25].From the research analysis, we have identified that traditional algorithms are very effective to the initial cluster size and cluster centers. If these clusters vary with different initial inputs, then it creates problems in classifying pixels. In the existing popular fuzzy cluster mean algorithm, the cluster centroid value is taken randomly. This will increase the time to get the desired solution. Manual segmentation and evaluation of MRI brain images carried out by radiologists are tedious; the segmentation is done by using machine learning techniques whose accuracy and computation speed are less. Many neural network algorithms have been used for the classification and detection of the tumor where the accuracy is less. The detection accuracy is based on the segmentation and the detection algorithms used. So far, in an existing system, the accuracy and the quality of the image are less.

III. PROPOSED SYSTEM

The proposed technique is an effective technique to detect tumour from MRI images. In the proposed technique, different classifiers are used. The proposed system should be capable of processing MRI, multislice sequences, accurately bounding the tumor area from the preprocessed image via skull stripping and morphological operations. The region should be segmented by Berkeley's wavelet transformation and extract the texture features using ABCD, FOS, and GLCM features. Classifiers such as Naïve Bayes, SVM-based BoVW, and CNN algorithm should compare the classified result and must identify the tumor region with high precision and accuracy. Finally, based on the classifier result, the tumor region is classified into malignant or benign.

The rest of the article is intended to continue: section 1 presents the background to brain tumors and related work; section 2 presents the construction techniques with the measures used throughout the method used; section 3 describes the results and analysis and the comparative study; and, finally, section 4 presents the conclusions and upcoming work.

IV. ARCHITECTURE OF THE PROPOSED ALGORITHM

We propose a threefold complete architecture to classify and segment brain tumors using a T1 weighted MRI sequence. The proposed system architecture consists of three cascaded algorithms, namely, in the order of application, convolutional neural network for classification, Faster R-CNN for tumor localization, and Chan–Vese algorithm for precise tumor segmentation. The flow diagram of the complete architecture is illustrated in Figure 1.

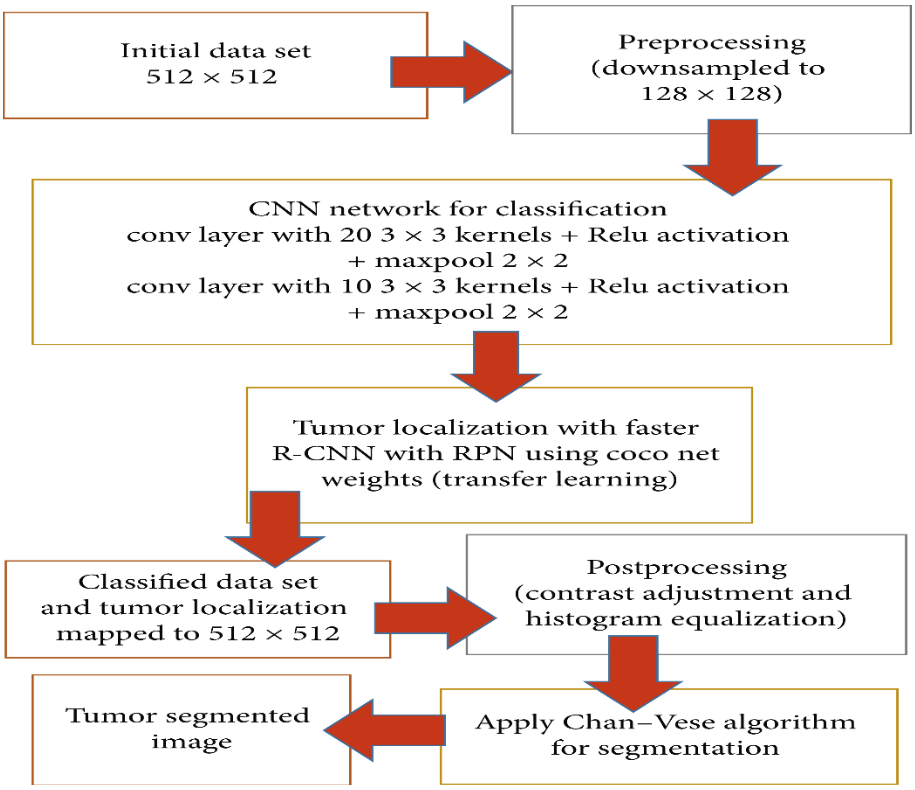


FIGURE – FLOW CHART OF PROPOSED SYSTEM

The classified image goes through a faster RCNN for tumor localization. The faster RCNN model adopted uses the pretrained weights generated using COCO net data for its feature extracting CNN, which is followed by a Region Proposal Network (RPN) and a classifier. The output of this second step is a boundary box around the tumor in 128∗128 downsampled image. As the third step, these boundary box coordinates are mapped to 512*512 image with the original resolution, and the Chan–Vese algorithm is applied only for the boundary box area. This approach assures that the Chan–Vese algorithm converges to an accurate boundary. Hence, we were able to obtain a much precious boundary for tumor segmentation within a low computational time.

