A Convolutional Neural Network (CNN) approach for Brain Tumor Classification

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***Abstract*—Accurate brain cancer classification is crucial and relies on physician skills. The incorporation of automated tumor classification methods has become critical in augmenting radiologists' and physicians' abilities to identify brain tumors. There is a need to improve accuracy for optimal treatment outcomes. This study focuses on brain tumor segmentation and classification on BraTS-2019 dataset using advanced deep-learning approaches. Feature selection plays a role in machine learning since it boosts model performance but Traditional ML requires manual feature engineering, in which domain experts select suitable features. Deep learning eliminates and automates the feature engineering process. we conducted 2 experiments to check the performance of different deep-learning approaches for brain tumor classification on the BraTS-2019 dataset, U-Net and AlexNet respectively. U-Net, with its encoder-decoder architecture and fine-detail incorporation via skip connections, exhibited commendable performance, starting with a loss of 0.0137 and reaching 0.0089, achieving excellent training and test accuracy at 99.58%. In our 2nd experiment, we chose AlexNet because of its powerful image classification skills. It demonstrated high training accuracy with a slight upward trend, contributing to an overall performance improvement from 94.233% to 98%. The comprehensive evaluation favored U-Net for brain tumor classification, attributed to its consistently high accuracy and effective hierarchical feature extraction.**

***Index Terms*—Brain Tumor, BraTS-2019 Dataset, AlexNet, U-Net, Deep Learning, Evaluation Metrics, Training Loss, Validation Loss.**

I. Introduction

BRAIN tumor diagnosis is critical for optimal treatment planning and improved patient outcomes. The growing volume of medical imaging data has highlighted the importance of efficient and accurate automated solutions. Using advanced machine learning algorithms, this study addresses the critical challenge of trustworthy brain tumor classification to increase diagnostic capacities. Motivated by the difficulties of manual tumor diagnosis and the potential of automated solutions, we explored the use of deep learning models on the BraTS-2019 dataset, specifically U-Net for segmentation and AlexNet for classification. With 259 patients and four separate classes, the BraTS-2019 dataset [3] provides a broad and comprehensive record of brain images. Each subject comprises native (T1), post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2-FLAIR volumes, which permits a multi-modal approach to brain tumor diagnosis. We employed two distinct models, U-Net and AlexNet, for classification purposes. U-Net, originally designed for image segmentation applications, has proven to be particularly valuable in the medical imaging industry. Its unique characteristics make it widely adopted as a primary tool for segmentation tasks within this field. U-Net its encoder-decoder architecture to speed up feature engineering. This approach is extremely beneficial in extracting complex hierarchical and contextual information. AlexNet is also applied for classification, contributing to its prowess in image classification tasks.

To ensure optimal input for subsequent model training, the proposed approach includes intensive preprocessing techniques such as data normalization, one-hot encoding, and data downsizing. A wide range of metrics, including but not limited to train loss, train accuracy, train dice coefficient, validation loss, validation accuracy, and validation dice coefficient, make extensive evaluation of the models' performance achievable. This strong set of measures enables a sophisticated and complete examination of how effective the methodologies and models used.

The following are the main contributions of this study:

- We provide a computerized approach for brain tumor classification with the goal of supporting radiologists and clinicians in recognizing different forms of brain tumors.
- We use revolutionary deep learning models like U-Net to automate feature extraction and image segmentation, allowing us to extract significant features from brain images without requiring extensive manual intervention.
- We also use a well-established pre-trained AlexNet architecture for classification. Its ability to detect complex patterns in medical images not only tackles the issue of overfitting but also improves training efficiency.
- The suggested method is carefully tested on the BraTS-2019 dataset, with evaluates such as loss, dice coefficient, accuracy, precision, recall, and intersection over union (IOU) utilized to evaluate the performance of both models.

The next sections go into U-Net and AlexNet's extensive methodology after an extensive literature review, experimental environment, and outcomes, offering insight into how they contribute to the larger objective of enhancing brain tumor detection and classification.

