Multi-Model Fusion for Prediction and Segmentation of Brain Tumor using Convolutional Neural Network for Streamlined Healthcare

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Abstrast:- In order to improve brain tumour analysis, our research uses MRI and CT data in a Flask-based web application. Our research focuses on advancing brain tumor analysis through a sophisticated approach that integrates MRI and CT data within a user-friendly Flask-based web application. The landmark-based registration ensures precise alignment of diverse patient images, establishing a standardized coordinate system for meticulous anatomical comparisons. To enhance the VGG-19 CNN architecture's analytical capabilities, we employ transfer learning, enabling nuanced analysis. The subsequent Image Fusion process optimizes tumor segmentation accuracy by leveraging the complementary strengths of CT and MRI data. The Watershed transformation isolates regions of interest, facilitating a more refined segmentation process. Additionally, a CNN predicts the presence of brain tumors, streamlining detection and prognosis, ultimately contributing to a healthcare paradigm that is both efficient and patient-centered. These advancements not only streamline the intricate examination of brain tumors but also enhance accessibility and accuracy in healthcare practices.

Keywords:- *CNN, Flask, VGG -19, Image Fusion, Watershed Transformation.*

I. INTRODUCTION

The integration of medical imaging, specifically Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), has significantly advanced our understanding of brain anatomy within the healthcare domain. Our initiative addresses the crucial need for accurate and effective brain tumor analysis. To initiate this advanced analysis, users seamlessly upload CT and MRI scans through our Flask-based web application. A pivotal component of our methodology is the landmark-based registration, ensuring precise alignment of images for thorough comparison across diverse patient datasets. To further enhance the accuracy of tumor segmentation, we employ transfer learning with a Convolutional Neural Network (CNN). This sophisticated approach allows our system to leverage pre-existing knowledge, improving the nuanced analysis of brain images. The culmination of our methodology is the novel Image Fusion method, a process that merges information from both CT and MRI scans. This fusion enhances the precision of tumor segmentation, providing more detailed insights for improved diagnostic outcomes in healthcare practices.

II. RELATED WORKS

Numerous studies have been done in the field of disease prediction using different machine learning techniques and algorithms which can potentially be used by various medical and healthcare institutions. This paper reviews some of those studies done in research papers using the techniques and results proposed by them.

➢ *Deep Multi-Modal Fusion for Brain Tumor Segmentation by Smith, J., et al.*

- This work explores a deep multi-modal fusion approach for brain tumor segmentation, similar to our project. The authors leverage a combination of CT and MRI data, employing advanced fusion techniques and deep learning methodologies. Their study provides valuable insights into the challenges and advantages of integrating multi-modal information for enhanced segmentation accuracy.

➢ *Convolutional Neural Networks for Brain Tumour Segmentation by Abhishta Bhandari, Jarrad Koppen and Marc Agzarian*

- The advent of quantitative image analysis, particularly in the form of radiomics, has become pivotal in predicting clinical outcomes for brain tumors like glioblastoma

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multiforme (GBM). This involves assessing various quantitative features, including shape, texture, and signal intensity, providing a comprehensive understanding of the pathology.

- The study emphasizes the role of Convolutional Neural Networks (CNNs) in addressing inconsistent manual segmentation in brain tumor analysis. It further explores the innovative field of radiomics, aiming to extract quantitative features for predicting critical clinical outcomes such as survival and therapy response. This dual approach highlights the potential of advanced technologies in automating and enhancing the accuracy of brain tumor segmentation.

➢ *Deep Learning for Brain Tumor Segmentation: A Survey of State-of-the-Art by Tirivangani Magadza and Serestina Viriri*

- The paper reviews state-of-the-art deep learning methods for brain tumor segmentation, emphasizing their effectiveness in overcoming challenges. Deep learning, with its remarkable performance, emerges as a solution for quantitative analysis. The discussion concludes with a critical examination of ongoing challenges in the realm of medical image analysis.
- Notable architectures like ensemble methods and UNet models show promise but require careful considerations such as pre-processing, weight initialization, and addressing class imbalance issues.

