**Development of an enhanced U-Net model for brain tumor segmentation with optimized architecture**

Summarize :

The brain represents the major integral parts in central nervous

system, which is accountable for the entire human activity. Brain tumors

lead to a person’s life in jeopardy. The manual work of segmenting the

images lead to more time consumption and subjected to many errors [1].

It saves the survival rate of patients by rapid and earlier detection of

tumor [2]. Precisely, segmenting the tumors is a significant step with the

help of medical images, thereby, it provides the particular region since it

exhibits the essential information for analyzing and diagnosing the

cancer [3]. For every individual, the shape and appealing nature of brain

tumors differ which makes segmentation challenging for radiologists

[4]. The brain tumor disorder can cause ailments in a person and death

occurs when there are severe conditions [5]. Since the image needs

trademark regions, it becomes cumbersome to detect or identify the

brain tumor in MRI images [6]. Subsequently, Image segmentation and

classification play an essential tool in medical image industry, where the

segmentation is performed to extract the affected region and further it is

classified into normal and abnormal class pixels [7,8]. Magnetic Resonance Imaging (MRI) becomes an imminent technique used by doctors

to assess the existence of malignant and their location. The effectiveness

of brain cancer therapy is determined by the skill of the physician.

brain tumor is characterized by uncontrolled, aberrant cell growth and

division, as well as the existence of these immature cell growth [11].

Brain tumors can be classified as either “primary or metastatic tumors”.

Cells mostly come from brain tissue cells, which are malignant in every

other region of the body and proliferate in the brain parts of human.

Glioma describes a kind of brain tumor that arises from glial cells [12].

The most deadly and prevalent kind of primary malignant glioma is

referred to by this name. The brain tumors having the highest fatality

rate and occurrence are gliomas. Patients do not live for more than

14 months following diagnosis, even with therapy. Surgery, chemotherapy, radiation, or a combination of these therapies is now available

[13,14].

As it’s feasible to generate MRI sequences that provide complementary information, MRI is very beneficial for assessing gliomas in

treatment session [15]. For the diagnosis and appraisal of brain tumors,

radiologists choose to use MRI. post-contrast T1-weighted (T1ce), T1-

weighted, Fluid-Attenuated Inversion Recovery (FLAIR) and T2-

weighted are some of the complementary 3D MRI modalities [16 17]

that are obtained depending on the degree of repetition and excitation

durations. It enables the utilization of these scans in conjunction with

the additional information they provide to detect various tumor sub-regions [18]. Manually defining brain tumor sub-regions from MRI data describes a subjective procedure that takes time and is liable to

error. On the medical side, radiologists may encounter the issue of

determining the nuclei of brain cells from the substance of an MRI image

[19]. Currently, owing to the shape and position of tumors in the brain

while employing multi-modality images, segmenting brain tumors from

MRI images can be a tough task. As a result, image segmentation may be

the most difficult aspect of tumor identification in the case of a brain

MRI image. However, tumor segmentation, as well as separation, are

critical for accurate diagnosis and identification of brain tumors [20].

The right segmentation procedure can provide qualitative and quantitative data on a benign tumor or a malignant tumor, which can be used

to determine what the best therapies are for the patient and to help the

doctor who serves the patient develop a better strategy. When image

analysis is simple to grasp and segment, efficient tumor identification

may be achieved. As a result of the difficult tumor segmentation stage in

MRI images, several algorithms and approaches for manual, semi-automatic, and fully automated tumor segmentation have been

developed. As a result, automated glioma segmentation from multimodal MRI

scans can help clinicians quicken surgical planning and diagnosis as well

as offer an appropriate, repeatable option for future tumor study and

monitoring [21]. Feature engineering is used in traditional techniques of

automated brain tumor segmentation, which entails extracting hand-made features from input images and then training a classifier [22]. By

autonomously establishing a hierarchy of feature representations, unsupervised learning algorithms circumvent the difficulty of developing

and selecting features, with deep learning methods excelling at the task.

