Multimodal Brain Tumor Detection Using Loss Aware Residual UNet Model

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Abstract *This research introduces a novel approach to multimodal brain tumor detection using the Residual UNet architecture. By integrating various imaging techniques, such as MRI and CT, the study offers a comprehensive perspective on brain anomalies. The Residual UNet architecture, an enhancement of the conventional UNet, is tailor-made for biomedical image segmentation. The architecture's residual connections optimize deeper network training, making it suitable for detecting intricate patterns in multimodal brain images. This paper details a structured approach that amalgamates advanced imaging techniques and machine learning to develop an efficient tumor detection system. The study utilizes the BRATS brain tumor MRI datasets and incorporates sophisticated preprocessing, data augmentation, and the innovative Loss-Aware ResUNet model for optimal results. It outperformed other top models with a peak accuracy of 97%.*

Keywords: Brain tumor detection, MRI dataset, Deep learning, Medical Imaging Diagnostics, ResUNet.

1. INTRODUCTION

Brain tumors represent an irregular and unchecked growth of cells within the brain [1,2]. They can be either malignant (cancerous) or benign (noncancerous). The confined space inside the skull can promote the rapid progression of a brain tumor, posing a risk of damage to the brain, which can have severe consequences. It's projected that in 2020, around 18,020 adults might succumb to malignant brain tumors and those associated with the central nervous system (CNS) [3]. The characteristics and categories of brain tumors can be distinguished through magnetic resonance imaging (MRI) patterns [4,5]. Consequently, MRI scans are a favored method to identify and categorize these tumors, guiding medical professionals in strategizing treatments. The treatment plan is shaped by various elements like the tumor's dimension, form, type, severity, and precise location. As these factors can vary immensely between patients, precise detection and categorization of brain tumors are vital for effective treatment [6]. Manually pinpointing brain tumors and monitoring their evolution over time can be both time-consuming and prone to mistakes [7]. This underscores the importance of automated systems to supplant traditional manual approaches. Over the past few years, deep neural networks (DNNs) have showcased remarkable outcomes, a fact supported by recent studies like the BraTS challenges [8]. Another promising deep learning strategy is the convolutional neural networks (CNN), which have consistently delivered impressive results for both 2D and 3D medical imaging [9,10]. Transfer learning, a technique beneficial when data or computational resources are limited, leverages insights from one task to address related challenges [12]. The fusion of features seeks to combine correlated attributes to identify a core set of significant features, aiming to boost detection precision. Moreover, smart feature selection becomes imperative to minimize computational time and complexity [13,14].

