Tumor Localization And Classification From MRI Of Brain Using Deep Convolution Neural Network

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Abstract
The medical field's most significant elements are early disease detection, appropriate treatment decisions, pre-and post-surgical patient behavior, and caretaker burdens. All such elements work towards improving the patient's quality of life. Hence, this study aims to localize and classify the grade of brain tumors using an interactive deep-learning technique, which assists us in measuring the impact of brain tumors on a patient's quality of life. The present study also proposes the physiological and psychological quality of life (PPQOL) model.
In this study, we collected data from a population 150, comprising brain tumor patients, caretakers, and medical professionals. We categorized the population as patients, caretakers, and medical expert team members. We also categorized patients based on pre and post-surgical status. For processing brain tumor MR images, an interactive automated deep learning technique is developed to localize and classify the various brain tumor grades.Further, a hybrid convolution neural network is developed by combining U-net and Z-net models. To measure patients' quality of life, we developed a matrix through questionnaire formulation to analyze physical, psychological, and social well-being. In summary, we classified brain tumor grades, identified the patient's surgical status, and further developed the quality of life matrix for a particular patient.
Our proposed methodology, evaluates the relationship between brain tumor grades, pre- and post-surgical analysis, and its impact on a patient's quality of life. Proposed method gives the highest accuracy for tumor grade classification. The model was trained for 100 epochs, and the benchmark results obtained outperformed those of existing models. The proposed Hybrid-CNN model achieved 0.9261 for dice, 0.9957 for pixel accuracy, and for F1-scores 0.8178. Based on the segmentation, the accurate identification of the tumor grade is categorized as T1, T2, T1ce, and FLAIR. The classification of tumor grades is further correlated with the developed quality of life matrix, which evaluates the effect on physiological, psychological, and social behavioral factors.
As neurological surgery needs a very precise location of brain tumors, our automated hybrid-CNN segmentation model provides clear visibility of brain tumor boundaries using accurate tumor segmentation, which can assist surgeons during surgical events. Furthermore, classification results are mapped with the quality of life matrix, which is beneficial to measure patients' progress in the pre-and post-surgery phases. The proposed research helps medical experts and caretakers deal with the various corrective measures for improving patients' lives.

Keywords: Quality of life, brain tumor, classification, segmentation, U-net, Z-net, CNN, deep learning

Introduction
The prognosis of a brain tumor is a life-changing situation for sufferers and households. High-grade gliomas are not curable, and long-term survival is narrow. Sufferers, family members, and caregivers also describe disproportionately high cooperative attention goals, which often vary from those of various other systemic cancers (Walbert T. et al., 2023). Traditionally, oncologic care has emphasized gaining the medical endpoints of survival, native influence, and avoiding recurrence. The psychological elements, although crucial, are frequently forgotten at the time of medical practice. Research describes a high rate of depressive disorder and stress among brain tumor patients and their caregivers (Shah et al. et al., 2023).
Already being at medical diagnosis, various brain tumor sufferers have distressing signs of illness and might require encouragement and palliative affluence. Much research has pointed out inequity in cancer care and attention early on in the disease trajectory and the End-of-Life (EOL) stage (Lindskog, M. et al 2022). Clinical evaluation of brain diseases is commonly accomplished by bio-signal-based approaches, even though imaging-based methods can provide clearer details compared to signal-based approaches(Sivakumar, J. et al. 2022).
Various other vital components that trigger a decline in the quality of life (QoL) of brain tumor sufferers include sleep disruption and sleep apnea, which are extremely common concerning sufferers. Patients with unhealthy sleep are dissatisfied with the administration of their signs of illness and describe openness to possibly medicinal or behavioral concurrence for sleep apnea. All these conclusions underscore the call for an enhanced screening process for sleep hindrance by medical professionals in the clinic and for upcoming research to evaluate the effectiveness of both

medicinal and behavioral concurrence (Willis et al., 2022). Caregivers' capacity for distress is frequently directly connected with, and raised by, the development of brain tumor in the family member. Irrespective of the significant and well-evidenced influences of tending to somebody with brain tumor (BT), emotional and supporting care for BT patients' caregivers stay poor, with insufficient caregiver support offered as part of common care and insufficient facts for the efficiency of existing aides (Heinsch, M. et al. 2022).

