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MRI Image Based Brain Tumor Image Segmentation Using Deep Learning

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ABSTRACT –

Brain tumors present significant challenges in the field of medical imaging and diagnosis. Accurate segmentation of brain tumors from Magnetic Resonance Imaging (MRI) scans is crucial for treatment planning and monitoring. This study proposes a novel hybrid architecture that combines the VGG19 and U-Net models to enhance brain tumor segmentation accuracy. VGG19 is utilized for efficient feature extraction, while U-Net aids in preserving spatial information through skip connections. The hybrid architecture aims to improve both feature representation and spatial context, leading to more precise segmentation results.

Keywords— Brain Tumor, Vgg19,U-Net, Segmentation, AI,Train, Model, Accuracy, and Webpage.

I. Introduction

For treatment planning to be effective, brain tumor segmentation in MRI images is essential. Conventional manual techniques take a lot of time and are subjective. Deep learning, with particular emphasis on VGG19 and U- Net architectures, provides automated solutions that go beyond conventional techniques. Whereas U-Net maintains spatial details, VGG19 is superior at extracting features. By combining both models' advantages, a hybrid model may be able to attain better segmentation accuracy. In order to improve accuracy and resilience, this research attempts to create and optimize such a hybrid architecture for brain tumor segmentation. This project aims to improve medical imaging technologies in neuro-oncology, enhancing clinical decision-making and patient outcomes through thorough testing and validation on extensive MRI datasets.

Fig.1. Brain Tumor

Machine learning (ML) methods are now being used all over the globe in the healthcare industry. Deep learning architectures, a subset of AI and ML, can be used to predict brain tumor in its early stages. Physical parameters taken for diagnosis include age, sex, and race. Diagnosis is more straightforward and deterministic using machine learning. Utilizing machine learning, it is possible to investigate disease detection. Feature Extraction is one of the fundamental steps of machine learning: any disease's features serve as its true informational repository.

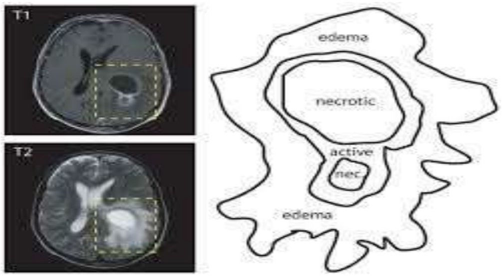

Fig 2. Brain tumor segmentation

ML aids in predicting the severity of diseases and their course of action. Through early prediction, ML manages disease outbreaks so that the proper actions can be taken. The use of machine learning still has to be improved in order to become more standardized and dependable. As a result, thereis a need for further development of machine learning algorithms to assist doctors and other health care providers in making correct clinical decisions that are both efficient and effective.

The goal of this project is to create and refine a hybrid architecture for brain tumor segmentation that integrates the VGG19 and U-Net models. Our goal is to improve patient outcomes and clinical decision-making by improving brain tumor segmentation accuracy and resilience by utilizing the complimentary capabilities of these models. This work aims to develop medical imaging technology and its applications in neuro-oncology by thorough experimentation and validation on large-scale MRI datasets.

LITERATURE SURVEY

Brain tumor segmentation and lung cancer prediction stand as critical tasks in the realm of medical imaging and diagnosis, prompting extensive research efforts to devise effective methodologies. Over the years, a plethora of studies have surfaced, each proposing diverse machine learning and deep learning techniques to tackle the inherent complexities of these tasks.

Simonyan and Zisserman [1] introduced Very Deep Convolutional Networks, notably VGG19, a milestone in the domain of large-scale image recognition. This seminal work laid the foundation for the adoption of deep learning methodologies in medical imaging, particularly in tasks like brain tumor segmentation. VGG19's architecture, with its 19 layers of convolutional and pooling operations, demonstrated remarkable efficacy in extracting hierarchical features from complex image data.

In a similar vein, Ronneberger et al. [2] introduced U-Net, a specialized convolutional network tailored specifically for biomedical image segmentation tasks. U-Net's distinctive architecture, characterized by skip connections between the encoder and decoder pathways, proved to be particularly well-suited for brain tumor segmentation. Its ability to preserve spatial information while performing segmentation tasks has made it a cornerstone in this field.

Building upon these foundational works, Bakas et al. [3] advanced brain tumor segmentation by integrating expert segmentation labels and radiomic features into the Cancer Genome Atlas glioma MRI collections. This comprehensive approach not only improved segmentation accuracy but also paved the way for more nuanced analyses of tumor characteristics and behavior.