2. RELATED WORK

Shah et al. [1] enhanced the EfficientNet-B0 CNN model for brain tumor image classification, achieving 98.87% accuracy. Jabbar et al. [2] introduced the Caps-VGGNet hybrid model, which excels in feature extraction and classification, achieving accuracy, specificity, and sensitivity of 0.99, 0.99, and 0.98 on the Brats20 dataset, respectively. Sekhar et al. [3] used transfer learning to classify brain tumors into three types, leveraging GoogLeNet and classifiers such as SVM and K-NN. Their model outperformed other existing models on selected datasets. Hao et al. [4] proposed a fusion method of multiple deep models for brain HSI classification, achieving over 96% accuracy in different classification tasks. Han et al. [5] developed a two-step GAN-based data augmentation technique that improved tumor detection results, boosting sensitivity from 93.67% to 97.48%. Roy et al. [6] proposed CNN-based models, S-Net and SA-Net, for brain tumor image segmentation. These models showed promising Dice Similarity Coefficient measures on HGG and LGG datasets. Lu et al. [7] introduced a framework combining CNN and LSTM. Their proposed network achieved prediction accuracies ranging from 89.50% to 99.56% on different datasets. Xing et al. [8] presented a learning-based framework for nucleus segmentation in histopathology images, which can be applied across different staining scenarios. Wang et al. [9] suggested a method that combines Gabor representation of multi-CNN and a fuzzy neural network, achieving improvements in various metrics compared to other multimodal fusion methods. Subramanian et al. [10] showcased AI-based deep learning models for automating cancer detection, with their transfer learning models outperforming current state-of-the-art techniques. Ani et al. [11] developed a low-complexity CNN model based on the best-performing AlexNet. Their improved model, with 22 layers, achieved 99.4% accuracy, 99.67% precision, 99.02% recall, and 99.35% F1 score. Hu et al. [12] explored multiple deep learning models for brain tumor diagnosis. Although they found that the YOLO model decreased classification accuracy, deep learning showed potential in increasing diagnosis speed and accuracy. Duvvuri et al. [13] experimented with pre-trained models and eventually developed a hybrid CNN-SVM model, aiming for higher accuracy and better predictions. Dharashini et al. [14] introduced a hybrid method using CNNs and BAT algorithms for brain tumor detection. This model optimizes the CNN parameters and demonstrates the potential for accurate and rapid diagnosis. Ankireddy et al. [15] designed an assistive diagnostic tool based on transfer learning with Mask R-CNN. Their application, built on Flask, can diagnose and segment brain tumors in MRI images, showing 90% accuracy with the ground truth. Kesana et al. [16] conducted a study on a Kaggle dataset and found YOLOv5 to be significantly precise in brain tumor detection. Bhanothu et al. [17] proposed an algorithm using VGG-16 architecture and Region Proposal Network (RPN) for tumor detection and classification, achieving a mean average precision of 77.60% across tumor types. Pathak et al. [18] introduced a strategy combining deep learning and Fourier transformation. Their approach outperformed other models, improving accuracy by 5%. Kumar et al. [19] worked with an open-source dataset, pre-processed images, and proposed a CNN model. Their model exhibited improved accuracy compared to other contemporary models. Dutta et al. [20] introduced the channel split dual attention (CSDA) attention module. It captures feature dependencies in both spatial and channel dimensions, surpassing other brain tumor detection methods in classification accuracy. Achraya et al.[21] developed a Deep Neural Network (DNN) model for MRI brain tumor segmentation. Their approach outperformed existing models in both accuracy (90% vs. 78%) and processing time (34 ms vs. 73 ms). Gyanganga et al.[22] introduced an automatic tumor edge intensity detection technique based on CNN. It utilizes Canny edge detection, Wavelet transform, and Hough transform for surgical applications. Raun et al.[23] designed a CNN model for brain tumor detection. They used augmented MRI images and applied back propagation for accurate results. Cinar et al[24] compared five CNN architectures for brain tumor classification. ResNet101 and VGG19 were the top performers. Mohan et al.[25] proposed a segmentation method using ResUnet. The method combined with CLAHE showed improvements in accuracy and other metrics.

3. METHODOLOGY USED

Multimodal brain tumor detection combines various imaging techniques, like MRI and CT, to offer a comprehensive view of brain pathologies. Deep Learning, particularly using the Residual UNet architecture, has become pivotal for analyzing these datasets. The Residual UNet, an evolution of the standard UNet, is designed for precise biomedical image segmentation, with its residual connections aiding in more effective training of deeper networks. When applied to multimodal brain images, this architecture can discern intricate patterns and abnormalities, ensuring accurate tumor segmentations. The blend of advanced imaging and sophisticated computational models like Residual UNet heralds a promising future for neuro-oncology diagnostics. Therefore, in this paper, a residual Unet model is presented for multi-modal brain tumor detection.