➢ *A Deep Multi-Task Learning Framework for Brain Tumor Segmentation by He Huang, Guang Yang, Wenbo Zhang, Xiaomei Xu, Weiji Yang, Weiwei Jiang and Xiaobo Lai*

- Glioma, the most common CNS tumor, poses challenges in manual segmentation from MRI due to time constraints and the potential confusion with strokes. Deep learning offers automation, but class imbalances make brain tumor segmentation in MRI one of the most complex tasks.
- To address these challenges, a deep multi-task learning framework is proposed, integrating a multi-depth fusion module and a distance transform decoder based on V-Net. The model, evaluated on BraTS datasets, achieves high-quality segmentation with an average Dice score of 78%, showcasing its potential for accurate and automatic brain tumor segmentation.

➢ *Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks Convolutional Neural Networks by Dinthisrang Daimary, Mayur Bhargab Bora, Khwairakpam Amitab, Debdatta Kandar*

- Proposed hybrid models, including U-SegNet, Seg-UNet, and Res-SegNet, blend features from popular architectures like SegNet, U-Net, and ResNet18. The depth variations and skip connections in these models are designed for enhanced accuracy.
- Evaluation using the BraTS dataset reveals that the hybrid architecture consistently achieves higher accuracy in brain tumor segmentation, showcasing their potential in improving segmentation techniques.

III. PROPOSED APPROACH

Our suggested method for analyzing brain tumors makes use of the complementary strengths of magnetic resonance imaging (MRI) and computed tomography (CT) in a Flask web application. Users can easily submit their MRI and CT images, which starts a registration process based on landmarks for accurate alignment across various patient datasets. We use transfer learning with a Convolutional Neural Network (CNN) to increase accuracy by utilizing prior information. Our methodology culminates in the novel Image Fusion procedure that combines CT and MRI data to improve the accuracy of tumor segmentation. By streamlining and improving brain tumor analysis, this all-encompassing strategy hopes to enhance patient-centered healthcare procedures and diagnostic results.

➢ *Following are the Steps Involved in our Proposed Methodology:*

- Landmark-Based Registration operates by identifying and precisely matching distinct points or 'landmarks' on both types of scans, effectively overlaying them to a shared anatomical reference.
- Integration of VGG-19 CNN, which is equipped with pre-trained parameters, into our methodology ensures an additional layer of accuracy in the registration process.
- DWT effectively splits image details into varying frequency bands, leading to an optimized fusion process in the next stage.
- Wavelet Decomposition breaks down each image into a series of coefficients that capture both the broad, overarching features as well as the fine-grained, detailed aspects.
- VGG-19 CNN acts on the decomposed coefficients, individually evaluating each set (LL, LH, LV, and LD) from the CT and MRI scans. By discerning and assimilating the best features from each modality, the VGG-19 network facilitates the creation of a richer, more comprehensive representation.
- Inverse Wavelet Transformation effectively re-layers the coefficients, weaving them back together into a coherent whole resulting in a fused image.
- The segmentation stage is next where the fused image is acted upon by the model by individually evaluating each set (LL,LH,LV and LD).
- The Watershed algorithm is used to mimick a water-filling simulation, eventually defining distinct catchment basins.
- The resultant segmented image presents a clear and segmented view of the brain, making the task of tumour identification and prognosis straightforward.
- The prediction module makes use of the dataset and the resultant image to predict the presence or absence of a possible brain tumour in the patient.

➢ *The Pipeline Diagram given below Depicts the same Process in a Sequential Manner:*