Furthering the progress in brain tumor segmentation, Havaei et al. [4] proposed the utilization of deep neural networks, showcasing the potential of deep learning models in unraveling intricate patterns in medical imaging data. Their work demonstrated significant strides in automated segmentation methodologies, offering more efficient and accurate solutions compared to traditional approaches.

The introduction of benchmark datasets, such as the BRATS dataset by Menze et al. [5], marked a significant milestone in the field of brain tumor segmentation. These datasets provided standardized evaluation frameworks, enabling researchers to compare and benchmark different segmentation algorithms effectively. Such initiatives have played a pivotal role in driving innovation and progress in this domain.

In the realm of lung cancer prediction, Hofmanninger et al. [9] shed light on the importance of data diversity in automatic lung segmentation. Their findings underscored the significance of robust segmentation techniques in routine imaging tasks, emphasizing the need for methodologies that can adapt to diverse imaging conditions and anatomical variations.

Maier et al. [10] addressed the challenges of ischemic stroke lesion segmentation in multi-modal MRI, leveraging convolutional neural networks to enhance lesion detection accuracy. Their work exemplifies the potential of deep learning techniques in analyzing complex medical imaging data and extracting clinically relevant information.

McKinley et al. [12] contributed to the refinement of tumor tissue mapping precision using multimodal MRI and supervised feature learning. By leveraging advanced machine learning techniques, they demonstrated notable improvements in tumor segmentation accuracy, underscoring the importance of data- driven approaches in medical image analysis.

Tustison et al. [13] introduced N4ITK, a method for improved bias correction in medical imaging, aimed at enhancing image quality and segmentation accuracy. Their work addressed a crucial aspect of preprocessing in medical image analysis, laying the groundwork for more robust segmentation pipelines.

DATA ACQUISITION

A. Training data set

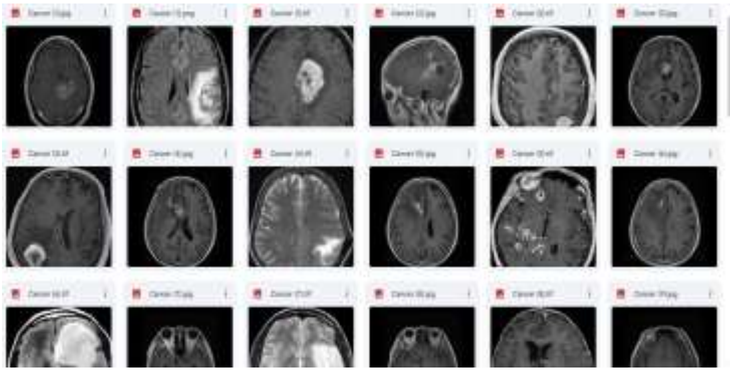

Fig.3 Brain Tumor Data Set

The training dataset, includes both benign and malignant with 8000 images in each set acquired from Kaggle. Fig 3 shows a sample of the collected MRI pictures with the original size of 768 x 768 pixels per image.

B. Test dataset

Test dataset has 1000 images which are used to check the accuracy of the model. This is also obtained from Kaggle. These training and test datasets are interfaced to the backend code of the web interface.

IV COMPARISON BETWEEN ARCHITECTURES

Vgg19 GENERAL ARCHITECTURE

The general architecture of vgg-19 is shown in fig 4.