This section outlines a systematic approach to detect brain tumors by harnessing the capabilities of feature engineering coupled with machine learning techniques. In this framework, we leverage advanced imaging techniques in tandem with machine learning algorithms, as illustrated in Figure 1. The subsequent steps detail this methodology:

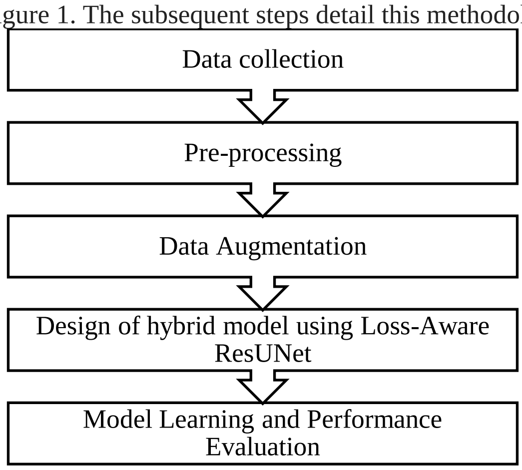

Figure 1: Research Methodology

Machine learning has capability to learn patterns from unlabeled and unstructured data either it is from image or others. In this step, deep learning-based Loss-Aware ResUNet and their performance is investigated on brain tumor segmentation using imaging technology.

3.1 Data Collection

The results are presented on brain tumor MRI datasets on BRATS 2021. The primary objective of BraTS has always been to assess novel methods for brain tumor segmentation in multimodal magnetic resonance imaging (MRI) data. Typically, the BRATS challenge involves several tasks that focus on the segmentation of different tumor sub-regions in the MRI scans, using various modalities such as T1, T1c, T2, and Flair. Participants employ a wide range of methods, often involving deep learning models, especially convolutional neural networks, to achieve the segmentation.

3.2 Pre-processing

Therefore, it is not easy to distinguish healthy area from the anomaly area in image. That’s why pre-processing is required before segmentation of abnormality/anomaly area. Due to the constraint of dynamic range, the medical images are not able to expose all pixels of an image in a better way. As more exposure can be achieved by increasing the area of some under-exposed regions. This is mathematically represented as in eqn (1).

$$A^b = \sum_{j=1}^{M} X_{i^0} q_i^b \qquad (1)$$

Where, M is the number of exposure samples, q_i is the i_{th} image in the exposure set, X_i is the mass map of the i_{th} image, b is the index of three-color channels and A is the improved final outcome. The mass is standardized so that $\sum_{j=1}^{M} X_i = 1$.

3.3 Data Augmentation

Data augmentation plays a crucial role in enhancing the performance of deep learning models, especially when the amount of available data is limited. For multimodal brain tumor detection, where multiple imaging modalities (such as MRI T1, T2, FLAIR, etc.) are utilized, augmentation techniques can significantly improve detection accuracy by presenting the model with a more diverse set of data.

Common Augmentation Techniques for Brain Tumor Detection:

- Rotation: Slight rotations can be applied to the images. It's essential to ensure that all modalities of a particular case are rotated identically to maintain spatial alignment.
- Flipping: Images can be flipped horizontally or vertically. This is especially useful as tumors can appear anywhere in the brain.
- Scaling and Zooming: Images can be zoomed in or out. When zooming in, it's important to ensure that no vital information from the edges is lost.
- Elastic Deformation: This technique simulates the natural variations and deformations in biological tissues.
- Brightness and Contrast Adjustment: Varying the brightness and contrast can simulate different imaging conditions and enhance certain features in the images.

3.4 Loss-Aware ResUNet

Convolutional neural networks (CNN) excel in image processing tasks, such as target retrieval and image segmentation. CNNs utilize various methods to process vast amounts of image data, and their success relies on both the dataset size and the network structure. U-net, introduced in 2015, is a standout CNN architecture specifically designed for medical image analysis and offers end-to-end training. This network is crucial for semantic segmentation in medical imaging. U-net's upsampling component is rich in feature channels, allowing the transfer of contextual information to higher-resolution layers. It can tackle diverse biological segmentation challenges, handling images of any size. U-Net is versatile, compatible with various medical imaging systems like CT, MRI, ultrasound, X-ray, OCT, and PET. The U-Net structure, depicted in Figure 2, has two pathways: contracting and expanding. The contracting part follows the conventional CNN layout with specific operations and gradually increases the feature channels.

