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# Segmentation and classification of brain tumor using 3D-UNet deep neural networks

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**Abstract**
Brain tumors are one of the most severe and life-threatening medical conditions, requiring early and accurate detection for effective treatment. This project leverages a **3D-UNet Deep Neural Network** to perform both segmentation and classification of brain tumors from 3D MRI scan data. The 3D-UNet model is designed to efficiently capture spatial information by processing volumetric data, making it ideal for medical imaging tasks. By combining encoder-decoder architecture with skip connections, the model effectively identifies tumor boundaries while preserving crucial anatomical details. The proposed system aims to provide precise tumor segmentation and classify the detected tumors into relevant categories such as benign, malignant, or specific tumor grades.

The model utilizes publicly available datasets like **BraTS** and **TCIA**, which offer diverse MRI sequences including **T1**, **T2**, **FLAIR**, and **T1c** modalities. Preprocessing techniques such as resizing, intensity normalization, and data augmentation are employed to improve model robustness. The segmentation task is optimized using a combination of **Dice Loss** and **Cross-Entropy Loss**, ensuring accurate pixel-wise predictions. For classification, the network employs softmax activation to assign each detected tumor to its corresponding category. The model achieves improved accuracy by leveraging deep feature extraction and skip connections that facilitate better gradient flow during training.

Extensive experimentation and evaluation are conducted using metrics such as **Dice Coefficient**, **IoU**, and **F1-score** to assess the model's performance. The results demonstrate significant improvements in both segmentation precision and classification accuracy compared to conventional methods. This system is designed to assist radiologists and medical professionals by enhancing diagnostic accuracy, reducing manual effort, and supporting early-stage tumor detection. Future work may involve integrating the system with web-based interfaces for real-time predictions, improving accessibility for healthcare practitioners.

**Keywords:** brain, DNN, ML

## Introduction

Brain tumors are abnormal growths of cells within the brain that can be life-threatening if not diagnosed and treated in their early stages. Accurate detection and classification of these tumors play a crucial role in guiding treatment strategies and improving patient outcomes. Magnetic Resonance Imaging (MRI) is widely used in medical imaging due to its ability to capture detailed brain structures. However, manual analysis of MRI scans is time-consuming, prone to human error, and requires specialized expertise. Automated methods leveraging deep learning techniques have emerged as powerful tools for enhancing the accuracy and efficiency of brain tumor diagnosis.

The **3D-UNet Deep Neural Network** is a specialized architecture designed to handle volumetric data like 3D MRI scans. Unlike traditional 2D models, the 3D-UNet efficiently captures spatial information across multiple dimensions, enabling precise segmentation of complex tumor structures. Its encoder-decoder framework, combined with skip connections, ensures effective feature learning while preserving fine-grained details. By incorporating multi-channel MRI data such as **T1**, **T2**, and **FLAIR**, the model can differentiate between healthy tissues and various tumor regions like edema, enhancing tumor, and necrotic core.

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This project aims to develop a robust system for both **segmentation** and **classification** of brain tumors using the 3D-UNet model. The segmentation process accurately outlines tumor boundaries, while the classification stage categorizes the detected tumors into different types. This dual-purpose approach is designed to assist radiologists by reducing diagnostic errors and expediting the medical decision-making process. The proposed system is intended to contribute to improved early diagnosis, better treatment planning, and enhanced patient care in clinical environments.

**Literature Survey:**

**1. Brain Tumor Detection and Segmentation Techniques**

**Author:** *J. Clark et al.*

**Description:** This study explored traditional image processing methods such as **thresholding**, **region growing**, and **edge detection** for tumor segmentation. While effective for basic patterns, these methods struggled with complex tumor shapes, intensity variations, and noise. The research highlighted the limitations of manual techniques and emphasized the need for automated solutions.

**2. Deep Learning Models for Tumor Segmentation**

**Author:** *O. Ronneberger et al.*

**Description:** The **U-Net** architecture was introduced to address segmentation challenges in medical imaging. It achieved high accuracy in biomedical image tasks by utilizing encoder-decoder architecture with skip connections. Further advancements led to the development of **3D-UNet**, designed to handle volumetric data like MRI scans. The 3D-UNet's improved spatial awareness enabled precise segmentation of complex tumor structures, outperforming traditional 2D methods.