The existing analysis explores older care requirements in China from the point of view of immediate caregivers by extracting text messages posted by authorized individuals on the issue of older care and executing thematic modeling and emotion evaluation. Emotion evaluation is utilized to quickly obtain the belief produced by text messages published on particular subject areas. Currently, there are three types of emotion evaluation means: lexicon and rule formulated methods, typical machine learning established methods, and deep learning structured techniques (Wang, Y. et al. 2022). On the other hand, there is hardly any study that can associate the BT grade/stage and its effect on the QoL of sufferers, caregivers, and medical experts. Hence, the proposed study presents the impact of BT progression on QoL.

BT classification is vital and can protect patient's lives. An appropriate and well-timed analysis of a BT is crucial for the patient's treatment methods plan. Even so, tumor classification is a complicated concern. Through the early years, professionals have set up critical time and effort to build considerable developments in classifying tumors in brain MR images. Various approaches for attaining strong classification effectiveness have been launched (Aamir M. et al., 2022). As outlined by WHO, a BT is classified into grades I-IV. Grades I and II tumors are deemed as slow-growing, whereas grades III and IV tumors are considerably more intense and have a less well-off treatment.

Along with the distinction of brain tumors, segmentation is scientifically crucial as it extracts the necessary region from input images. Thus, segmenting correct lesion areas is a much more important process. The manual segmentation procedure may need to be corrected, so there is a demand for semi-automatic or automatic segmentation. Deep learning and quantum machine learning strategies are extensively employed for tumor localization and classification (Amin, J. et al., 2022).

Specifically, Grade-I considered as a benign tumors with almost ordinary cells in histopathological assessments. Grade-II islow-grade-gliomas (LGG). Several LGGs ultimately progress to high-grade-gliomas (HGG), which consist of grades-III and grades-IV. Automatic perseverance of the category of lesion or its pertinent region applying the images is important, considering it enables therapeutic diagnoses to be generated even in the absence of specialists and in the quickest practical period (Badrigilan, S. et al. 2021). One of the drawbacks of these kinds of standard imaging strategies is that they ought to draw out hand-crafted features before further evaluation. Deep learning-based strategies are suggested for glioma grading on MRI images to conquer the concern. (Pei, L. et al 2021).

Further, the paper provides a detailed literature survey of a proposed research methodology with a discussion on the existing Unet and Znet models; the methodology also provides data and dataset details, a proposed algorithm, new Hybrid-CNN architecture, and details about the training and validation of BT MR images. We also discussed the proposed QoL model method. In the results and discussion section, we discussed the findings of the new Hybrid-CNN model, which classifies the BT grade. We also presented the association between identified BT grade and QoL elements concerning patients, caregivers, and medical professionals. The results reveal that the proposed system performs better and can measure the brain tumor grade impact on physiological and psychological aspects. Finally, the paper concludes with a summary and suggests the future directions of the research.

Literature Review

The analysis of brain tumors frequently turns to difficulties that are possibly interrelated to the tumor on its own or the tumor-directed and then supporting treatments, raising the pressure on the patient's QoL and possibly survival. Several articles examined the medical and neurological circumstances that generally present difficulties in the disease course of brain tumor sufferers (Youssef, G. et al 2021). On the other hand, it is crucial to figure out the patient's mental perception for measurement of QoL and related elements such as brain tumor development, grade of tumor, as well as the level of care expected. According to the author, a couple of analyses have contemplated health-related QoL (HRQOL) as a major result strategy in adult survivors of primary brain tumors (PBT). Few still have analyzed the intellectual elements that may impact it. The study implies that executive functions (EFs) are linked with HRQOL. However, short facts support this (Cantisano, N. et al. 2021). Hence, the proposed study targets the classification and segmentation of brain tumors, further evaluating the physiological and proposed QoL model named 'psychological quality of life' (PPQOL) model.