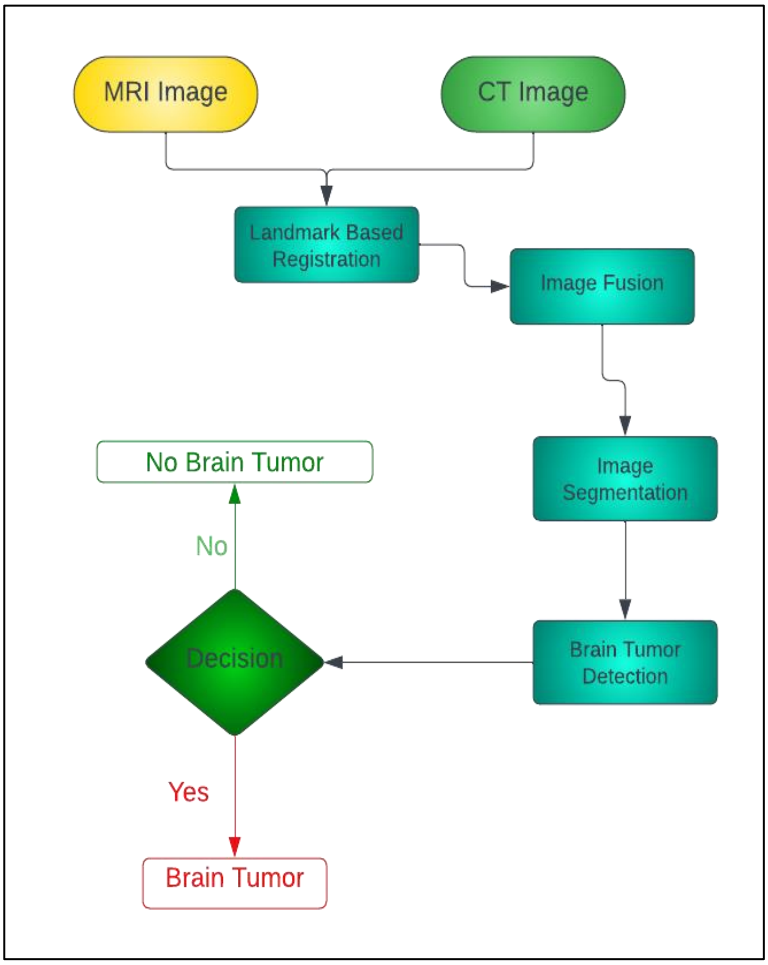

Fig 1 Pipeline Diagram: Brain Tumor Prediction

➢ *Architecture Diagram*

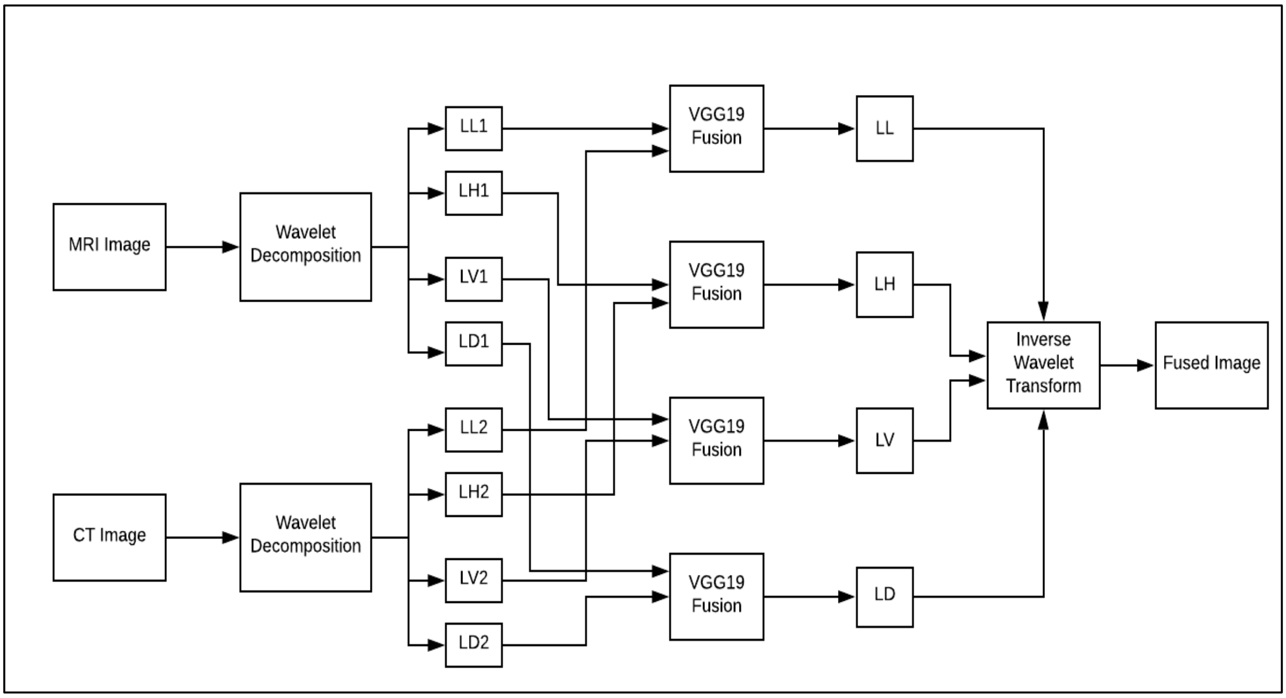

Fig 2 Architecture Diagram: Brain Tumor Prediction

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- *Motivation*

This project is driven by the urgent need for precise tools in neuroimaging, specifically in the realm of brain tumor analysis. Existing methods often lack the accuracy required for effective diagnosis and treatment planning. The integration of Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) provides a foundation, but challenges persist in aligning and interpreting multimodal data. Motivated by the critical importance of accurate tumor analysis, our project employs advanced techniques such as landmark-based registration and Convolutional Neural Networks (CNNs). The goal is to enhance the efficiency and precision of brain tumor detection, addressing a significant gap in current healthcare practices. Beyond immediate clinical applications, our project aspires to contribute to the broader landscape of healthcare by leveraging cutting-edge technologies. The integration of advanced imaging and deep learning holds the potential to not only improve diagnostics but also to usher in a new era of personalized and effective patient care. Ultimately, the motivation lies in making a substantial impact on brain tumor diagnosis and prognosis, with the overarching goal of enhancing the quality of life for individuals affected by these challenging medical conditions.

- *Convolutional Neural Network*

An especially effective deep learning technique for applications involving picture identification and processing is the convolutional neural network (CNN). Convolutional, pooling, and fully linked layers are some of the layers that make it up.

The essential part of a CNN is its convolutional layers, which are where elements like edges, textures, and forms are extracted from the input picture by applying filters. After the convolutional layers' output is processed through pooling layers, the feature maps are down-sampled to lower the spatial dimensions while keeping the most crucial data. One or more fully connected layers are then applied to the output of the pooling layers in order to categorize or forecast the picture.