II. Related Work

Early diagnosis of brain tumors, whether malignant or benign, relies on physician expertise, providing patients with a chance for better life and survival outcomes [11]. As indicated by the literature, considerable advances have been made in © medical image analysis, notably in the context of brain tumor segmentation and classification. [1] introduced the U-Net architecture, which has become a cornerstone in biomedical image segmentation. Their work addresses critical challenges in this domain, laying the foundation for subsequent studies. Havaei et al. [4] explored the application of deep neural networks for brain tumor segmentation, providing insights into the potential of these networks in accurately delineating tumor regions. Kamnitsas et al. [5] proposed an efficient 3D CNN with a fully connected CRF for accurate brain lesion segmentation, contributing to the ongoing efforts to enhance segmentation precision. In the realm of image classification, Krizhevsky et al.'s work [6] on "ImageNet Classification with Deep Convolutional Neural Networks" played a pivotal role in popularizing deep learning, particularly convolutional neural networks, for image classification tasks. [10] presents a hybrid feature extraction strategy combining a regularised extreme learning machine (RELM) for brain tumor classification, increasing accuracy from 91.51% to 94.233% [7], showcasing improved segmentation performance by combining multiple models. The contribution of [8] to the Multimodal Brain Tumor Image Segmentation Benchmark (BraTS) is noteworthy, as it introduced a crucial dataset for evaluating segmentation algorithms. Litjens et al. Additionally, [9] explored brain tumor classification using long-term learning and transfer learning methodologies. While these studies collectively advance the understanding and application of deep learning techniques, it's essential to acknowledge common limitations such as model interpretability, computational resources, and the demand for extensive labeled data.

III. Proposed Approach

A. Data Preprocessing

The research focuses on refining the dataset through three key preprocessing techniques. These techniques aim to enhance the compatibility, standardize pixel values, and ensure uniform dimensions across the diverse set of images as follows: **Data Normalization** Standardize pixel values to a common scale, ensuring numerical stability during model training. in our approach, image matrix normalization not only ensures equal feature contribution but also accelerates training, reducing computational load and enhancing accuracy.

$$X_{\text{rescaled}} = \frac{x}{\max(|x|)}$$

One-Hot Encoding Encode categorical class labels into binary vectors, facilitating compatibility with classification models. **Data Resizing** Resize images to a uniform dimension, addressing input size variations and ensuring model training consistency.

B. First Model: U-Net

U-Net is a convolutional neural network (CNN) architecture well-suited for image segmentation tasks. Train U-Net on preprocessed images to delineate tumor regions, leveraging both spatial and contextual information. The U-Net model, a convolutional neural network (CNN) architecture, is employed for accurate segmentation of brain tumor regions. This segmentation provides a detailed spatial understanding of the tumor boundaries, aiding in subsequent classification. For UNet we have used an input image size of 128x128x2 and an output size of 128x128x4. We have also used 19 2D convolutional layers, four 2x2 Max pooling layers, 1 dropout layer, four 2x2 upsampling layers, and four merged layers. Furthermore, the Softmax activation function is used in the output layer and ReLU activation function is used for other layers. He_Normal initializers have also been used for initializing the weights.

C. Second Model: AlexNet

Employ AlexNet, a deep CNN architecture, to classify brain tumor types. For classification purposes, the well-established AlexNet architecture is utilized, leveraging its capacity to discern intricate patterns in medical images. The classification aims to categorize tumors into predefined classes, contributing to a nuanced understanding of the tumor types. For AlexNet we have used 5 convolutional layers, 7 Batch normalization layers, three 2x2 Max Pooling layers, 3 dropout layers, one flatten layer, three dense layers and one reshape layer. We have also used the Softmax activation function for the output and the ReLU activation function for the other layers which is the same as the U-Net model. Train AlexNet on preprocessed images with one-hot encoded labels to classify tumors into predefined categories (0=No tumor, 1=Necrotic/Core, 2=Edema, 3=Enhancing).

D. Evaluation Metric

Assess the performance of the proposed dual-model approach using metrics such as cross-entropy loss, dice coefficient, intersection over union (IoU), accuracy, and precision-recall employed to assess the performance of the proposed methodology on Training, validation, and datasets. Validate the models on a separate test set to ensure generalization to unseen data and robustness in real-world scenarios. The details of the main evaluation metrics are as follows:

1) **Categorical Cross Entropy:** It serves as the loss function for a multi-class classification model. The function computes the difference between the actual-value labels and the expected labels under conditions where actual-value labels are one-hot encoded. This encoding method represents the data's true class, with the label vector indicating the true class with a value of 1 and assigning 0 to the rest elements.