The author identified the most commonly employed practical popularity evaluation tools for sufferers with brain tumors, reviewed their belongings, and employed the International Classification of Functioning, Disability, and Health (ICF) and psychometric elements (Ģiga, L. et al. 2021). However, such methods can map statistical factors. Further, this can be clubbed for MR image classification and segmentation results so the medical expert team can get the ready-to-use clinical line of action to plan patient-specific psychological support. Research on the association between hrQoL and NCF in the primary brain tumor populace has been short. Retrospective cross-sectional research of sufferers with primary brain tumors at a solitary time frame and a longitudinal analysis of sufferers with metastatic brain tumors have proven a link between NCF and hrQoL. However, to our understanding, no potential longitudinal analyses of this correlation in sufferers with primary brain tumors have been carried out (Salans, M. et al. 2021). Hence, the proposed research focuses on the multi-faceted brain tumor patient study to improve the QoL.

Multiclass classification of brain tumors is a significant analysis region in therapeutic imaging. Seeing that accuracy is important in classification, computer vision experts have unveiled numerous methods; on the other hand, they even now encounter the concern of poor accuracy. The author mentions an unique automated deep-learning approach for the classification of multi-class brain tumors (Sharif et al., 2021).
According to metaheuristics, the author suggested the changed genetic algorithm solutions. The suggested threshold-function depending features are combined, making use of a non-redundant serial-based process and classified applying a multi-class SVM cubic classifier. The author employed two datasets, incorporating BRATS2018 and BRATS2019, and has attained approximately 95% accuracy.
The author's analysis reveals Edge-based Contourlet Transformation for diverse input image registration, collaboration, and pre-processing; the region-growing segmentation protocol provides appropriate boundaries, in feature-extraction (Mudda, M. et al 2022). Incorporating hand-crafted functionality with deep features can maximize accuracy of the classification. Comparative to this, light-weight alternatives like quantum machine learning are critical in accuracy boosting, thus diminishing the time-frame predicted by radiologists as well as elevating the proportion of sufferers who survive their disease.
However, employing the deep learning model needs to be collaborated with quality-of-life analyses to evaluate the physiological, psychological, as well as social parameters for better individual survival levels.

Methodology
In the domains of deep learning methods, a convolutional neural network is among the popularly employed types for categorizing brain tumors. So, a critical volume of improvement has been formed. Right now, a few diverse methods may be used in classifying brain tumors, which is visible in the analysis that was checked through.
In the classic Unet model (Ronneberger, O. et al. 2015); skip connection links low-level and high-level features in one level rather than immediate monitoring and loss backpropagation. This ensures that further local features are merged into the feature maps. Nevertheless, the convolution of the classic Unet model (refer Fig.1) will trigger the loss of image information. Even while an up-sampling procedure can restore components of the dropped fine boundary details, it does not satisfy the excessive medical image segmentation precision requirements. Consequently, because of the high requisites of tools and memory space in the 3D-Unet model, 3D images are replaced with two-dimensional (2D) images (Fang L. et al., 2023).

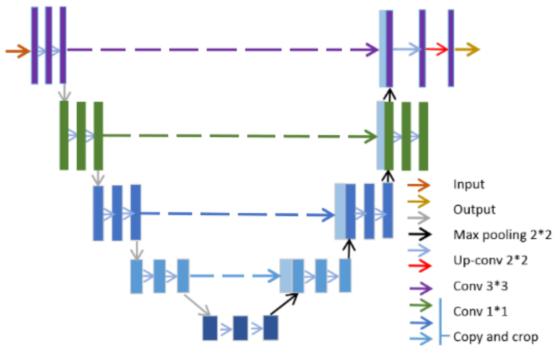

Fig. 1 Traditional Unet model (Fang, L. et al 2023)

The author recommended the Znet framework for segmentation of BT from MR images. Also, pixel-level precision analysis is not appropriate for semantic segmentation when class imbalances present in MR image segmentation. So, there is a possibility of wrong pixel precision values. Alternatively, substitute analysis metrics, like dice and IoU (Intersection over Union), are even more factual for semantic segmentation (Ottom A. et al., 2022).