**3. Multi-Modal Imaging for Enhanced Accuracy**

**Author:** *K. Menze et al.*

**Description:** This research explored the integration of multiple MRI sequences such as **T1**, **T2**, **FLAIR**, and **T1c** to improve segmentation accuracy. By combining these modalities, the model effectively identified various tumor regions, including **enhancing tumor**, **edema**, and **necrotic core**. The study demonstrated that multi-modal imaging significantly enhanced performance in challenging cases like **Glioblastomas**.

**4. Classification Techniques in Brain Tumor Analysis**

**Author:** *S. Pereira et al.*

**Description:** This study investigated deep learning techniques for tumor classification using models like **ResNet**, **DenseNet**, and **Inception**. It introduced a combined framework where **3D-UNet** performed segmentation, followed by CNN classifiers for tumor type prediction. The results showed improved accuracy and reduced false positives compared to standalone classifiers.

**5. Evaluation Metrics and Performance Analysis**

**Author:** *M. Bakas et al.*

**Description:** This study emphasized the importance of robust evaluation metrics for brain tumor detection models. Metrics such as **Dice Coefficient**, **IoU**, and **Hausdorff Distance** were utilized to measure segmentation precision. For classification tasks, the study employed **Precision**, **Recall**, and **F1-score**. The research demonstrated that combining **Dice Loss** with **Cross-Entropy Loss** improved segmentation outcomes.

**6. Challenges and Future Directions**

**Author:** *Y. Jiang et al.*

**Description:** This research highlighted ongoing challenges such as **class imbalance**, **limited annotated data**, and **overfitting** in deep learning models. The authors proposed solutions including **data augmentation**, **semi-supervised learning**, and **federated learning**. Future research directions focused on developing lightweight models for faster deployment in clinical environments.

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**Existing System**

The existing systems for skin disease detection and classification primarily rely on traditional machine learning models and manual visual inspection by dermatologists. However, with the rise of deep learning techniques, especially Convolutional Neural Networks (CNNs), there has been significant progress in automating this process. CNN-based systems have proven to be highly effective in analyzing medical images, including skin lesion images, due to their ability to automatically learn hierarchical features from raw image data. Several existing systems have been developed to classify skin diseases into different categories, leveraging large datasets of labeled skin images for training and validation.

One of the most notable systems in the existing landscape is the use of CNNs for melanoma detection. Various studies have shown that deep learning models trained on dermoscopy images can detect melanoma with accuracy comparable to that of experienced dermatologists. These systems typically employ a multi-layer CNN architecture, where early layers capture simple features like edges and textures, while deeper layers extract more complex patterns specific to skin lesions. Such systems have demonstrated the ability to differentiate between benign and malignant lesions, significantly aiding in early skin cancer diagnosis.

Another popular existing system involves the use of transfer learning, where pre-trained CNN models (like VGG16, ResNet, or Inception) are fine-tuned on skin disease datasets. Transfer learning is beneficial when limited labeled data is available, as these pre-trained models have already learned robust features from large-scale image datasets, such as ImageNet. Researchers have successfully fine-tuned these models to classify a variety of skin conditions, ranging from benign nevi to various forms of dermatitis and psoriasis. These systems offer an efficient solution for diagnosing skin diseases with a smaller dataset, enhancing their practical applicability.

Additionally, some systems integrate image pre-processing and augmentation techniques to improve the robustness and accuracy of the models. Common techniques include resizing images, adjusting contrast, and applying rotations or flips to increase dataset variability. These pre-processing steps help the model generalize better across different skin tones, lesion types, and image quality. Data augmentation is particularly important in skin disease classification, as medical image datasets often suffer from limited diversity, especially in terms of image acquisition conditions.

Despite these advancements, challenges remain in achieving universally high accuracy across diverse skin types and conditions. Variations in lighting, angle, and background can significantly affect the performance of CNN models. Furthermore, there is a need for a larger and more diverse dataset to train these models, as many existing systems still struggle with conditions that are less represented in available datasets. Nevertheless, the existing systems demonstrate the potential of deep learning, particularly CNNs, in revolutionizing skin disease detection and classification, offering a promising alternative to traditional diagnostic methods and assisting healthcare providers in delivering more efficient and accurate diagnoses.