- *Working of CNN*

The working of CNN algorithm can be broken down into following layers-

✓ *Convolution Layer*

A CNN's convolution layer uses convolution operations to extract features from the input data. In order to allow the network to spontaneously learn hierarchical representations, filters are applied to catch local patterns. In order to effectively extract features from visual input, this layer is essential for identifying elements like edges and textures.

✓ *ReLU Layer*

The Rectified Linear Unit (ReLU) layer applies the ReLU activation function, which creates non-linearity. It accelerates the rate of convergence during training by improving the network's ability to understand intricate patterns and gradients. ReLU helps to represent complex connections in data efficiently by substituting zero for negative values.

✓ *Pooling Layer*

Pooling helps in computational efficiency, increases the network's translational invariance, and focuses on the most salient features. It can reduce spatial dimensions while retaining essential information. A common technique is max pooling, which chooses the maximum value from a group of neighboring pixels, effectively downsampling the data.

✓ *Fully Connected Layer*

For the final classification or regression, high-level features from earlier layers are integrated by the fully linked layer. Because every neuron in this layer is linked to every other neuron in the layer before it, the network may learn complex associations throughout the whole input space. This layer completes the network's processing pipeline by converting retrieved information into predictions or judgments.

- *Dataset*

The dataset used in this research are a combination of fused images, segmentation images and CT/MRI scan of 50 patients with both positive and negative conditions of Brain tumor. The dataset provides useful data in training the model for prediction.