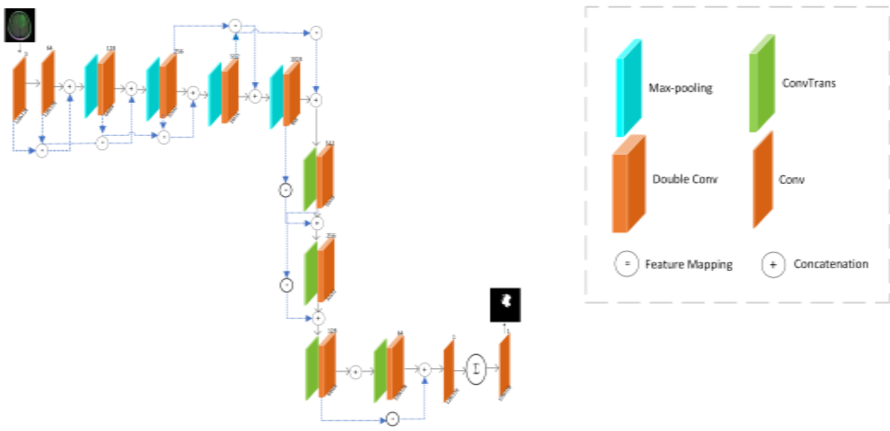

Fig. 2: Znet model (Ottom, M. A. et al 2022)

As demonstrated in Fig. 2 above, the encoder part is made up of 5 various sections, where every single encoder section is made up of dual convolutions merged by normalization of group with the ReLU function along with max-pooling. Hence, to eliminate the disadvantages of Unet and Znet, we developed a new hybrid-CNN model architecture where the pixel accuracy can further be improved using superimposing the convolution and deconvolution sections in such a way that the max-pooling gets automatically adjusted using normalization of most significance batches recurrently. The encoder section can be adjusted automatically for single or double-convolution requirements. In previous models, the convolution and deconvolution size (3*3) can be adjusted automatically to get higher pixel accuracy.

Data

The proposed study is evaluated in two parts: deep learning hybrid-CNN model execution and QoL assessment based on the brain tumor classification.

Deep Learning Hybrid-CNN Model

We used BRATS datasets 2018, 2019, and 2020 for the proposed model classification and segmentation. The dataset comprises HGG and LGG brain tumor MR images. BRATS 2018 includes 266MRIs, BRATS 2019 contains 285 MRIs, and BRATS 2020 has 335 MRIs of patients, so every patient possesses 155 slices. The comprehensive information of benchmark databases is specified in Fig. 3.

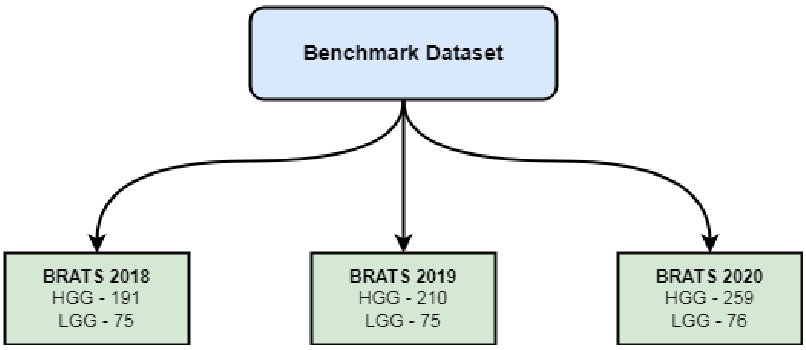

Fig. 3: Benchmark Datasets Structure

It can give unique images with distinct perimeters for positive segmentation outcomes with less time than other strategies. The strategy is considerably more effective and innovative as we can set the pixel cluster details throughout the borders of the impaired area and not on the middle pixel point. This approach can be executed step by step or automatically.

In the proposed approach, instead of central pixel-point evaluation, using the MR image, we can manually identify the imaginary localization region. We can initiate analysis of the main pixel point and sub-pixel region as a pixel-cluster region for the affected area.

We can selectsub-pixels formcluster of main pixels from x number of regions likeR_g1, R_g2, R_g3,…,R_gy. This gets executed as a recurrent evaluation. Each sub-pixel gets added to the main pixel region to form a final cluster of main pixel regions.