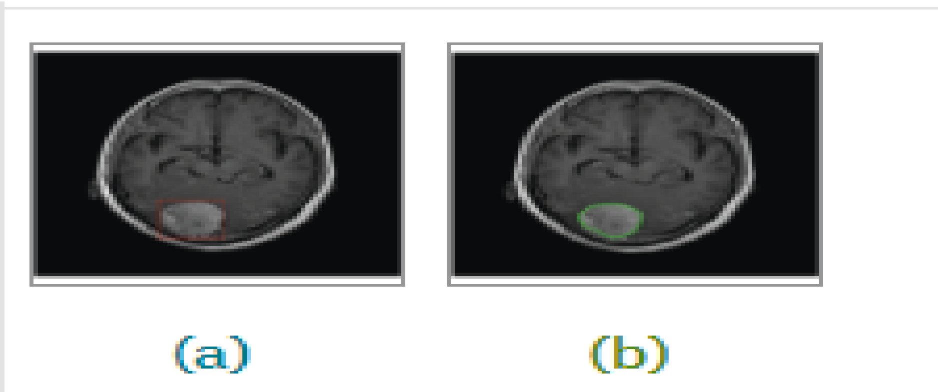


FIGURE- BRAIN Tumor localization, Tumor segmentation

V. BASIC OPERATION OF CNN AND R-CNN

CNN is a class of layered deep neural network architecture built using convolution, activation, pooling, and fully connected layers to analyse visual imagery. The convolutional layer uses a set of learnable filters with different sizes to extract various feature maps to learn the correlation between neighbouring pixels, while drastically reducing the number of weighted parameters. The pooling layer introduces nonlinear downsampling to the system architecture while the activation increases the nonlinear properties of the decision function of the overall network independent of the convolution layer. Followed by several combinations of convolution, pooling, and activation, CNN has the fully connected layers, where high-level decision-making takes place. At the final stage of the design, the dense layer or loss layer maps the trained outcome with the predefined output class. In a fully connected CNN architecture, these operations are executed forward and backward, through forward learning and backpropagation as a designed architecture fine-tune, that is, training cycle, to optimize the decision-making capacity of the CNN architecture.

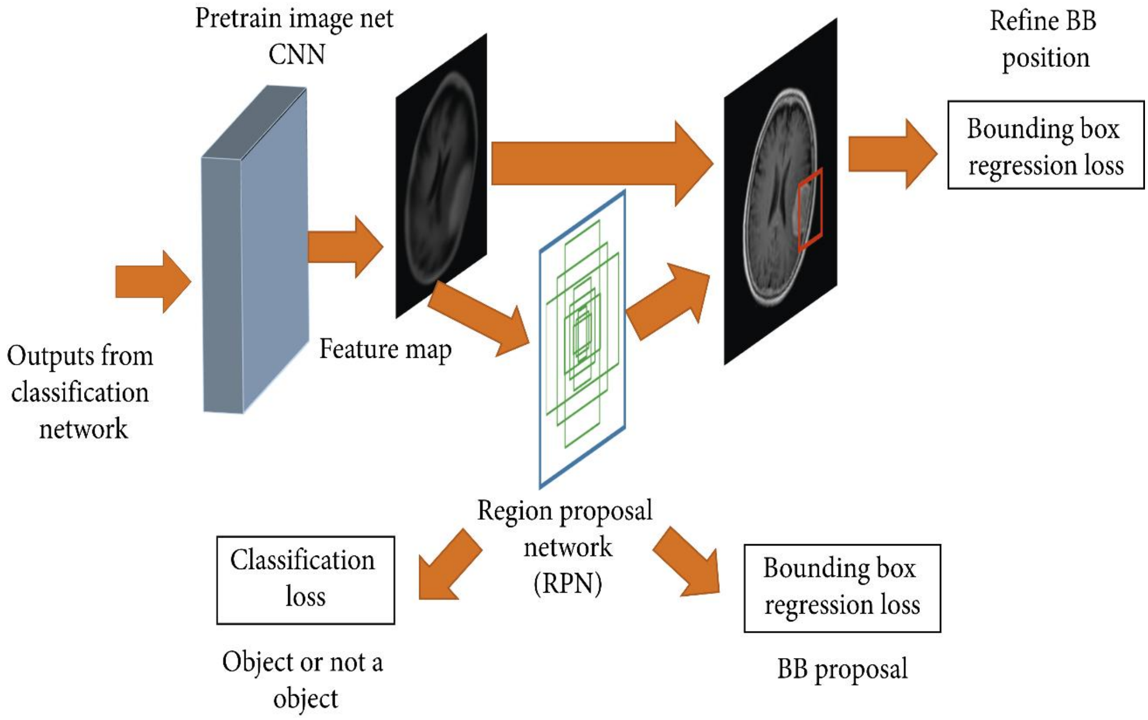
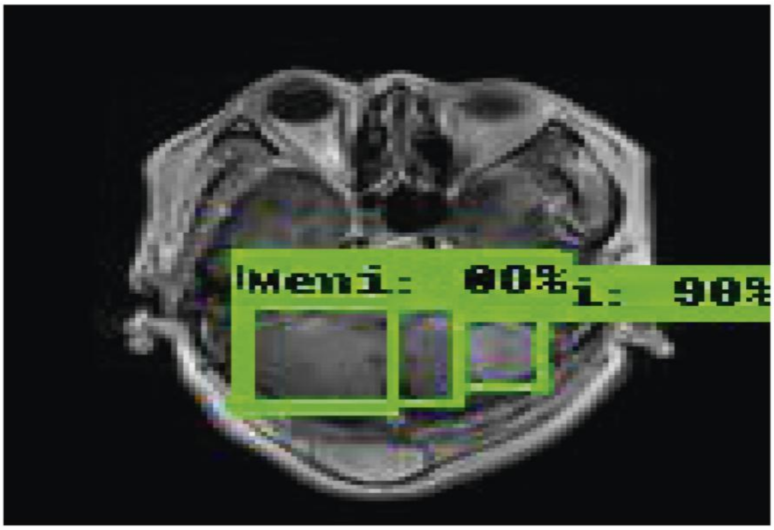