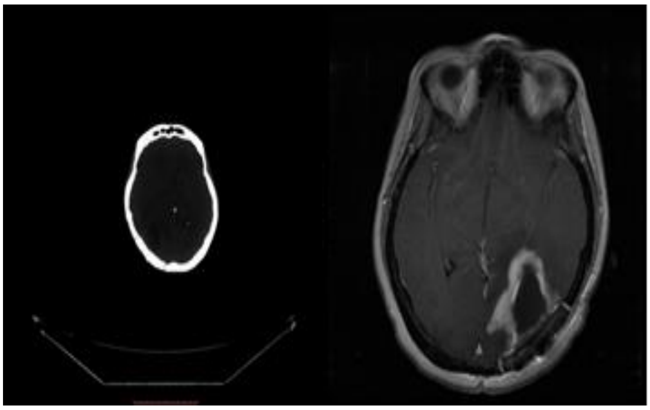

Fig 3 Dataset Sample: Positive CT and MRI Scan

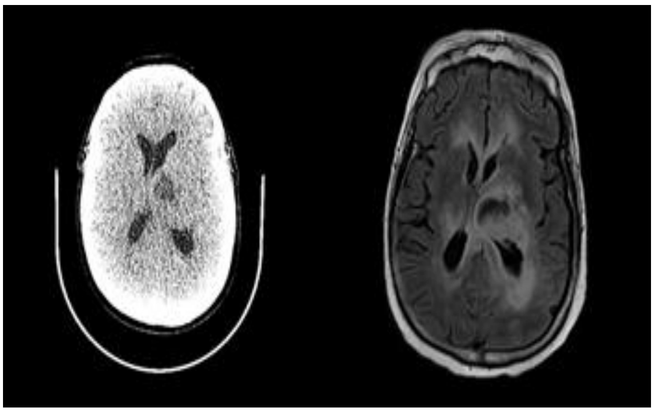

Fig 4 Dataset Sample: Negative CT and MRI Scan

➢ *Training*

- *Image Registration*

✓ *Landmark-Based Registration*

Achieving accurate alignment is a difficulty when combining several medical imaging modalities, such CT and MRI images. In order to overcome this, we have selected Landmark-Based Registration, which finds and matches certain places on both scans, or "landmarks." By matching the images to a single anatomical reference and removing differences for a cohesive depiction, this approach guarantees correct overlay.

✓ *Transfer Learning with VGG-19 CNN*

In image processing tasks, contemporary neural networks—particularly Convolutional Neural Networks (CNNs)—have demonstrated notable proficiency. We guarantee an extra degree of accuracy in the registration process by including the VGG-19 CNN, which has pre-trained parameters, into our technique. By utilizing information from large datasets, the system is able to achieve precise picture alignment thanks to this integration.

✓ *YCbCr Color Format Conversion*

Though widely used, traditional RGB formats may not be the best at capturing and maintaining finely detailed brightness subtleties. Our system changes these photos to the YCbCr format in order to get around this. This conversion accounts for the subtleties of chrominance (Cb and Cr) and highlights the luminance component (Y). A lossless and high quality depiction of the diagnostic scans depends on this phase.

✓ *Discrete Wavelet Transform Application*

Our technique uses the Discrete Wavelet Transform (DWT) to extract information about the frequency and spatial distribution of the pictures, allowing us to examine their finer aspects. By efficiently dividing picture features into distinct frequency bands, DWT prepares the groundwork for the following module's optimal fusion process.

- *Image Fusion*

✓ *Wavelet Decomposition*

A specific mathematical method for image processing called Wavelet Decomposition is used to handle the complex task of combining CT and MRI data. Using this technique, every picture is broken down into detail coefficients that show finer details and approximation coefficients that capture broad aspects. It's similar to removing layers to reveal a more complex picture. These coefficients combine macro-structure and fine features to enable well-informed picture fusion.

✓ *Fusion Leveraging VGG-19*

We have improved upon existing fusion techniques by including the well-known VGG-19 CNN model. VGG-19 analyzes each set of deconstructed coefficients (LL, LH, LV, LD) separately after processing them from CT and MRI images. VGG-19 creates a richer representation by utilizing its depth and complexity to identify and include the best elements from both modalities. High diagnostic value is ensured by deep learning, which also improves fusion accuracy.