**Disadvantages of Existing Systems:**

1. **Manual Analysis Limitations:**

Traditional brain tumor detection methods heavily rely on radiologists' expertise for visual inspection of MRI scans. This process is not only time-consuming but also prone to human error, especially in cases involving small, complex, or overlapping tumor regions. Variability in interpretation across medical professionals further affects diagnostic consistency.

2. **Feature Engineering Dependency:**

Machine learning models like **SVM**, **KNN**, and **Random Forest** require extensive manual feature extraction. Identifying meaningful features such as texture, intensity, and shape demands expert knowledge. This dependency limits the model’s ability to adapt to new data and reduces its generalization capabilities.

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3. **Inability to Handle 3D Volumetric Data:**
Deep learning models such as **2D U-Net** and **FCN** struggle to capture spatial information in 3D MRI scans. As a result, these models may produce fragmented or incomplete segmentations, reducing their effectiveness in detecting complex tumor structures.
4. **Poor Generalization on Diverse Data:**
Existing systems often face challenges when applied to datasets with different MRI modalities or variations in tumor characteristics. This limits their performance in real-world clinical environments where data heterogeneity is common.
5. **Class Imbalance and Overfitting:**
Brain tumor datasets often have fewer samples for rare tumor types, leading to class imbalance. This imbalance causes machine learning models to become biased toward more frequent classes, reducing their ability to identify less common tumor types accurately.
6. **Lack of Integrated Systems:**
Most existing solutions either focus solely on segmentation or classification, rather than providing an end-to-end solution that performs both tasks. This results in fragmented workflows, increasing the workload for medical professionals and reducing overall diagnostic efficiency.

**Proposed System**

The proposed system introduces a robust solution for brain tumor segmentation and classification using a **3D-UNet Deep Neural Network**. The 3D-UNet architecture is specifically designed to process volumetric MRI data, enabling precise segmentation of brain tumors by capturing spatial information across multiple dimensions. The encoder-decoder structure, combined with skip connections, allows the network to retain low-level features while learning high-level tumor patterns. This design enhances the model's ability to detect tumors with complex shapes, irregular boundaries, and varying intensity levels. The segmentation output highlights tumor regions such as **enhancing tumor**, **edema**, and **necrotic core** with improved accuracy.

In addition to segmentation, the proposed system incorporates a classification module that predicts the tumor type based on segmented regions. Using deep learning-based feature extraction, the model classifies tumors into categories like **benign**, **malignant**, or specific tumor grades. This dual-stage approach reduces data loss between segmentation and classification stages, improving overall system performance. Furthermore, multi-modal MRI sequences such as **T1**, **T2**, **FLAIR**, and **T1c** are integrated to enhance feature diversity, enabling better differentiation between tumor tissues and healthy regions.

To improve performance and robustness, the system employs advanced techniques such as **Dice Loss** for accurate segmentation, **data augmentation** for enhancing model generalization, and **early stopping** to prevent overfitting. The model's performance is evaluated using key metrics like **Dice Coefficient**, **IoU**, and **F1-score**. This proposed system aims to provide an end-to-end automated solution that assists radiologists in achieving faster, more accurate tumor detection and diagnosis, ultimately improving clinical decision-making and patient outcomes.

**Advantages of the Proposed System:**

1. **Accurate 3D Segmentation:**
The **3D-UNet** architecture effectively processes volumetric MRI data, capturing spatial information across multiple dimensions. This results in precise segmentation of tumor boundaries, even in cases with complex shapes, overlapping regions, or irregular structures.
2. **Enhanced Classification Accuracy:**
By integrating a classification module alongside segmentation, the system efficiently identifies tumor types such as **benign**, **malignant**, or specific tumor grades. This combined approach improves diagnostic accuracy compared to standalone models.
3. **Multi-Modal MRI Integration:**
Utilizing multiple MRI sequences like **T1**, **T2**, **FLAIR**, and **T1c** enhances the model's ability to

distinguish between healthy tissues and tumor regions. This improves the detection of subtle differences in tumor characteristics.