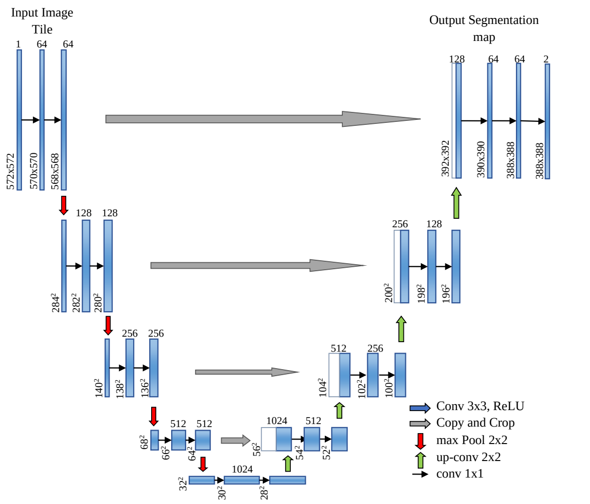

Figure 2: UNET Architecture

The U-Net CNN architecture has 23 convolutional layers. It can be broadly divided into an encoder (left) and a decoder (right):

Encoder:

- Comprises multiple 3x3 convolutions.
- Each convolution is followed by ReLU and batch normalization.
- Post convolution operations, a 2x2 max pooling is used to reduce spatial dimensions.
- As the spatial dimensions decrease, the feature channels double.

Decoder:

- Starts with upsampling of the feature map.
- A 2x2 transpose convolution is applied, cutting the feature channels by half.
- This is paired with a 3x3 convolution and combined with the corresponding feature map from the encoder. Each convolution is succeeded by a ReLU.
- The final layer uses a 1x1 convolution to map channels to the required number of classes.

All specific functionalities of the U-Net blocks are detailed in table 1.

Table 1: UNet Network Structure Description

S. No	Block Name	Meaning	Application
1	Conv 3X3	3 X 3 Convolution	Extract image features
2	Copy and Crop	Skip-connection	Splice feature maps
3	Max pool	Maximum pool layer	Dimension reduction
4	Up-Conv	Up-sampling process	Restore dimensions
5	Conv 1X1	1 × 1 convolution layer	Output results
6	Conv Block	Residual module	Amplify the dimension of feature layer
7	ReLU	Rectified Linear Unit, Activation Function	Make network have the ability of layered nonlinear mapping learning

Motivated with Unet model, this paper presented a Loss-Aware ResUNet architecture is proposed. It is made up of a contracting path (on the left) and an expanding path (on the right). Rather than basic blocks in the type of U-net, the contracting route uses four pre-activated residual blocks. Every block includes two convolution units, both having a Batch Normalization (BN) layer, a Leaky Rectified Linear Unit (LReLU) activation function, and Maxpooling with Stride = 1. The number of feature channels doubles with every down-sampling step. Every block begins with an up-sampling procedure that doubles the size of the feature map, followed by a double convolution and concatenation with the feature maps that correspond to the contracting route. MRI images collected with ground truth (labels) and were used to train the intended network. Finding the network parameters (weights and biases) that minimize a loss function is the main aim of the model. This is accomplished in this study by using the ADAM optimizer, which changes the parameters in the opposite direction of the gradients at each iteration.