$$J_{\text{cee}} = -\sum_{q=1}^{l}\sum_{k=1}^{p} d_{qk}\log(y_{qk})$$

2) **Accuracy:** It is calculated by adding the total number of True Positive (TP) and True Negative (TN) samples and then dividing the total number of samples by the total number of samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

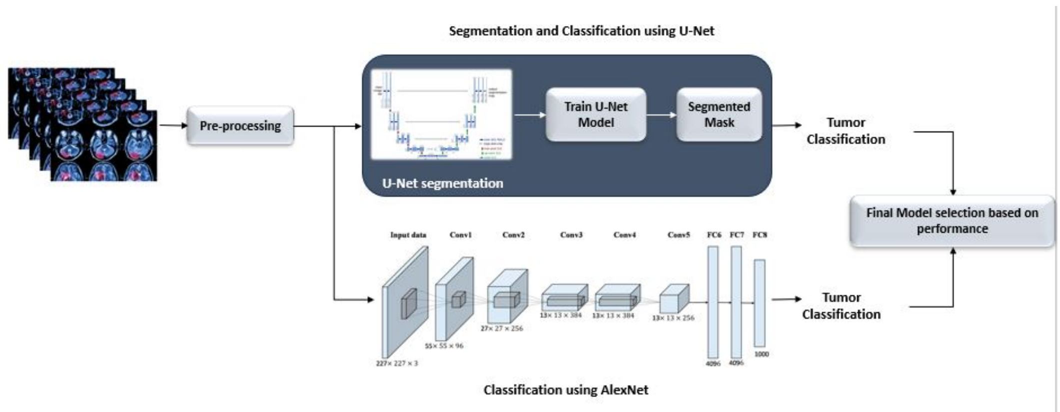

Fig. 1: Overview of our Proposed Methodology

3) **Dice Loss** The Dice loss function is a tool for statistical analysis used to compare the similarity of two images, which is often used in image segmentation tasks. The loss is obtained by subtracting one from the ratio of twice the intersection over the sum of the pixels in the two images, which is derived from the Dice coefficient. A smoothing factor is used in the calculation to avoid division by zero.

$$\text{DiceLoss}(y, \hat{p}) = 1 - \frac{2y\hat{p} + 1}{y + \hat{p} + 1}$$

IV. EXPERIMENTS AND DISCUSSION

A. Dataset

The BraTS (Brain Tumor Segmentation) dataset serves as a valuable resource for brain tumor segmentation endeavors, offering detailed information about distinct classes and image types associated with each subject. The four classes, ranging from ”No tumor” to ”Enhancing,” provide a comprehensive representation of tumor characteristics. Moreover, the availability of diverse images, including native (T1), post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (T2-FLAIR), enhances the dataset’s suitability for multiclass segmentation tasks. The richness of modalities ensures that a model trained on this dataset can effectively learn to segment and classify various tumor regions within brain images, contributing to the advancement of medical image analysis and diagnosis. See the figure 2 for image analysis:

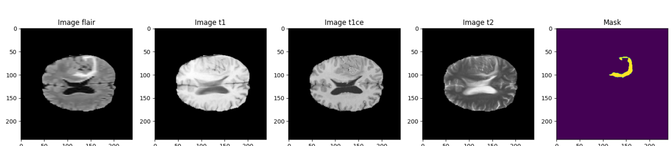

Fig. 2: Analysis of the dataset of one subject

After analyzing the dataset we have split it into train, test, and validation sets. We have used 175 samples for training, 52 samples for validation, and 32 samples for testing. We have also used Adam optimizer along with a 0.001 learning rate. figure 3 is showing the histogram of the dataset segregation.

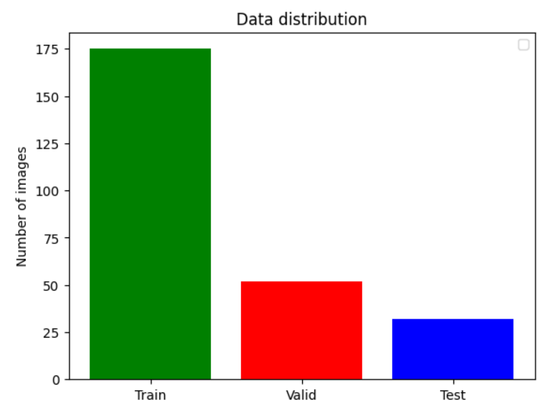

Fig. 3: Train, Validation and Test Split of BraTS dataset

B. U-Net Evaluation

The U-Net model looks to perform wonderfully in our proposed approach. The model’s high accuracy, precision, sensitivity, specificity, and Dice coefficient values show that it effectively segments the appropriate portions in brain tumor images.