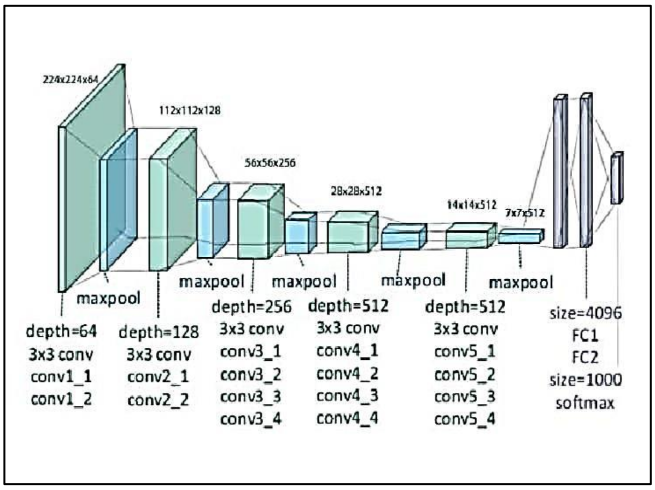

Fig 5 Network Architecture of VGG-19 model: Conv means convolution, FC means fully connected

✓ *Inverse Wavelet Transformation*

The Inverse Wavelet Transformation brings the fusion process to a close. It reassembles features from CT and MRI scans into a single, smoothly composed picture by carefully re-layering coefficients. Both strategies merge harmoniously as a consequence of this complex procedure that maintains data integrity.

- *Image Segmentation*

✓ *Watershed Algorithm*

The Watershed Algorithm views a picture as a topographic landscape with pixel intensities representing heights, drawing inspiration from geographical notions. It creates borders, dividing pictures into discrete catchment basins, much like natural watersheds. These basins represent possible tumor locations in our research therefore this approach is essential for precise point of interest delineation and segmentation.

✓ *Marker Selection*

Our fusion approach combines the well-known VGG-19 Convolutional Neural Network (CNN) model with deep learning capabilities. Using the VGG-19 adds a whole new level of complexity to the table, whereas conventional fusion methods may only use straightforward integration methods or simple averaging approaches. The decomposed coefficients are acted upon by the model, which evaluates each set (LL, LH, LV, and LD) from the CT and MRI images separately. The VGG-19 network makes it easier to create a richer, more comprehensive representation by identifying and incorporating the best elements from each modality. It can comprehend and record subtleties that may be missed by more basic fusion techniques because of its depth and complexity.

✓ *Transformation and Growth Based on Marked Points*

When the markers are placed, the Watershed Algorithm starts working to segment the picture. Regions surrounding each marker expand, thus establishing unique catchment basins, by simulating a water-filling scenario. The boundaries of these basins harden where they intersect as they get closer to one another due to growth. All of the image's pixels are accounted for and assigned to distinct regions thanks to this painstaking processing procedure. With each distinct zone representing a distinct anatomical or pathological component, the resulting segmented picture resembles a tapestry.

IV. RESULTS

The process showcased in our research starts with landmark-based registration that ensures the pictures are aligned in a common coordinate system before proceeding with the image fusion process, which is necessary for MRI and CT scans of the same patient. Therefore, the identical brain anatomical regions are depicted by the equivalent pixels in both images. Picture alignment is important for image fusion because it allows complementary information from multiple modalities, such as contrast, texture, and structure, to be fused together. Image alignment also reduces errors and artefacts including distortion, ghosting, and blurring that can arise from image misalignment. For the merging of brain images, landmark-based registration can achieve great accuracy and durability.

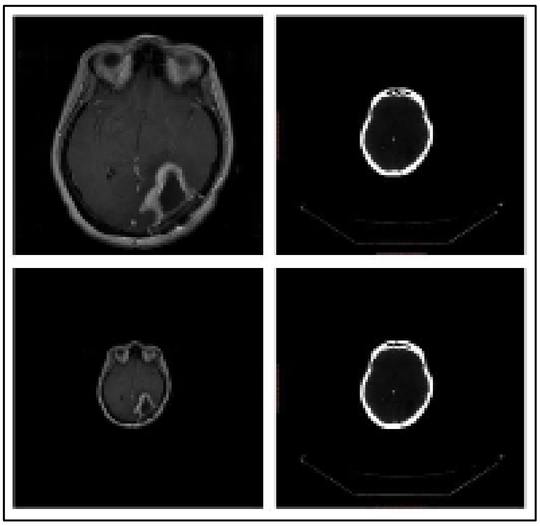

Fig 6 Landmark-based Registration

In the next stage, we divide the registered pictures into four separate sub-bands using the Discrete Wavelet Transform (DWT): LL (low-low frequencies), LH (low-high frequencies), HL (high-low frequencies), and HH (high-high frequencies). Then, the matching sub-bands from both photos are fed into the VGG-19 neural network by methodically pairing them. A fused sub-band is produced as the last convolutional layer's output. The merged image is then rebuilt using the inverse Discrete Wavelet Transform. The information from the four sub-bands is combined during this reconstruction procedure to create a logical whole. The successful creation of the fused image from the registered images is graphically shown in Figure 7, which highlights the usefulness of the image fusion method.