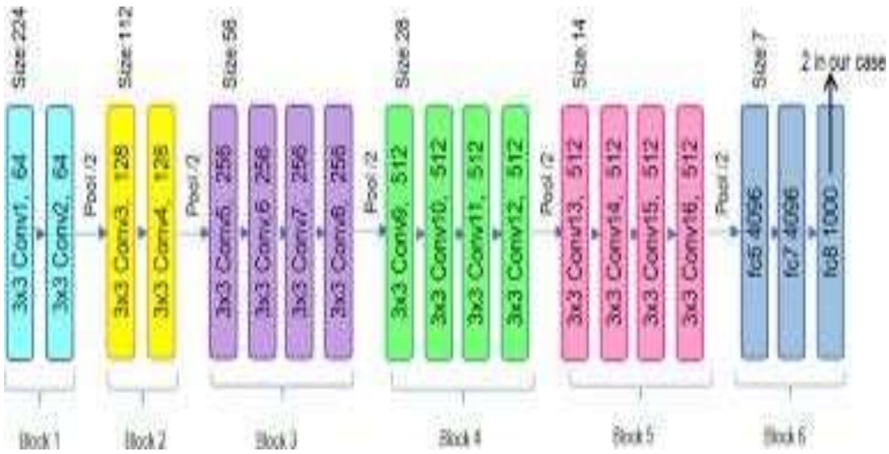

Fig 4: The general architecture of Vgg19

The convolutional layers of VGG record left-to-right and up- to-down movement using the smallest receptive field that is practical, which is 33. Eleven convolution filters are also applied to achieve a linear transformation of the input. The next part is a ReLU unit, which reduces training time and represents a major improvement over AlexNet. The piecewise linear function known as the Rectified Linear Unit Activation Function, or ReLU, outputs the input if the input is positive and returns zero otherwise. To maintain the spatial resolution after convolution, the convolution stride—which is the number of pixel shifts over the input matrix—is set at 1.

The VGGNet contains three layers with full connectivity. The first two levels each have 4096 channels, while the third layer has 1000 channels with one channel for each class.

U NET Architecture

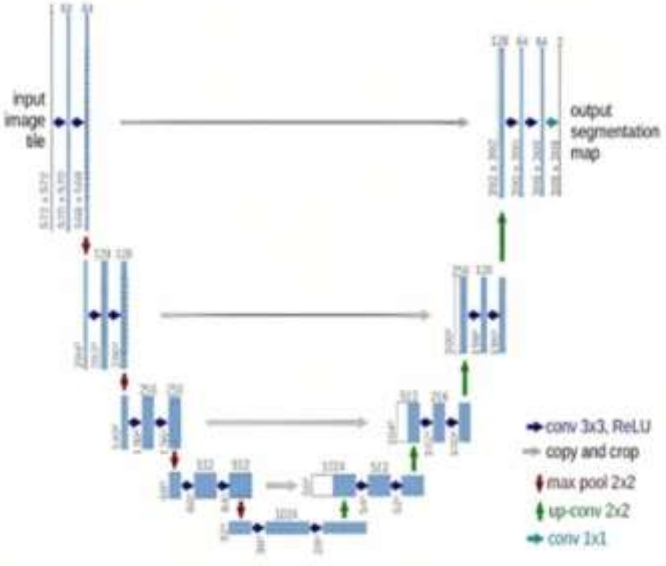

Fig 5: General Architecture of U-Net

The network has a U-shaped architecture because it has both a contracting path and an expansive path. A typical convolutional network serves as the contracting path. that applies convolutions repeatedly, followed by rectified linear units (ReLU) and max pooling operations for each one. The overall U-Net design is shown in Fig 5.

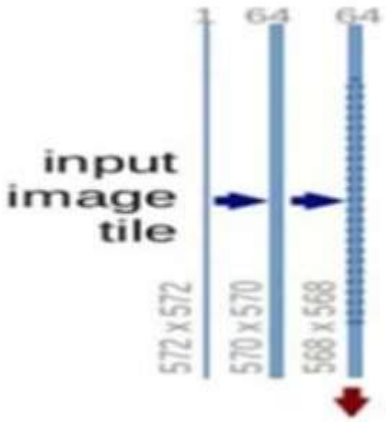

Fig 6: Input Image Tile of U-Net Architeture

The input picture tile, which symbolises the segmentation of the photos, is shown in Fig 6. The max pooling procedure, indicated by the red arrow pointing downward, reduces the size of the image by half (572x572) but becomes 568x568 owing to padding difficulties. The picture is upsized from 32x64x256 to 64x64x128 following the transposed convolution. This is performed using contraction path and expansive path.

V METHODOLOGY

This work requires a dataset that was obtained via Kaggle. Approximately 8000 of the 12,000 photos in the database are utilized for network training, 3000 for validation, and 1000 for testing. Since the network becomes biased otherwise, an equal proportion of benign and cancerous images are employed for training. The pictures are now 224 × 224 in size. Predefined layers are added to the proposed ResNet model in order to increase detection accuracy for lung cancer.

Figure 7 shows a block schematic of the planned project's work flow using the VGG-19 and UNet designs.