A low training loss begins at 0.0137 and falls across epochs to 0.0089 indicating that the model is effectively learning the patterns in the training data. The Dice coefficient quantifies the spatial overlap between expected and true segmentation masks. A result of 0.7327 indicates that the predicted and true masks are in a satisfactory range. The model’s accuracy, precision, and recall are all around 99.58%, indicating that it is making accurate predictions on the training data. We also measure IOU for segmentation evaluation and it Represents the average overlap between the predicted and true masks at an increasing rate. See the result of the segmentation in figure 5 and the output from the U-Net model in figure 4.

The test findings also indicate a high degree of generalization to fresh data. The test data evaluation metrics are consistent with the training metrics, showing that the model generalizes effectively to new data. See the figure 5 to see the testing evaluation.

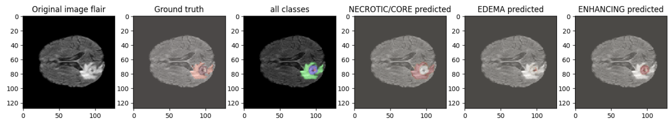

Fig. 4: Output of U-Net Model

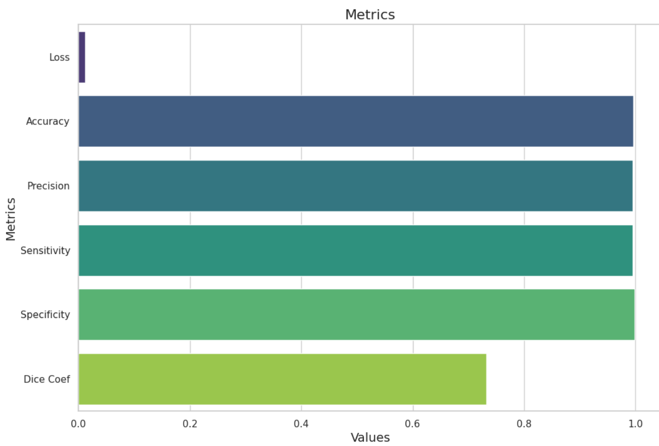

Fig. 5: Evaluation of the U-Net model on Test set

C. AlexNet Evaluation

The result of the training loss of the second experiment i-e-AlexNet is lowered steadily over epochs, suggesting effective convergence and the model's ongoing progress in minimizing the difference between predicted and actual values. Simultaneously, training accuracy remains consistently high, revealing the model's ability to correctly categorize a significant amount of the training dataset (see Figure 7 for a full visualization of these patterns).

Furthermore, the validation loss decreases initially but then increases in consecutive epochs. This discrepancy could indicate that, at a given point, the model overfits the training data, resulting in lower performance on unseen validation data. Despite this, the validation accuracy shows an overall improvement, demonstrating the model's ability to effectively generalize to new data. However, variations in afterward epochs raise concerns about potential overfitting or variance, highlighting the importance of careful monitoring and potential corrections. It is important to note that as the epochs move, the rising disparities between training and validation loss show possible overfitting. The model may be overfitting the training data, making it worthless on new, and unknown data. And the dice loss, precision, and sensitivity of the AlexNet is '0'

However, the AlexNet model performs wonderfully, with a high test accuracy of 98%. This demonstrates the model's capacity to reliably categorize unknown data for the brain tumor classification challenge. See the figure 6 for test evaluation.

When compared to AlexNet, U-Net clearly goes over it in terms of accuracy, precision, sensitivity, and specificity. While AlexNet has a higher specificity and a lower dice loss value, U-Net's overall superior performance, especially in accuracy, makes it the preferred option. Given the significant significance of improved model accuracy in the field of medical science, we chose the U-Net model as our best option.

