DIRECTIONAL CLASSIFICATION OF BRAIN TUMOR IMAGES FROM MRI USING CNN-BASED DEEP LEARNING

G MAHESH CHALLARI [1], J PRASHANTHI [2]

[1] Assistant Professor in Department of cse at Sree Dattha Institute of Engineering And Science,
[2] Assistant Professor in Department of cse at Sree Dattha Group of Institutions.,

---***---

Abstract - *A brain tumour is a dangerous development of unnatural cells in the brain. If not treated in time, it might prove fatal. It is therefore crucial to find the tumor early and start therapy as soon as possible. People with brain tumours had a significant fatality rate before the discovery of early diagnosis. The mortality rate lowers considerably after an early diagnosis is established. Accurate early diagnosis of a brain tumour increases a patient's chance of survival. The customary system used to detect tumors involved physicians studying the MRI scans and analyzing the abnormalities in the image. However, with the increase in the size of data and limited amount of time it becomes extremely strenuous for the physicians to analyze the image. Our research has resulted in the release of a convolutional neural network model for the detection of brain tumours, which further classifies the tumour into glioma, pituitary, or meningioma. This automated model is improving the detection and classification accuracy of tumours, demonstrating that it is a useful tool for physicians. The same brain MRI database is used to train and test all the types under consideration, including CNN, ResNet50, MobileNetV2, and VGG19. The effectiveness of each type is reviewed. Accuracy, error rate, and time to train are just few of the criteria used to evaluate the results from each CNN variant.*

Key Words: Convolutional Neural Networks, Brain Tumor, MRI, Medical Disorder, Healthcare.

1. INTRODUCTION

Analyzing biomedical data is growing significantly and is crucial in diagnosing and properly treating disease. Brain tumor contains more complex image data that needs image processing to analyze. There is a higher death rate and improper treatment of brain tumors, as the statistics taken by the National Brain Tumor Foundation (NBTF) worldwide [1]. Several approaches (or) frameworks have been developed to consider brain tumors in recent years. It comes across data classification, proper treatment planning and predicting outcomes. Images of tumours in the brain's structure are difficult to classify because of issues with contrast, noise, and missing boundaries. Magnetic Resonance (MR) imaging [2, 3], Positron Emission Tomography (PET) [3, 4], and Computed Tomography (CT) scan [5, 6] are used to assess the efficacy of the diagnostic procedure by analysing the aforementioned elements. Scanners use image processing to look for signs of illness. The scanning process is done to diagnose and treat the brain tumours better, which identifies tumor images to be analyzed effectively. Suppose the identification of predicting the tumor cells and locating them helps to diagnosis the disease properly. Making the analyses more qualitative and amount quantity improves the characteristics of a tumor diagnosis through data segmentation. Based on the development of the MR images generation, it can be processed manually, semi-automatically, and fully automatically [5]. Based on the image processing related to the medical field, information should be accurate while processing the image based on the segmentation and classification process. While processing the images, the execution should be time-consuming [6].

2. LITERATURE REVIEW

In computer vision, image segmentation is a highly effective technological procedure. In the field of image processing, segmentation is a useful tool. Pixels are organized into groups called segments, which are themselves artefacts. When an image is segmented, it is no longer necessary to analyze the entire thing at once. The three steps involved in the processing of an image are depicted in overall diagnosis of "skull," "brain," or "tumour" might be possible by labelling. One application of object detection is to identify certain objects inside a picture. In order to properly identify and categorize objects, segmentation is essential

In this section, we take a look at the various segmentation methods currently available in the literature for MR image processing. The author [66] proposes an appropriate, novel approach to tissue segmentation from MRI brain imaging. The "WM and GM and CSF" segmentation is useful for studying diseases and designing treatments. To eliminate the graininess and sharpen the image, anisotropic diffusion filtering is used. Tests of the proposed technique on 10 MRI images have been conducted, and the results have been compared to those obtained using existing methods (including "Otsu MT" "fuzzy C-means". The results of the experiments show that, in comparison to the existing approaches, the average segmentation accuracy is improved by 96.79%, the specificity is 96.55%, and the sensitivity is 96.55%