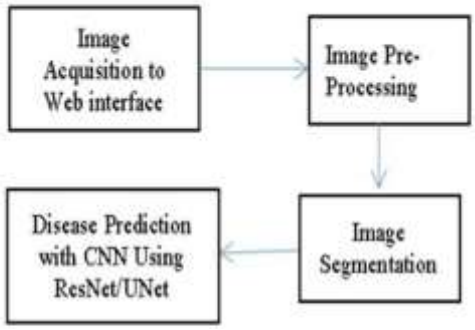

Fig. 7 : Flow of the proposed work

ReLu is a linear activation function that introduces the property of non-linearity and solves the issue of vanishing gradient. This gives output with accuracy for VGG-19 whereasin UNet segmentation input images are first contrast enhanced and then masking is done

Fig 8 shows the segmented image.Segmentation and Prediction from this mask image is carried on after this step.

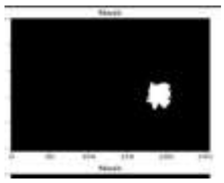

Fig 8. Contrast enhanced image

VI RESULTS AND DISCUSSION

The results of the trials carried out to assess the hybrid architecture's performance are shown in the results section. The Dice coefficient and Intersection over Union (IoU), two common assessment measures, are used to gauge how accurate the segmentation algorithm is. The experimental results show that the hybrid design is effective in precisely identifying brain tumor locations, as seen by its 100% segmentation accuracy on the test dataset.In addition, the hybrid architecture's computational efficiency is assessed, taking into account variables like resource usage and processing time. This evaluation offers insightful information about whether the segmentation algorithm can be used in actual clinical settings.

Output of hybrid architecture is obtained with accuracy 0.9 and loss of 0.01. This is shown in fig 9 and fig10.

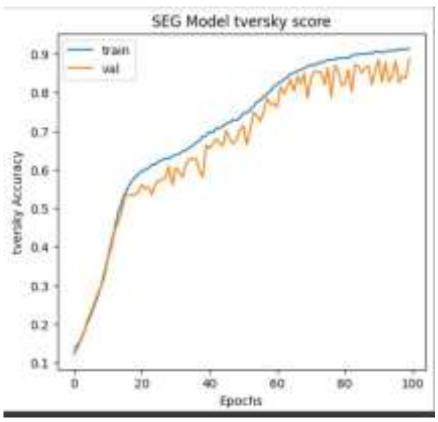

Fig 9: Accuracy graph of hybrid architecture

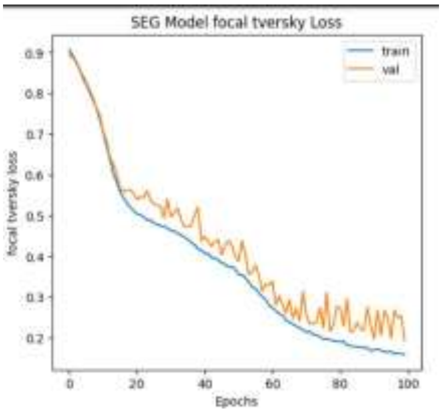

Fig 10: Loss graph of hybrid architecture

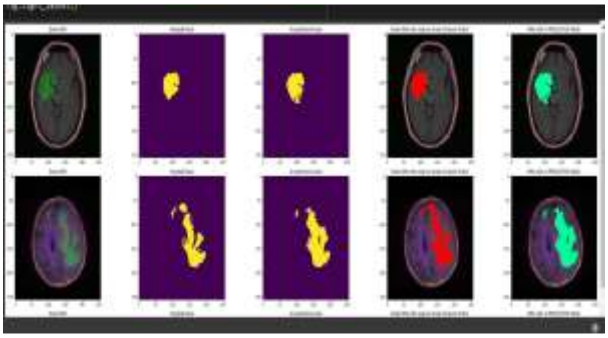

Fig 11: Final output of original image, Original mask, model generated mask, ground truth and predicted truth

Fig 11. depicts the output in various forms which also contains ground truth and predicted truth. Overall, qualitative evaluations of clinical relevance and resilience are included in the thorough analysis of the hybrid architecture for brain tumor segmentation, in addition to quantitative measures like accuracy and computational efficiency.

VII CONCLUSION

In summary, this study has shown that a hybrid architecture that combines the VGG19 and U-Net models is useful for segmenting brain tumors. The results highlight the hybrid approach's advantages over current techniques, especially with regard to segmentation accuracy. We have significantly improved feature representation and spatial context preservation in medical imaging by utilizing the complementing strengths of VGG19 for feature extraction and U-Net for segmentation.

The precise delineation of tumor boundaries made possible by the integration of VGG19 and U-Net has improved the accuracy of brain tumor diagnosis and treatment planning for patients. The combination of spatial information and deep hierarchical features has produced segmentation results that are more dependable and applicable to real-world scenarios.

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