By using the pixel cluster region$R_g i$ after $'s'$ steps and excluding cluster of pixels P.

$$P = \{u \cup_{y=1}^{x} R_g y \setminus Y(u) \cap \cup_{y=1}^{x} R_g y \neq \emptyset\} \ldots\ldots \ldots\ldots\ldots(1)$$

In case, Y(u) is the adjoining sub-pixel border of pixel u, u ∈ P means $Y(u)$associates with only one $R_g y$ and $y(u) = \{1, 2, .., i\}$with this condition,$Y(u) \cap \cup_{y=1}^{x} R_g y \neq \emptyset$ and δ(u) we can identify adjoining difference between other cluster regions of u. $\delta(u)$ can be given by:

$$\delta(u) = |g(u) - \text{mean}_{y \in R_g y(u)}[g(y)] \qquad \ldots\ldots\ldots\ldots(2)$$

$$\delta(u) = \text{mean}_{u \in P}\{\delta(u)\} \qquad \ldots\ldots\ldots\ldots(3)$$

where $g(u)$ is assumed as a gray-pixel value of sub-pixel cluster boundary pixels and $u \in P$assumed as u belongs to $R_g y$, this will be executed until all sub-pixels are evaluated for gray-scale values. The steps of the proposed Hybrid-CNN algorithm aregiven below, which will later be executed using new deep learning Hybrid-CNN architecture:

Proposed algorithm: Hybrid-CNN

Input: Brain MR Image

Output: Segmented region and classification of brain tumor

1. The main pixel points are selected from the outer skull region, traversing through all sub-pixel regions until the gray pixel is identified.
2. For each sub-pixel region, label the sub-cluster region.

3. Based on the sub-pixel intensity, white and gray sub-pixels will be grouped under separate labels, and the mean value for each region will be calculated.
4. Store the sub-pixel and subsequent main pixel region as a main mean region.
5. Store each main pixel mean region as a cluster neighbor matrix
6. Calculate the mean of the cluster neighbor matrix
7. If a gray pixel is identified outside of the identified gray-pixel cluster boundary,
8. Repeat Step-3
9. Else,
10. Store the extra gray pixel in a missing pixel matrix
11. Repeated Step-3 till all sub-pixel and main pixels form cluster pixels.
12. Compute the pixel traversal again to verify the size of the gray-pixel boundary and store details.

The proposed algorithm verifies the missing, false, and sub-pixel impressions to increase the visibility and accuracy of tumor boundaries. For implementation, the 5-fold cross-validation is used to analyze the proposed method. We divided data randomly for HGG and LGG in the ratio 2:8 for training and validation purposes. To increase the training sample size, we pre-processed sub-pixel regions of size 512 X 512, which gives better visibility. Further, we applied image augmentation techniques by flipping image patches along the axis with random rotations at 90° and 180°.

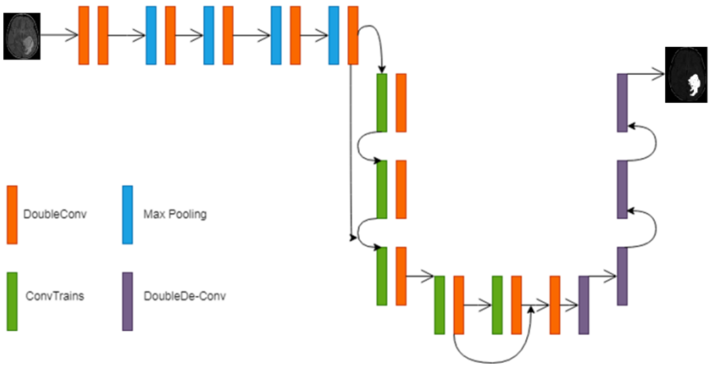

Fig. 4: Proposed Hybrid-CNN model architecture

As shown in Fig. 4 above, we combined Unet and Znet models; the initial encoder part of Znet is kept as a set of five sections. Each section contains double convolutions and is combined by convolutions rectified activation function ReLU, which is followed by max-pooling. Further, the output is fed by concatenation to the input section. At this point, the combined output is fed to Unet deconvolution, which optimizes the visibility utilizing double deconvolution. This deconvolution comprises five sections and uses ConvTranspose2d to get the original image dimensions at the Unet deconvolution phase by double deconvolution. Table 1 shows the details of hyper-parameters employed during the training and validation of data.