Brain tumour identification and increased breast cancer detection in MRI images were both targeted by the author of [82], who proposed a template-based K means and enhanced fuzzy C means (TKFCM) system. This algorithm outperforms the competition even when presented with a noisy MR image. In comparison to thresholding, area expanding, region splitting and merging, ANN, TK-means, and FCM, this algorithm performs better. It used a simulator to test out its proposed solution and see how well it worked. Besides, it has proven a consensus reached to be more reliable than the conventional statistical classification results. However, the time required for the TKFCM algorithm to detect brain tumors is concise compared to other traditional methods.

3. SYSTEM ANALYSIS

3.1.1 DETECTION OF BRAIN TUMOR USING RESUNET ARCHITECTURE

Using a classification technique, a brain tumour detection system aids in diagnosing and treating patients recently diagnosed with a tumour in the brain. Early diagnosis and treatment can be provided by using the MRI classification method, which helps identify the brain's tumour and determine the tumor's density. U-Net architecture is associated with a variety of classification methods in the literature. Based on a comparison of low-level and high-level feature information, this work proposes Residual U-NET with improved local feature information for improved medical image segmentation. As part of the modified Residual U-Net model, the dropout and wide context layers are addressed in addition to the residual module and attention gate. Large�sensitive scaled information and small-scale images benefit from adding salient feature information. After making certain adjustments, the gate attention model performed better than state-of-the-art methods like U-Net and CNN Densely.

3.1.2 LGG Dataset

This dataset has MR images of the brain and manual flare abnormality segmentation masks. In total, the Cancer Genome Atlas (TCGA) collection contains 3929 images, including 2556 non�tumor images and 1373 cancer images from 110 individuals.

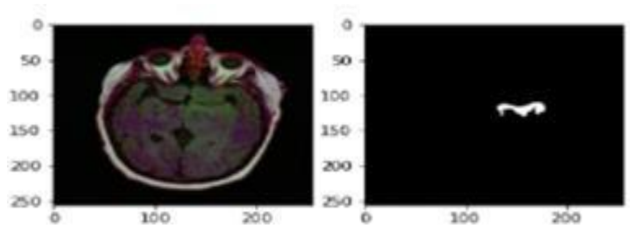

Figure 3.1.2 Brain Tumor image and Mask image

The ratio of training and test images are tested 70:30. The size of all images in this dataset is 256 x 256 pixels. Access the dataset at 'https: //www.kaggle.com/mateuszbuda/lgg-mri-segmentation'...

4. PROPOSED METHODOLOGIES

4.1.1 Image Pre-processing

The deep learning model is crucial in making the network less sensitive to the noise in the data and images it is given to analyze. Because of how consistently it analyses images across the board, the N4ITK method is utilized for correcting bias-based image processing. Several algorithms exist that perform the data pre-processing for brain tumor. From the existing N4ITK algorithm provides reliable data as it collects the data based on the capability of bias field for MRI Images.

4.1.2 Modified Residual U-Net

As residual network associate the U-Net backbone with more residual blocks in Deep framework to gradient mitigation problem. In this U-Net architecture, the convolutional neural network is related to performing image segmentation into three elements, Encoder and decoder, based on the process of contraction and expansion. For the purpose of expanding the blocks, the suggested architecture takes into account the Convolutional 2D, Max pooling 2D, Wide Context, Transpose 2D, Residual Block, and Concatenate metrics.

4.1.3 Max Pooling Layer

Layer will supply the down feature extraction mapping, highlighting the feature patches depending on the feature map approach, in addition to max and average pooling. Maximum presence pooling uses extracted features to calculate an average presence and then uses that to activate the presence of those features. Simply said, this convolutional layer is the neural network-based convolutional layer that is used to generate the mapping feature extraction by filtering learning based on input images. It is determined through research that the layer functions best when extracting simple features.