In this approach residual Unet is hybridized with making the layers loss aware. For this a hybrid weighted loss function is designed that combined Weighted Cross Entropy (WCE) and Generalized Dice (GDL) in used for softmax probability loss.

$$WCE = -\frac{1}{B}\sum B \sum_{i}^{L} w_i\, gt_{ib} \log(s_{ib}) \qquad (2)$$

$$GDL = 1 - 2\frac{\sum_i^C w_i \sum_B gt_{ib}.s_{ib}}{\sum_i^C w_i \sum_B (gt_{ib} + s_{ib})} \qquad (3)$$

Where, C= total number of class/labels, B = batch size, w_i= the weight assigned to the i_{th} label, s_{ib}= the value of the (i_{th}, b_{oth}) pixel of the segmented binary image, gt_{ib}= the value of the (i_{th}, b_{th}) pixel of the binary ground truth image.

4. RESULTS AND ANALYSIS

The designed framework is implemented in Python using Google Colab. The implementation is done in Keras, using TensorFlow as backend. The entire dataset is divided into 70:30 ratio of training and testing. The model is implemented on BRATS2021. For training, Adam optimizer is used with learning rate of 0.0001. All networks are trained for 100 epochs on Tesla P100-PCIE GPU.

4.1 Performance Parameters

Sensitivity/ Recall: Also termed as True Positive Rate that refers to the proportion of those who have the condition that received a positive result on this test. It is Defined as:

$$Sensitivity = \frac{(TP)}{(TP + FN)} \qquad (4)$$

Accuracy: It is the ratio of the correctly labelled subjects to the whole pool of subjects. It is Defined as:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \qquad (5)$$

Precision: It is the ratio of the positive labelled subjects to all predicted positive labels. It is Defined as:

$$Precision = \frac{(TP)}{(TP + FP)} \qquad (6)$$

Where, TP stands for True Positive. (This is the overall test samples that are anticipated to be Anomaly and whose true label is also Anomaly).

TN stands for True Negative. (This shows overall test samples that are expected to be Normal and whose true label is Normal).

FP stands for False Positive. (This is the overall test samples that are anticipated to be Anomaly but are labelled as Normal).

FN stands for False Negative. (This is the total value of test samples that are projected to be Normal but are labelled as Anomaly).

4.2 Results and Discussions

Figure 3 shows the Accuracy Vs Epoch Graph for training and Validation accuracy for Loss-Aware ResUNet for brain tumor detection. The epochs vary from 0-100, Firstly, the accuracy linearly increases from 0 epoch to around 10 epochs. After 100, the accuracy for both training and validation accuracy becomes constant. The average accuracy for this graph is around 97.7 %. Figure 4 shows the dice-coefficient vs epoch graph for training and validation accuracy for Loss-Aware ResUNet for brain tumor detection. The epochs vary from 0-100. The training and validation dice coefficient fluctuates between 60 epochs. After 60, the Dice coefficient becomes constant. The average dice coefficient for this graph is around 80%. The loss vs epoch graph for training and validation loss for Loss-Aware ResUNet for brain tumor detection is shown in Figure 5. First, from 0 to around 80 epochs, the Loss decreases. The Loss for both Training and Validation becomes constant at about 80 epochs.