Table 1: Hyper-parameters used for training

Parameters	Value
Epochs	100
Type of Optimizer	Adam
Batch-Size	32
Learning-Rate	$l_r = 5 * e * -4$
Input-Size	$3 * 128 * 128$

The training is achieved with 100 epochs and adaptive moment estimation (ADAM) optimizer is used, three sub-pixel regions of 128 × 128 pixels, and a batch size 32. We used half of the data of tumor slices from the dataset for training and the rest of the data for validation. Following Table 2 specifies the classified image details.

Table 2: Details of the image classification

Dataset (BRATS)	Training	Testing
2018	20,614	20,614
2019	22,086	22,086
2020	25,961	25,961

Proposed Physiological and Psychological quality of life (PPQoL) Assessment:

Further to the classification of the brain tumor grades, for Physiological and Psychological QoL assessment, we used data recorded from 150 subjects (50 brain tumor patients, 50 caregivers, and 50 medical professionals' team members). The demographic information is collected, such as age, gender, profession, number of days of hospitalization, tumor grade of patient, education, and monthly income. Based on the questionnaire responses from participants, the association was identified between the brain tumor grade of the patient and the proposed QoL model, which is discussed in the next section.

Results and Discussion

As the proposed Hybrid-CNN algorithm mentioned in the early section of this paper, the model training executed for 100 epochs.The configuration used as a server is NVidia 12GB-GPU. The epoch execution time recorded about 3 to 4 minutes. Further, the benchmark results revealed the performance values as 0.9261 for dice, 0.9957 for pixel accuracy, and an F1-score of 0.8178. To prevent over-fitting issues we divided the whole training set in two parts as first is the Hybrid-CNN model training set and second as the Hybrid-CNN model validation set.

Table 3: Comparison of the proposed (Hybrid-CNN) and existing Znet, Unet Models

	Unet	Znet	Hybrid-net (Proposed)
DICE	0.8554	0.9158	0.9261
DICE_loss	0.1452	0.0839	0.1611
Accuracy	0.9922	0.9955	0.9957
F1 Score	0.7878	0.8098	0.8178
Trainable Parameters	14,788,929	44,384,833	46,571,356

The performance comparison accomplished by comparing the proposed research results with existing segmentation algorithms Unet and Znet. The testing was accomplished on the BRATS dataset MR images and actual patient images. The results show that `the proposed Hybrid-CNN outperforms Unet and Znet as shown in Table 3 above, and Fig.5 shows the training and validation loss and accuracy graph for epoch 100.