4.1.4 Dropout Layer

It is the method used to stay away from the convolutional neural network model's overfitting issue. When the training phase is updated, the main cause of dropout is a random setting on the hidden edge units being set to 0 as neurons. Using a sigmoid activation function and a numerical representation of the residual u-net

4.1.5 Attention Gate with Residual U-Net

The coming step of data preprocessing is to handle missing Two parallel connections are used as input for the two convolutional layers in a broad context block. Use both 1 x N and N x 1 filters on the initial link. The connection uses 1 x N filter with a convolutional model and N x 1 filter with a convolutional model. In this process, the information's are extracted to form the data similarity by considering the wide context. It is further classified into different convolutional sub-class networks for brain tissue.

4.1.6 Wide Context Information

Two parallel connections are used as input for two convolutional layers in a large contextblock. Use both 1 x N and N x 1 filters on the initial link. The connection uses 1 x N filter with a convolutional model and N x 1 filter with a convolutional model. In this process, the information's are extracted to form the data similarity by considering the wide context. It is further classified into different convolutional sub-class networks for brain tissue.

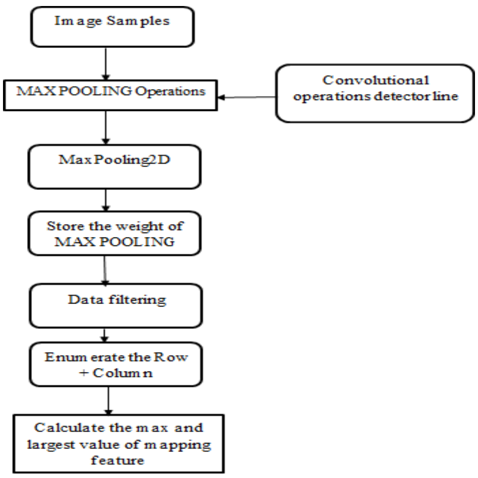

Figure 4.1.3 Max pooling layer

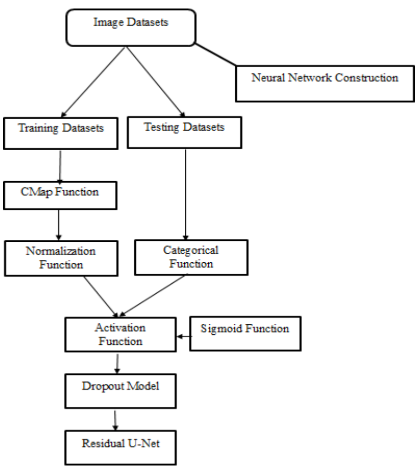

Figure 4.1.4 Dropout layer

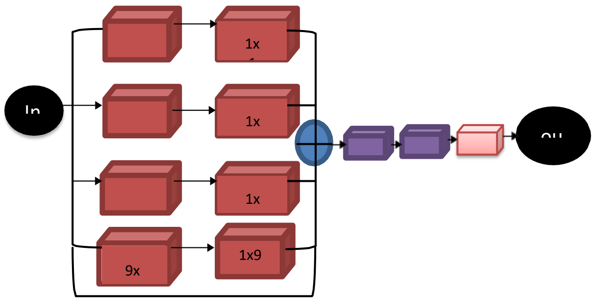

Figure 4.1.5 Residual U-Net Architecture with Gate Attention Mechanism

5. RESULTS

The quantity of photos given careful consideration is one indicator of performance in the analysis of results. Tensor Flow, along with the proper modules, can be used as a checkpoint and scheduler for the learning process. Patient, RNSseq cluster, laterality, tumour location, and ethnicity are just some of the granular characteristics that may be found in the Kaggle dataset. Those datasets with photos are the result of a checkpoint- driven sorting procedure. Patient id, picture path, and mask path are all included in the final dataset as shown in Table 3.1. To compare the count value to the mask and find the mask count plot.