Figure: R-CNN Architecture.

The R-CNN is an object detection and localization mechanism evolved from CNN architecture. It is a region-based segmentation method which follows segmentation using a recognition approach. It first extracts the free-form regions of interest from the input image and then conducts region-based classification on the extracted region of interest (ROI). The faster R-CNN consists of two main subnetworks, R-CNN and RPN [16]. RPN itself narrows down the number of search regions in the image by generating anchors as in Figure and works as a classifier that trains CNNs to classify these selected ROIs, called hereafter "region proposals," into object categories. At first, R-CNN takes an input image and segments it into many subimages called regions with different dimensions. Next, each region is treated as an isolated image, and this isolated image is classified into a predefined set of object labels. Finally, a greedy algorithm is used to recursively combine subimages with similar regions to generate the region proposals with the predicted object labels.

VI. RESULTS AND DISCUSSION

The experimental outcome of the implemented architecture presented in Figureis analysed at two stages, namely, first after the classification stage and second after the segmentation stage. Both the training and validation accuracies of the classifier are presented using the confusion matrices in Figure. The ROC curves of the training and validation stages of the classification model are presented in Figure. Also, the performance of the segmentation algorithm is illustrated visually in Figure. summarises the statistical performance evaluations of the complete model for selected MRIs, whereas presents the overall performance summary of the segmentation performance at the final stage of the proposed architecture.



We present a confusion matrix to illustrate the performance of the classification model against the ground truth. The confusion matrices for the training dataset and the test samples are shown in Figure In each confusion matrix, green squares represent TP and TN values, light orange squares represent FP and FN values, and blue squares were used to represents positive predictive value (PPV), negative predictive values (NPV), specificity (Sp), and sensitivity (Sn), respectively, in clockwise, from the top right to bottom left. Overall correct classification rate (accuracy) was given in the purple square. The classification error for the training and testing set is equal to 7.69% and 6.42%. Overall summery of the classification process is tabulated.

VII. CONCLUSION

We have proposed R-CNN and Chan–Vese algorithms based model for meningioma and glioma brain tumor classification and segmentation. The proposed model is validated using Figshare dataset with 5-fold cross-validation and objective quality metrics Dice Score, RI, VOI, GCE, BDE, PSNR, and MAE are calculated to analyse the performance of the proposed architecture. We have used R-CNN to obtain the initial tumor boundary box which is followed by active contouring to obtain the exact tumor outline. We adopt level set functions based Chan–Vese algorithm which is independent of Rician noise, for both meningioma and glioma brain tumor segmentation and we compare the performance of the proposed segmentation method against that of the typical-gradient based edge detection algorithm Prewitt. We were able to achieve a much more accurate segmentation result through the Chan–Vese algorithm with an average Dice Score of 0.92 for both tumor types.

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Shilpa R. “R Model for Prediction of Brain Tumour Status Using MRI Image Data.” *International Journal of Humanities and Social Science Invention (IJHSSI)*, vol. 11(04), 2022, pp 12-17. Journal DOI- 10.35629/7722