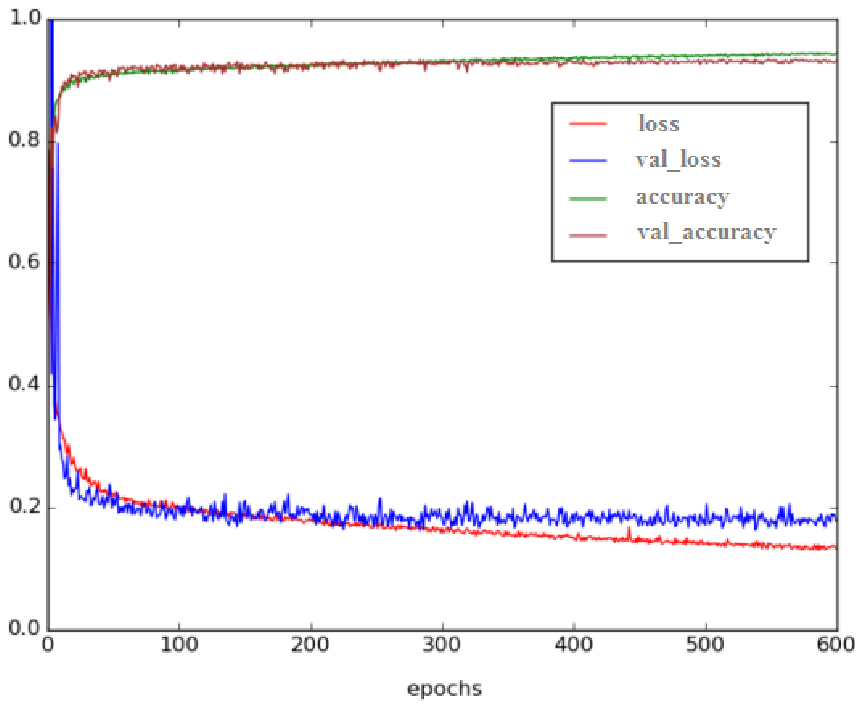

Fig. 5: Analysis of loss and accuracy for the proposed model

The segmentation results help localize the tumor border, and region and classification are conducted using the Hybrid-CNN model, which gives tumor grades as T1, T2, T1Ce, and FLAIR. Thus, we also tested 10% of the patient's actual MR images for tumor grade classification, which gives the patient's physiological state. Further to that, we used questionnaires to understand the patient's psychological state. We correlated physiological parameters (i.e., classified tumor grades) and psychological parameters, as represented in Table 4.

Table 4: Impact of Brain Tumor Grade onproposed QoL model

Brain Tumor Grade	**Patient**	**Caregiver**	**Medical Professional**
T1	• Fear • Anxiety and depression	• More care prone behavior • Analysis for	• Pre-surgical analysis • Counseling for

		best treatment option	patient and caregiver
T2	• Unconsciousness • Detached behaviors • Anger and Confusion • Sleep disorder	• Fatigue • Sleep disorder • Burdon and fear	• Outlined medical treatment • Step by step analysis about patients response to treatment
T1Ce	• Positive about treatment • Survival queries and family bonding • Anxiety and seizers	• Financial burden • More emotional about patient • Lack of self management	• Steady treatment • Development of affinity towards patient • Surgical decisions and professional pressure
FLAIR	• Extreme fear • Communication withdrawal • Phobia • Non-supportiveness • Digestive disorders • Sleep disorder • Worry about family • End of life thoughts • Rare strong desire to win against the brain tumor cancer	• More supportive and self organized behavior • Positivity towards patient • Trying to ease end of life symptoms • Expecting miraculous results via spiritual practices	• Steady and positive treatment and counseling for patient and caregiver • Search for better treatment options to elaborate survival

Based on the actual patient, caregivers, and medical experts' survey, we identified multiple elements as a proposed QoL model matrix. Surprisingly, based on the classification of brain tumor grade, the psychological elements are almost matched with all the same brain tumor grade patients, caregivers, and medical experts. The proposed QoL model matrix can be a significant tool for deciding the options for a better survival rate, motivational treatment options, and, in a few serious cases, better end-of-life support.

Based on the proposed study, future research can use actual patients' brain MR images for analysis; however, such datasets are imbalanced, so unsupervised learning model development is required. Also, there is a scope for further development of the hybrid-CNN model by designing a soft-plug-in using sentiment analysis, which can achieve automated analysis of the Quality of Life of patients, caretakers, and medical professionals where participants' opinions can be fed to identify the level of psychological imbalances. Such psychological measurements are useful for hormonal studies, drug adverse effect studies, and clinical trial analysis, where physiological and psychological parameters play significant roles.

Conclusions

In this paper, we proposed a new algorithm based on the deep CNN for MR image segmentation and classification of brain tumors. The proposed interactive hybrid model, Hybrid-CNN, is developed based on existing Unet and Znet models. The proposed model performance reveals that the Hybrid-CNN model outperforms by increasing accuracy. Further, the classification of tumor grades accomplished based on the segmentation and proposed system accurately analyzed BRATS 2018, 2019 and 2020 datasets for the performance evaluation. As the aim of the proposed research is to analyze the impact of tumor grade on the physiological and psychological quality of life of patients, caregivers, and medical experts, we surveyed opinions and results segregated based on the T1, T2, T1Ce, and FALIR brain tumor grades. This study is helpful for the palliative care line of action for patients, caregivers, and medical professionals, which can reduce the stress due to the patient's illness. Also, family members and patients with end-of-life symptoms can be psychologically and emotionally controlled for better life phases. This study is beneficial to increase the positivity among patients with curable stage and can motivate positive responses to medical treatment. Importantly, as less research is done in this area, the scope of future research can lead to policy development for palliative care in the healthcare field.

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