S.No.	Mask	Dtype
1	0	2556
2	1	1373

Table 5.1 Mask Count part

To locate the tumour on the mask, we use photos of brain tumours with varying pixel colours. Using parameters like image path, mask path, and mask, a new dataset is generated. Brain_df_train, test size = 0.15 is used to test and divide trained data according on the chosen model. After that, those pictures are confirmed

Using a classifier model trained with data from the Residual Network ResNet50, we examine the photos. Conv2D, Input, ZeroPadding2D, Batch Normalization, Activation, MaxPooling2D, and batch normalized images are classified in the input layer. Using an image classification model to determine whether or not the tumour is present, the classifier model achieved a loss in data of 0.2353, with an accuracy of 94.745%. Tables 3.2 and 3.3 depict the metrics used to generate the confusion matrix from the original and forecast images: accuracy score, confusion matrix, and classification report

Mask_Value	Precision	Recall	F1-Score	Support
0	0.93	0.99	0.96	382
1	0.98	0.87	0.92	208

Table 5.2 Attribute metrics based on mask value

Mask_Value	Precision	Recall	F1-Score	Support
Accuracy	-	-	0.95	590
Macro Avg	0.96	0.93	0.94	590
Weighted Avg	0.95	0.95	0.95	590

Table 5.3 Attribute metrics based on mask value (Accuracy; Macro Avg; Weighted Avg)

Training and validation loss values, or how well they predicted, are plotted against epochs (the X-axis in Figure 3.6). The loss ranges from zero to one. For the proposed Res U-Net architecture, the loss is calculated using data from the first 30 epochs. Since the validation set is probably not representative of the complete dataset, the validation loss varies greatly. The validation sample should be randomized or resampled, in my opinion

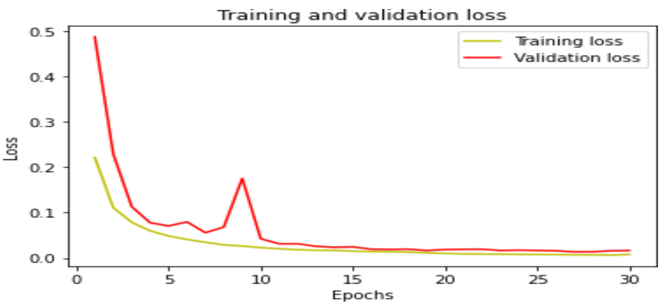

Figure 5.1 Epochs Vs Training &Validation loss

Figure 5.2 depicts how the dice coefficient for the proposed Residual U-Net architecture is calculated using epochs ranging from 0 to 30 for both training and testing data. The value of the dice rises steadily with the number of epochs Accuracy for the suggested Residual U-Net architecture is shown in Figure 3.8, where epoch ranges from 0 to 30 are used for the trained data and Val. As more time has passed (more epochs have been added), the accuracy value has risen steadily

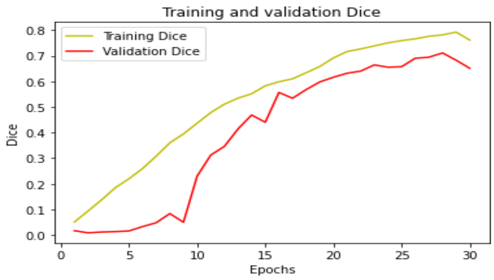

Figure 5.3 Epochs Vs Dice coefficient

Data pre-processing, encoding, and decoding on MRI image datasets are all carried out using the suggested architecture. Segmentation of improved images is used as the basis for this analysis. Loss and Accuracy are determined by comparing the values of the training and test epochs, respectively. The data categorization model uses the Epochs value to calculate data loss and accuracy. The proposed Res U-Net achieves better accuracy than the current Res U-Net method as the number of iterations increases, as measured by the loss function, Dice co-efficient value, 95% Accuracy.