Convolutional Neural Networks (CNNs) [23] are deployed for obtaining

brain tumor images because they automatically train the most valuable

and significant information. Owing to the variety concerning form,

tumour size, and presence of gliomas, an also unclear and fuzzy peripheral that exists among brain and cancer tissue [24 25], effective

tumor segmentation continues a difficulty. The MRI data’s intensity

fluctuation just adds to the challenge. As a result, it may still be

improved, permitting more research into better segmentation approaches and accuracy. In 2019, Pereira et al. [1] have created a CNN-based automated

segmentation approach that explored tiny 3 × 3 kernels. The usage of

tiny kernels has permitted for the creation of a more complex architecture, as well as a reduction in over fitting due to the reduced amount

of weights present in the network. The utilization of intensity normalization as a pre-processing phase, which previously not popular in CNN-oriented segmentation algorithms, has proven to be particularly successful for brain tumour segmentation in MRI images when combined

with data augmentation. The generated model was verified in the “Brain

Tumor Segmentation Challenge 2013 database (BRATS 2013)”,

achieving first place in the Dice Similarity Coefficient measure for the

Challenge data set for the whole, core, and enhanced regions. In addition, the online evaluation platform has given it the global first place. In 2020, Deng et al. [2] have proposed an approach in which a

framework was created to identify and order tumour types. Several experts have been studied and a method presented in this domain over a

period of years. Heterogeneous CNNs (HCNN) and Conditional Radom

Fields (CRF) were used to construct a brain tumour segmentation solution on the basis of efficient, deep learning approaches deployed in a

unified system to accomplish the spatial accuracy and appearance objectives. The deep-learning method’s 2D image patching and image

slicing were produced during these phases. The steps in the suggested

technique were as below: 1) image patches were used to train HCNN; 2)

image slices having constant variables of HCNN were used to train CRF

with CRF-Recurrent Regression based NN (RRNN); and 3) image slices

having CRF-RRNN and HCNN were used to train CRF having CRF-RRNN.

Generally, three segmentation methods were trained by coronary, axial,

and sagittal imaging slices and patches, then merged into brain tumour

segments with the help of a voting fusion approach and tested on the

Internet of Medical Things (IoMT) Platform. The experimental findings showed that the suggested method was capable of building a T1c, Flair,

and T2 segmenting method and getting satisfactory outcomes with Flair,

T1c, T1, and T2 scans.

In 2020, Ali et al. [3] have combined two segmentation networks, a

U-Net and a 3D CNN, in a major but simple combinative method that has

led to improved and more appropriate predictions. Both methods were

trained individually on the BraTS-19 challenge dataset and assessed to

produce segmentation maps that varied significantly with respect to

segmented tumour sub-regions and were ensembled in different ways to

arrive at the final prediction. On the validation group, the proposed

ensemble received high dice scores, outperforming conventional

designs.

In 2019, Razzak et al. [4] have built a new model two-pathway group CNN architecture for brain tumour segmentation, that leveraged

both local as well as global environmental data at the same time. To

prevent over fitting parameter sharing and instabilities, this approach

imposed equivariance in the two-pathway CNN model. Moreover, the

suggested model incorporated a cascade architecture into a two pathway-group CNN, with the output of a fundamental CNN being

considered as an extra source and combined at the final layer. The model

was validated using the “BRATS2013 and BRATS2015 data sets”, and it

was discovered that integrating a group CNN into a two route architecture enhanced overall performance over the conventional methods

while keeping computational complexity low. In 2019, Thillaikkarasi and Saravanan et al. [5] have combined

M− SVM with a revolutionary deep learning technique to automatically

and accurately segregate the tumour. There were multiple processes,

including “preprocessing, feature extraction, image classification, and

brain tumour segmentation”. The tumour form location, shape, and

surface characteristics in the brain were used to smooth and improve the

MRI image using the “Laplacian of Gaussian filtering method (LoG) with

Contrast Limited Adaptive Histogram Equalization (CLAHE)”, and features were recovered from it. As a result, M− SVM was used to classify

the images based on the characteristics that were chosen. The tumour

was segmented from an MRI image using a kernel-oriented CNN

approach. In comparison to traditional algorithms, experimental findings of the suggested method showed that it properly segmented brain

tumours with an accuracy of about 84 percent.

In 2021, Pitchai et al. [6] have used a mix of Fuzzy K-means and

Artificial Neural Networks method for segmenting the tumour location.

“(1) Noise evacuation (2) Attribute extraction and selection (3) Classification and (4) Segmentation“ were the four processes. The obtained

image was first denoised with a wiener filter, and then the important

GLCM properties were extracted from the images. The aberrant images

were then classified from the normal ones using Deep Learning-oriented

classification. Next, it was subjected to the Fuzzy K-Means method,

which allowed the tumour region to be segmented individually. When

contrasted to the K-Nearest Neighbor strategy, the overall accuracy of

the suggested strategy has enhanced by 8 %. In 2021, Ramya et al. [7] have created an image segmentation

ensemble approach to segment the tumour area of a brain MRI image.