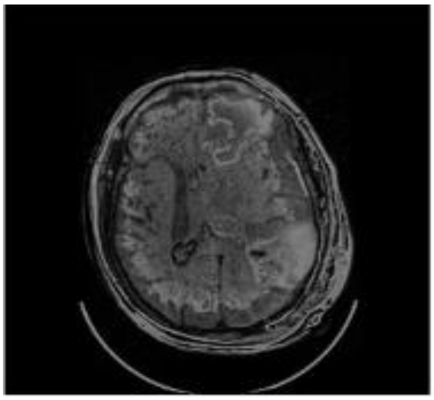

Fig 7 Fused Image

We then use the Watershed Algorithm, a region-based method based on image morphology, in the segmentation step. The Watershed Algorithm is well known for its capacity to separate touching or overlapping objects in an image, which is an extremely useful feature when it comes to brain tumor segmentation. This algorithm is applied to the fused image, and the result is the segmented image, as shown graphically in Figure 8.

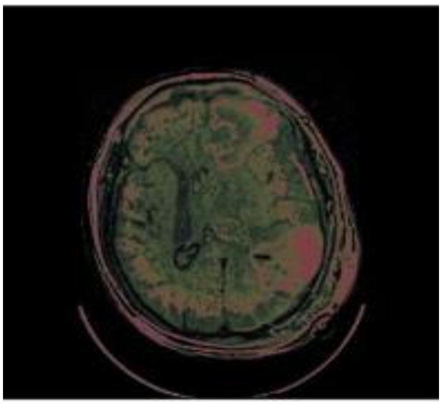

Fig 8 Segmented Image

The last figure, which graphically depicts the crucial stage of brain tumor detection, is the conclusion of our research endeavour. Our classification algorithm, which is based on the Regional Convolutional Neural Network (RCNN), takes on the important duty of identifying if brain tumors are present in the divided areas in this visually engaging picture. The graphic illustrates how deep learning, image segmentation, and diagnosis accuracy interact, and it is a testimonial to the efficacy of our suggested methodology. The result presented highlights the capacity of our technology to deliver accurate and rapid evaluations, providing priceless insights into the healthcare industry.

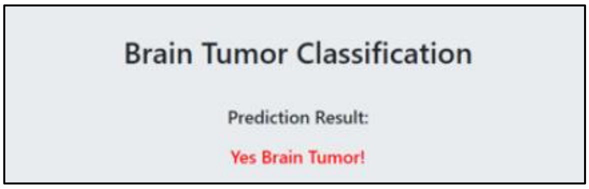

Fig 9 Prediction

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V. CONCLUSION

By utilizing state-of-the-art algorithms to combine the powers of Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), our novel project represents a major advancement in the field of healthcare. This project offers a strong methodology intended to improve brain tumor diagnosis and prognosis. Our method's main component is a Flask-based web application that gives users a smooth way to combine and harmonize MRI and CT scans. This integration improves the overall effectiveness of diagnostic processes by enabling a more thorough and extensive study of possible brain tumor locations. The VGG-19 Convolutional Neural Network, a potent instrument that uses deep learning for nuanced analysis, is the foundation of our system. When combined with the Watershed transformation, our approach highlights the accuracy of image analysis and guarantees that regions that may have tumors are detected with a high degree of precision. Our method represents the possibility of fusing cutting-edge technology with medical procedures, highlighting a dedication to improved patient care results, and goes beyond being a simple diagnostic tool. Our research is a testament to the revolutionary potential that emerge when innovation converges with the necessity of increasing patient well-being, as we negotiate the junction of technology and healthcare.

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