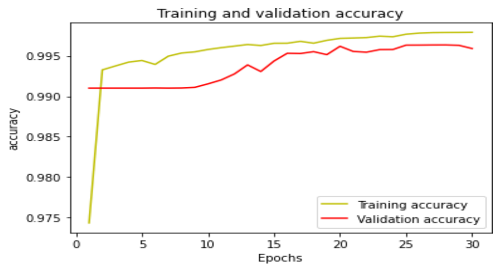

Figure 5.4 Epochs Vs Accuracy

6. CONCLUSION

In the recent era, health care plays a significant role based on biomedical datasets related to brain tumor images and other classification and segmentation processes. Various types of tumor are discussed based on different grades. At first, we talk about how the dataset influences the preprocessing of images. After that, a set of feature photos is generated and categorized usingestablished methods. Tumour detection and image segmentation processing are described. To better segment medical images and focus on the attention module in tumour images, we first present the design of Residual U-NET with some improved local feature information. In this, local information on image feature are considered by improving the image segmentation through the proposed Residual U-Net as it integrates both residual and attention gate modules and considers both dropout and wide context layer. Focal Trversky Loss and Trversky Accuracy are computed using training and test data, and Epochs value variation is evaluated for large-scale images through whole, core, and enhancing image segmentation.

Brain tumor segmentation using Spatial Attention ResU-Net gives best results compared to existing U-Net models. With increasing training data, we can further improve dice and IoU scores. And also with more research on the classes labelled on the data we can predict the stage and severity of the disease. After segmenting the MR Image, it is possible to measure the tumour's size in brain tissues

REFERENCES

[1]. Robert Tufel, "The National Brain Tumor Foundation": Giving Help, Giving Hope"; Journal of Neoplasia, 3(3): 264-265, 2001.

[2]. Soltaninejad, Mohammadreza, Zhang, Lei, Lambrou, Tryphon, Yang,Guang, Allinson, Nigel and Ye, Xujiong," MRI Brain Tumor Segmentation and Patient Survival Prediction Using Random Forests and Fully Convolutional Networks", Computer Methods and Programs in Biomedicine, 157,69-84, 2018.

[3]. Langen KJ, Bartenstein P, Boecker H, Brust P, Coenen HH, Drzezga A, Grünwald F, Krause BJ, Kuwert T, Sabri O, Tatsch K, Weber WA, Schreckenberger M, "German guidelines for brain tumour imaging by PET and SPECT using labelled amino acids", Nuclear Medicine, 50(4), 167-173, 2011.

[4]. Irene Neuner, Joachim B. Kaffanke, Karl-Josef Langen, Elena Rota Kops, Lutz Tellmann, Gabriele Stoffels, Christoph Weirich, Christian Filss, Jürgen Scheins, Hans Herzog & N. Jon Shah, "Multimodal imaging utilising integrated MR-PET for human brain tumour assessment", European Radiology volume 22, 2568–2580, 2012.

[5]. B. Johnston; M.S. Atkins; B. Mackiewich; M. Anderson, "Segmentation of multiple sclerosis lesions in intensity corrected multispectral MRI", IEEE Transactions on Medical Imaging, 15(2), 154-169, 1996.

[6].Erena Siyoum Biratu; Friedhelm Schwenker; Yehuala shet Megersa Ayanoand TayeGirma Debelee, "A Survey of Brain Tumor Segmentation and Classification Algorithms", J. Imaging, 7(9), 2021.

[7]. Lim Jia Qi, Norma Alias, FarhanaJohar, "Detection of brain tumour in 2D MRI: implementation and critical review of clustering-based image segmentation methods", Oncologyand Radiotherapy, 1(52), 1-10, 2020.

[8]. Dr. Thejaswini P; Ms. Bhavya Bhat; Kushal Prakash, "Detection and Classification of Tumour in Brain MRI", I.J. Engineering and Manufacturing, 2019.

[9]. G. Preethi; V. Sornagopal, "MRI image classification using GLCM texture features", International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE), 2014.

[10]. Sindhu Devunooru, AbeerAlsadoon, P. W. C. Chandana&Azam Beg, "Deep learning neural networks for medical image segmentation of brain tumours for diagnosis", Journal of Ambient Intelligence and Humanized Computing, 12, 455-483, 2021.