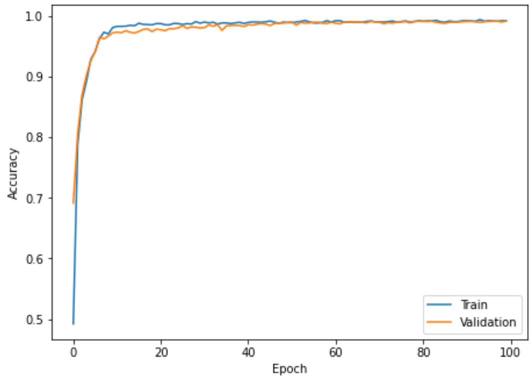

Figure 3: Accuracy Graph for Multi-Modal Brain Tumor Detection

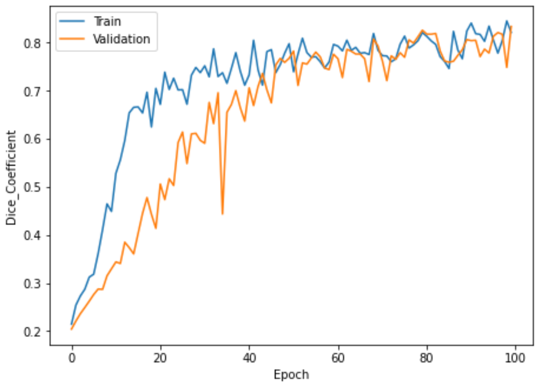

Figure 4: Dice Coefficient Graph for Multi-Modal Brain Tumor Detection

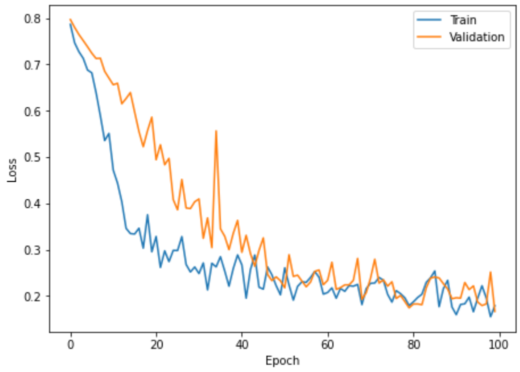

Figure 5: Loss Graph for Multi-Modal Brain Tumor Detection

Table 2 presents the performance metrics of a model termed "Loss-Aware ResUNet". The table summarizes the values of various parameters used to evaluate the model's performance:

- Loss: The value is 0.352. It indicates the difference between the predictions made by the model and the actual data. Lower values generally signify better model performance.
- Accuracy: The model has an accuracy rate of 96.7%.
- Dice Coefficient: The coefficient is at 64.1%. The Dice coefficient is a measure of overlap between two samples. A Dice coefficient of 1 represents perfect overlap, while 0 indicates no overlap. In the context of image segmentation, a higher Dice coefficient means that the segmented region closely matches the actual region.
- Precision: The precision of the model is 93.8%. Precision gauges how many of the positive identifications were actually correct. A higher precision indicates fewer false positives.
- Sensitivity: Also known as the true positive rate, the sensitivity of the model is 98%. It measures the proportion of actual positives correctly identified. A higher sensitivity means the model correctly identifies most of the positive cases.

Table 2: Performance Evaluation of Loss-Aware ResUNet

Parameters	Values
Loss	0.352
Accuracy	96.7%
Precision	93.8%
Sensitivity	98%

Table 3 shows a comparative analysis of accuracy among different modelling techniques, with the proposed model achieving the highest accuracy. Ensemble Tree [26] achieves an accuracy of 89.16%. Ensemble Tree methods combine the predictions from multiple machine learning algorithms to make more accurate predictions than any individual model. ELM [26] has an accuracy of 93.40%. The proposed model achieves the highest accuracy of 97%. It outperforms the other listed state-of-the-art models in the accuracy metric. It highlights the progress made in modelling and provides a benchmark for comparing different approaches.

Table 3: Comparative State-of-Art

Models	Accuracy
Ensemble Tree [26]	89.16%
ELM [26]	93.40%
Ours	97%

5. CONCLUSION

The research successfully implemented a Loss-Aware ResUNet architecture for multimodal brain tumor detection, demonstrating its efficacy on the BRATS MRI dataset. The model showcased a commendable accuracy rate of 96.7% after being trained. Notably, the presented architecture surpassed other state-of-the-art models in accuracy metrics, achieving a peak value of 97%. The combination of advanced imaging techniques and deep learning architectures, such as Residual UNet, sets a promising trajectory for advancements in neuro-oncology diagnostics. This study underscores the potential of integrating cutting-edge imaging and computational models in refining the precision of brain tumor segmentations, paving the way for future breakthroughs in medical imaging diagnostics.

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Conflict of Interest

The corresponding author, on behalf of all authors, confirms that there are no conflicts of interest to disclose.