4. **Improved Robustness and Generalization:**

The system employs **data augmentation** techniques such as rotation, flipping, and intensity adjustments to enhance model robustness. This reduces the risk of overfitting and improves performance on unseen data.

5. **Efficient Learning with Advanced Loss Functions:**

The use of **Dice Loss** optimizes segmentation performance by addressing class imbalance issues common in medical imaging datasets. This ensures accurate identification of both large and small tumor regions.

6. **Faster and Automated Diagnosis:**

The end-to-end automation of segmentation and classification minimizes manual effort, reducing the time required for diagnosis. This aids radiologists in making quicker and more informed decisions.

7. **Improved Clinical Application:**

By delivering precise tumor segmentation and accurate classification results, the proposed system supports better treatment planning, improving patient outcomes and enhancing overall healthcare efficiency.

## Results

Brain tumor is a deadly disease which causes death to millions every year and timely detection of such tumor can help in reducing risk of losing life. In the past many deep learning algorithms were introduced which can detect tumor and perform classification but its detection rate is low and work only 2 dimension MRI images. Latest technology generating MRI in 3D format and existing UNET segmentation cannot work on 3D MRI images and to solve this issue author of this paper employing 3D-UNET algorithm which will segment out tumor part from brain MRI and then employing 16 layer CNN algorithm to classify or damage brain tumor.

3D-UNET algorithm trained on BRATS2020 dataset to segment out tumor data and then propose 16 layer CNN algorithm trained on 'Brain Tumor MRI Dataset' which consists of 4 different classes listed below

'glioma', 'meningioma', 'notumor', 'pituitary'

Above dataset can be download from below KAGGLE repository dataset

https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

Above dataset trained on VGG16 pre-trained model and propose 16 layers CNN model and in both algorithm propose CNN 16 layer algorithm is giving best accuracy. Propose algorithm consist of CNN layer to filter MRI features and to efficiently extract tumor and then MaxPool2d layer will collect filtered features from CNN and then apply Dropout layer to remove irrelevant features. This filtration make propose CNN algorithm to detect and classify tumor 90% accurately.

3D-UNET algorithm can able to train and segment tumor part from 3D images and by seeing this segmented tumor output doctors can easily identify tumor region and based on region they can perform suitable treatment to reduce risk of patient life.