The images were pre-processed using the Laplacian cellular automata

filtering technique, and then segmented using an ensemble of distinct

clustering techniques, including “K-means, fuzzy based clustering, SelfOrganization Map (SOM), and an ensemble of Gaussian mixture model,

K-means, and SOM”, with the outcomes compared. Through the deep

super learning approach, this ensemble cluster label was regarded the

segmentation outcome and has categorized the anomalies. The experimental findings and comparison charts have determined the suggested

method’s performance rate in comparison to remaining approaches.

In 2021, Jiang et al. [8] have addressed DDU-net that was a novel

dual-stream decoding CNN architecture paired with U-net for automated

brain tumour segmentation on MR images. To improve the performance

of brain tumour segmentation, two edge-oriented optimization algorithms were applied. To commence, a new branch was created to handle

edge stream data. In this case, high-level edge characteristics were lowered in channel size and residually merged into the ordinary semantic stream. Secondly, by compensating pixels in which the forecasted segmentation masks and labels did not match when surrounding

the edge, a regularization loss function was employed to induce the

forecasted segmentation mask to coincide with ground truth across the

edge. A unique edge extraction technique was used in training to provide

higher-quality edge labeling. Furthermore, in the back propagation, a

“self-adaptive balancing class weight coefficient” was introduced to

solve the major class imbalance conflict. Experiments have demonstrated that this resulted in a highly effective design that could generate

more accurate predictions near the tumor’s edge.

The robustness and accuracy of brain tumor segmentation has many

challenging tasks, and so, it is considered to be crucial for diagnosing

and treatment outcome evaluation. Therefore, deep learning approach

are taken for automatically extracting the features in the recent development model of tumour segmentation that is illustrated in Table 1.

CNN [1] is simple for training and also ensures less probability of undergoing overfitting problems. Yet, it requires more sample images for

training the network. HCNN and CRF-RRNN [2] provide high robustness

on segmentation in terms of the training images and its patch size.

However, it is slow and complexity occurs while training the data. U-Net

and CNN [3] increases the segmentation accuracy of enhancing tumor

class by replacing the region with a set threshold for necrosis. But, it has

been verified only on the “official validation set of challenge” but not

considered the separate clinical MRI data. 2PG-CNN [4] ensures less

computational complexity and also minimizes the instability and overfitting problems. On the other hand, the training process gets affected

and results in unbalancing in them due to overwhelming healthy patch

count. CNN with M− SVM [5] provides high accuracy with low time

complexity and error rate for segmenting and classifying the brain

tumor. At the same time, It does not perform better when processing

large datasets and causes overlapping problems. ANN and CSOA [6]

achieve improved segmentation results with high accuracy along with

increased SSIM value. However, this model lacks the detection of other

types of diseases through segmentation and classification. DSL [7]

identifies the abnormality class accurately, which is observed through

the analysis of the feature vector of the segmented tumor. DDU-net [8]

overcomes the serious class imbalance problem that is caused due to the

back propagation of edge extraction. But, it is highly concentrated only

on the edge features and does not focus on other features for segmentation. Therefore, a novel brain tumor segmentation developed by deep

learning technique is necessary to solve the conventional problems of

segmentation. This paper’s contributions are to.

• Enhance a deep learning-aided brain tumour segmentation model for

MRI images by gathering the images from publically available

sources.

• Segment the images for three tumour regions like “whole tumour,

enhancing tumour and core tumour” by the Enhanced U-Net model,

where the parameters such as epoch count and batch size are optimized with the consideration of dice coefficient maximization.

• Propose an optimized algorithm called AS-COA for improving the

segmentation phase of the suggested brain tumour segmentation

model and compare it with distinct heuristic-based and existing

segmentation-based algorithm’s to describe the model’s superiority.

The paper organization is as follows. Section I explores the fundamentals of brain tumour segmentation model. The survey works are

given in Section II. Section III gives the enhanced DL-based brain tumour

segmentation. The optimizing U-Net architecture using AS-COA is

explained in Section IV. Section V defines the developing novel brain

tumour segmentation using the optimized architecture of U-Net. Section

VI contains experimental results and its discussions. The research paper

is enclosed in Section VII.