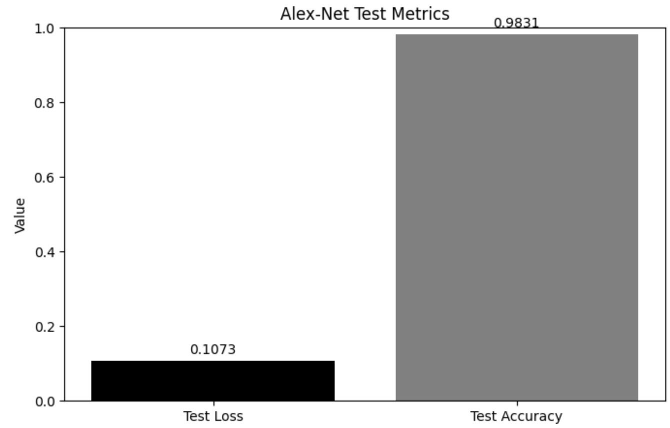

Fig. 6: Evaluation of the AlexNet model on Test set

D. Limitation of the Approach and Future Direction

1) Improve model generalizability by incorporating additional data augmentation techniques while keeping in mind potential biases in the training data and the model's vulnerability to artifacts or anomalies in medical images.
2) The model's ability to effectively capture and utilize all relevant features, indicates potential shortcomings in feature extraction. Based on domain-specific knowledge and feedback from medical specialists, enhancements can be made.
3) Dependency on other techniques such as PCA for dimensionality reduction, image patching, and the addition of various activation functions, and weight initializers, highlight a potential limitation in the model's inherent ability to adapt to diverse data characteristics without requiring such extensive modifications.

V. CONCLUSIONS AND FUTURE WORK

In conclusion, this study addresses the fundamental challenges of precise brain cancer classification through the use of automated tumor classification methods, hence improving radiologists' and physicians' capacities. On the BraTS-2019 dataset, the use of deep learning models, particularly U-Net and AlexNet, proves to be a promising method. U-Net's automatic feature extraction, supported by hierarchical and contextual analysis, and effective segmentation performance highlight its appropriateness for brain tumor image segmentation. In contrast, AlexNet, which is known for its superior picture classification abilities, has a high level of accuracy in diagnosing brain tumors but a precision of 0. The experimental results validate the proposed methodology, with U-Net demonstrating a significant reduction in loss and an amazing accuracy of 99.58%. AlexNet improves classification accuracy from 94.233% to 98%. These findings highlight the efficacy of the automated approaches used, indicating U-Net as a reliable option for brain tumor classification. In the future, our work can improve with a special focus on feature extraction. We

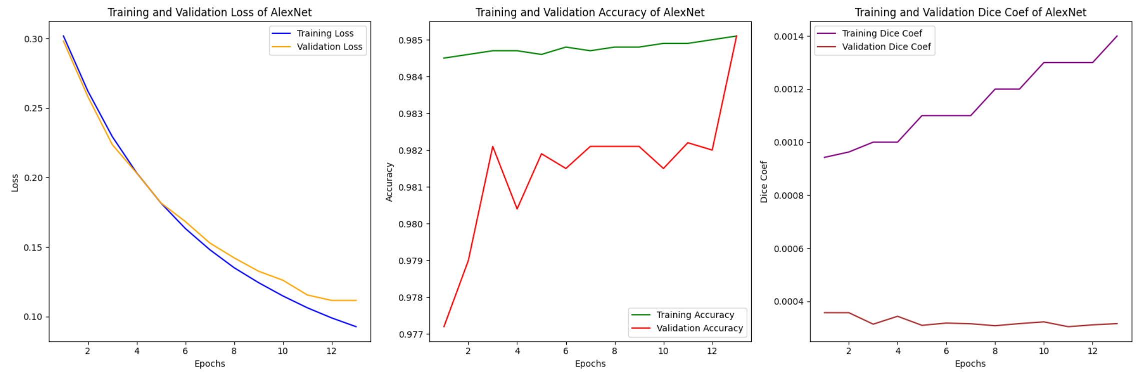

Fig. 7: Visualization of Training and Validation Loss and accuracy of AlexNet

TABLE I: Model Performance Metrics for U-Net and AlexNet

Model Name	Accuracy	Categorical Cross Entropy Loss	Dice Loss	Precision	Sensitivity	Specificity
U-Net	99.6%	1.2%	74.3%	99.6%	99.5%	99.9%
AlexNet	98.3%	10.7%	0.1%	0.00%	0.00%	100%

will also do image patching like segmenting the image into different parts and fitting it to the model to increase the model performance. In addition, we should include alternate activation functions in the future, such as Leaky ReLU, as well as using ”he_uniform” and ”glorot_uniform” as weight initializers. Furthermore, we should test our dataset to several models such as LeNet and VGG 16, indicating our dedication to improving efficiency and embracing innovation in our approach.

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