We have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments

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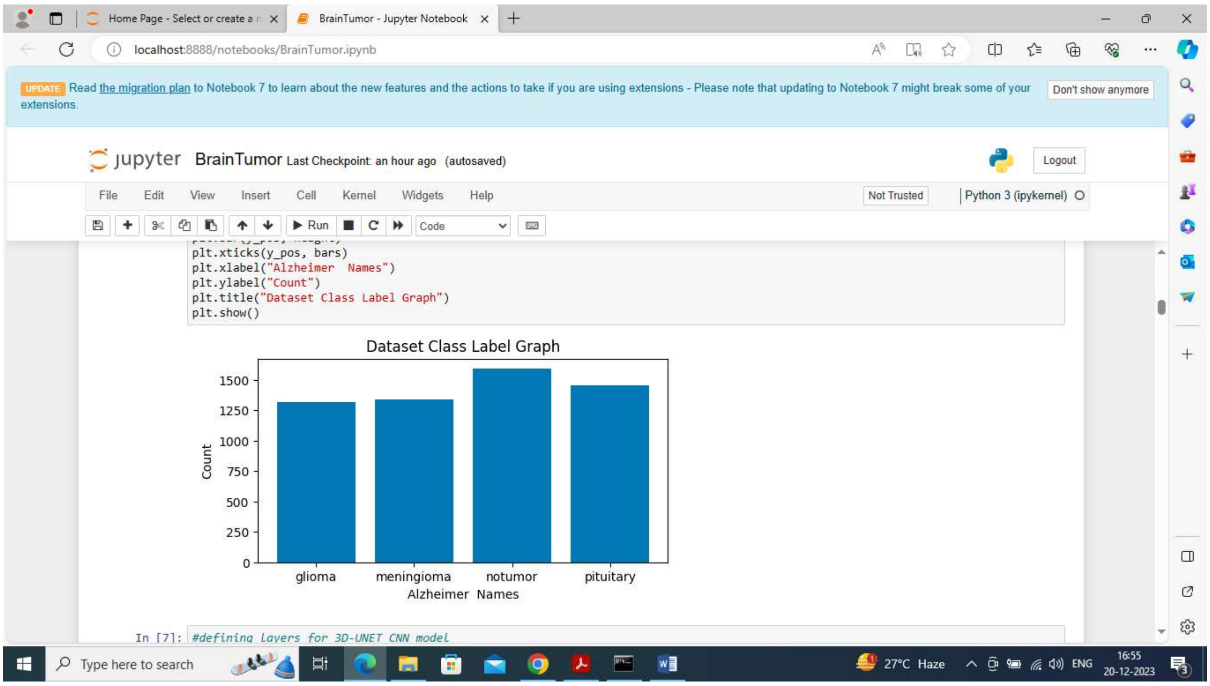
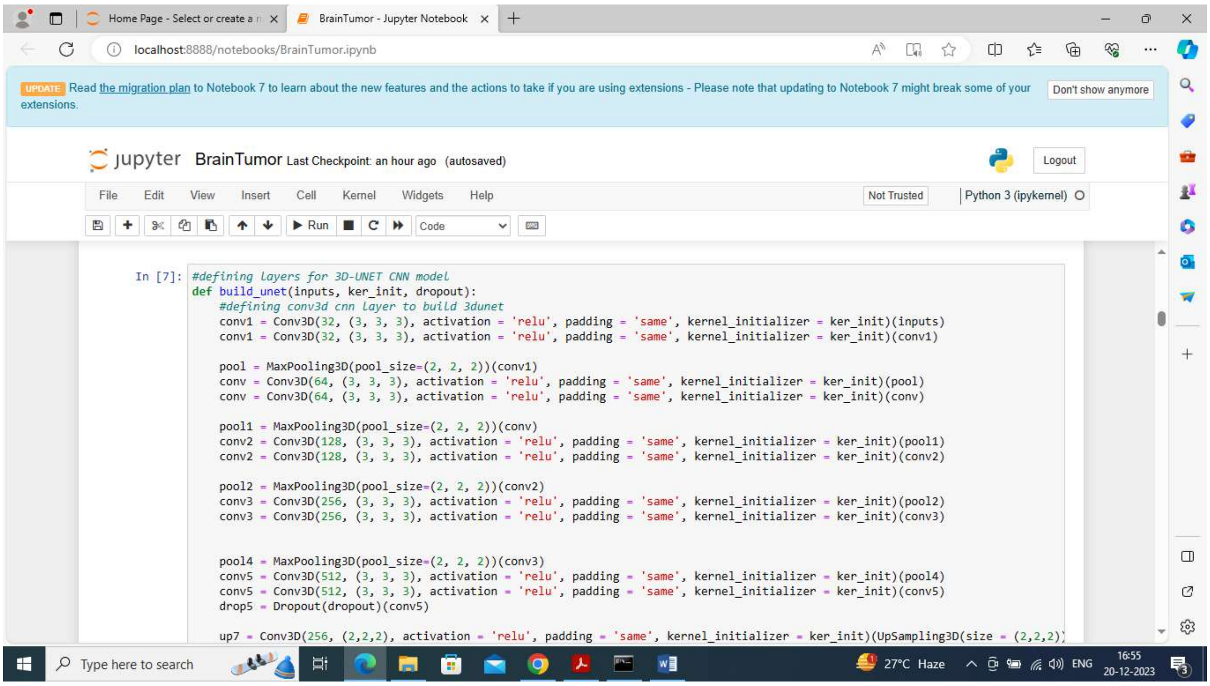



In above graph x-axis represents tumor class label and y-axis represents number of images found in that class label