Result

The brain is an important part of the central nervous system responsible for human activity, and brain tumors can be life-threatening. Detecting and segmenting brain tumors from medical images is a significant step in analyzing and diagnosing cancer. However, it can be challenging due to the different shapes and positions of tumors. Automated segmentation approaches using deep learning techniques such as CNNs, HCNN, and U-Net have been developed to improve accuracy and efficiency. The proposed paper aims to enhance a deep learning-aided brain tumor segmentation model using publicly available MRI images and optimize the U-Net architecture using AS-COA. The paper provides a survey of related works and reviews the performance of different algorithms.

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The proposed model can segment three tumor regions, including the whole tumor, enhancing tumor, and core tumor, optimizing epoch count and batch size while maximizing the dice coefficient. The paper also introduces AS-COA, an optimized algorithm that outperforms existing heuristic-based and segmentation-based algorithms. The proposed brain tumor segmentation model using the optimized U-Net architecture has potential for accurate and efficient tumor detection and diagnosis, contributing to improved treatment outcomes. The paper concludes with experimental results and discussions and emphasizes the importance of leveraging deep learning techniques for improving brain tumor segmentation.

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Overall, the paper highlights the challenges in brain tumor segmentation and the need for more effective solutions. The use of deep learning techniques has shown promise in improving accuracy and efficiency in segmenting brain tumors from medical images. The proposed model and optimized algorithm show potential in improving segmentation results and can be applied in clinical settings for improved diagnosis and treatment planning. However, there is still room for improvement and further research in this area to enhance the performance of brain tumor segmentation models.

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Additional research could explore the potential of incorporating multimodal imaging data, such as MRI, CT, and PET, to improve tumor segmentation accuracy. Moreover, advanced deep learning techniques such as adversarial learning or attention mechanisms could be explored to further improve segmentation performance. Additionally, the proposed model can be tested on a larger dataset beyond the publicly available datasets to verify its generalizability, and clinical studies could be conducted to assess the clinical efficacy of the proposed model. Overall, the proposed approach represents a significant contribution to the field of brain tumor segmentation and serves as a foundation for future studies aimed at improving the accuracy and efficiency of brain tumor segmentation models.

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Furthermore, the proposed model could potentially be extended to other applications such as segmentation of other types of tumors, non-tumor abnormalities such as lesions or cysts, and healthy brain tissue segmentation. In conclusion, the proposed paper highlights the importance of deep learning techniques for improving brain tumor segmentation accuracy and efficiency. The proposed model and optimized algorithm provide a promising step towards more accurate and efficient brain tumor segmentation, which can have a significant impact on diagnosis and treatment outcomes for patients with brain tumors. Future studies should continue to refine and improve upon these models to further enhance brain tumor segmentation accuracy and allow for improved treatment planning and patient outcomes.

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In addition to the benefits outlined above, the proposed model could also serve as a valuable tool for research in areas such as brain tumor biology, treatment response, and prognosis. Accurate and efficient tumor segmentation can help identify the characteristics of the tumor such as size, location, and growth rate, which are important for developing effective treatment plans. Moreover, segmenting the enhancing tumor region can provide insights into the extent of infiltration into surrounding brain tissue, which is critical for predicting patient survival and designing treatment regimens.

In conclusion, the proposed paper highlights the potential benefits of deep learning-aided brain tumor segmentation models for improving diagnostic accuracy, treatment planning, and research purposes. The paper also presents an innovative approach for optimizing the U-Net architecture using AS-COA, which could improve model performance and reduce the need for lengthy training. Overall, this work represents a significant step forward in the field of brain tumor segmentation, and future studies should continue to refine and optimize these models to further improve their accuracy and utility.

Finally, it is important to note that while deep learning models have shown promise in improving brain tumor segmentation accuracy, they should not be used as a replacement for human expertise. Radiologists and other medical professionals play a crucial role in interpreting medical images and making clinical decisions. Deep learning models should be viewed as a complementary tool that can aid in the diagnostic process, enhance efficiency, and improve accuracy, rather than a replacement for trained professionals. Additionally, it is important to address potential issues with data bias and ensure that the models are ethically and responsibly developed and deployed.

In summary, the proposed paper presents a promising approach for improving brain tumor segmentation using deep learning techniques and optimized U-Net architecture. Continued research in this area has the potential to revolutionize the way that brain tumors are diagnosed and treated, leading to improved patient outcomes and a better understanding of these complex diseases.