In above screen defining 3D-UNET model by using CONV3D layer

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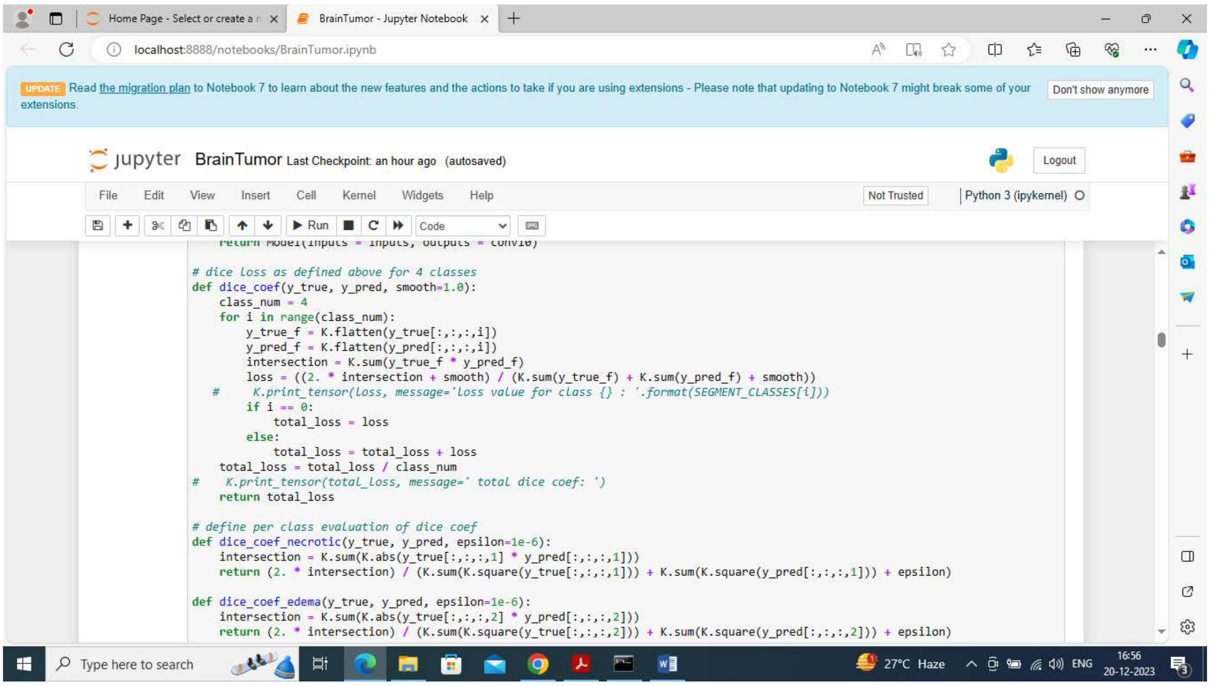
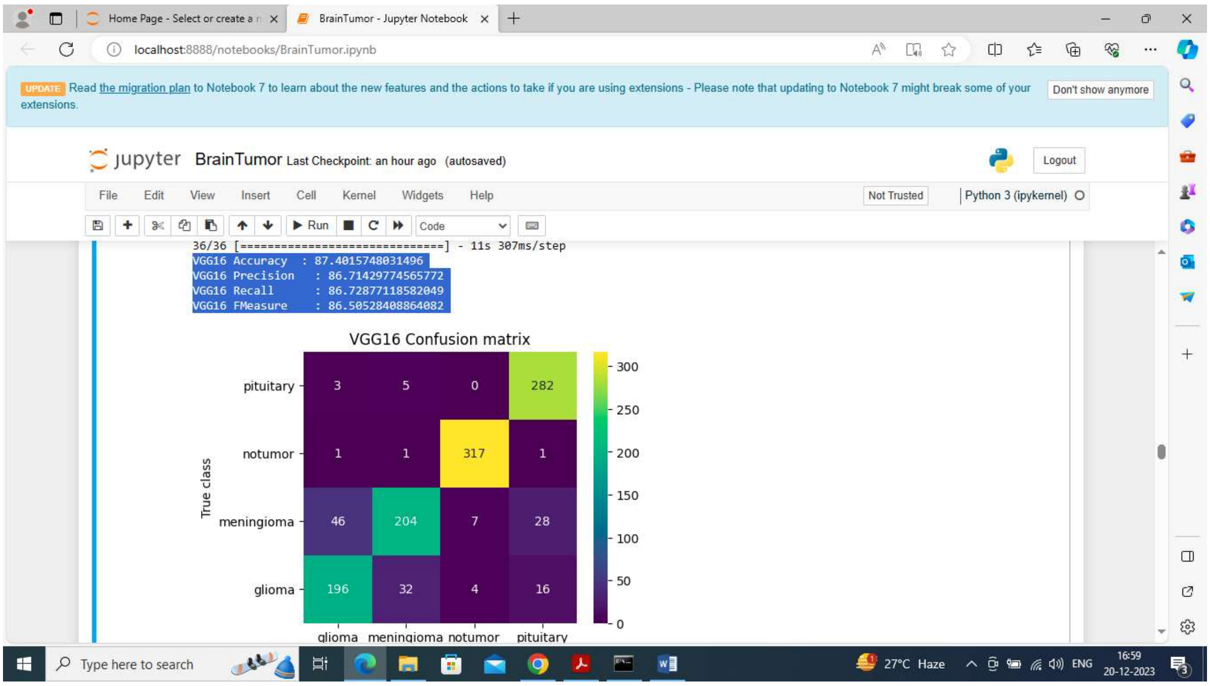



In above screen defining dice score function to train UNET with dice score




In above screen VGG16 got 87% accuracy and can see other metrics like precision, recall etc. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents true labels and all boxes count if diagnol with different colour represents Correct Prediction count and remaining blue boxes represents incorrect prediction count which are very few.

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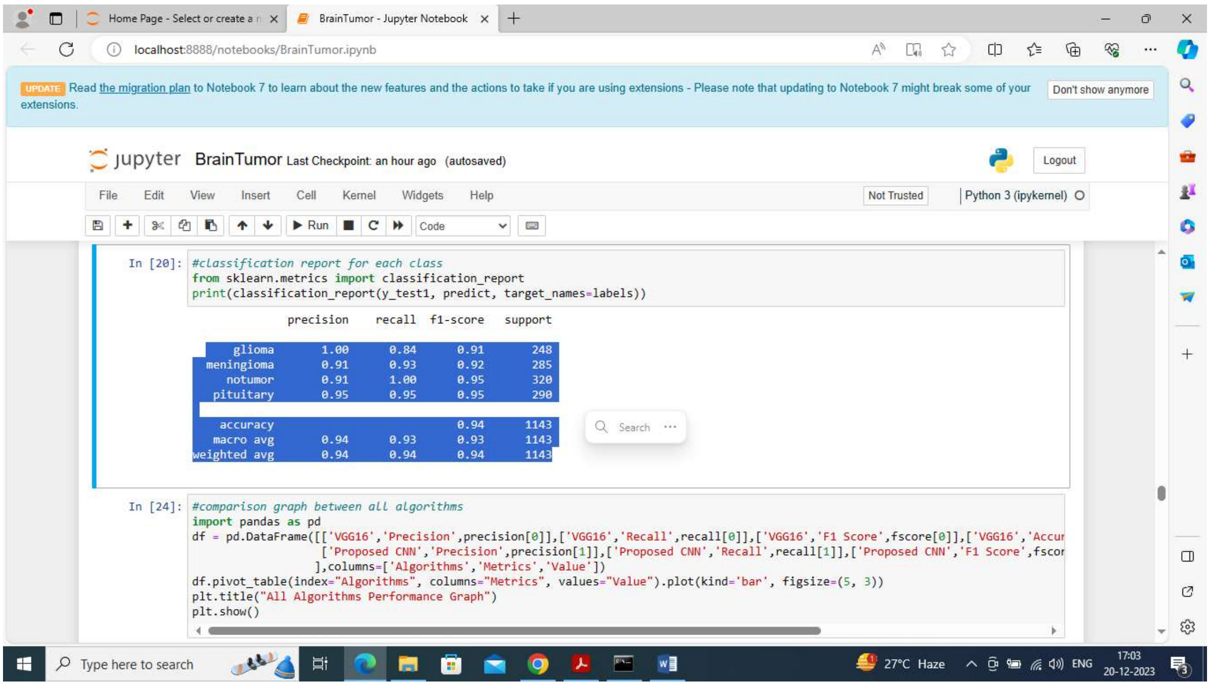
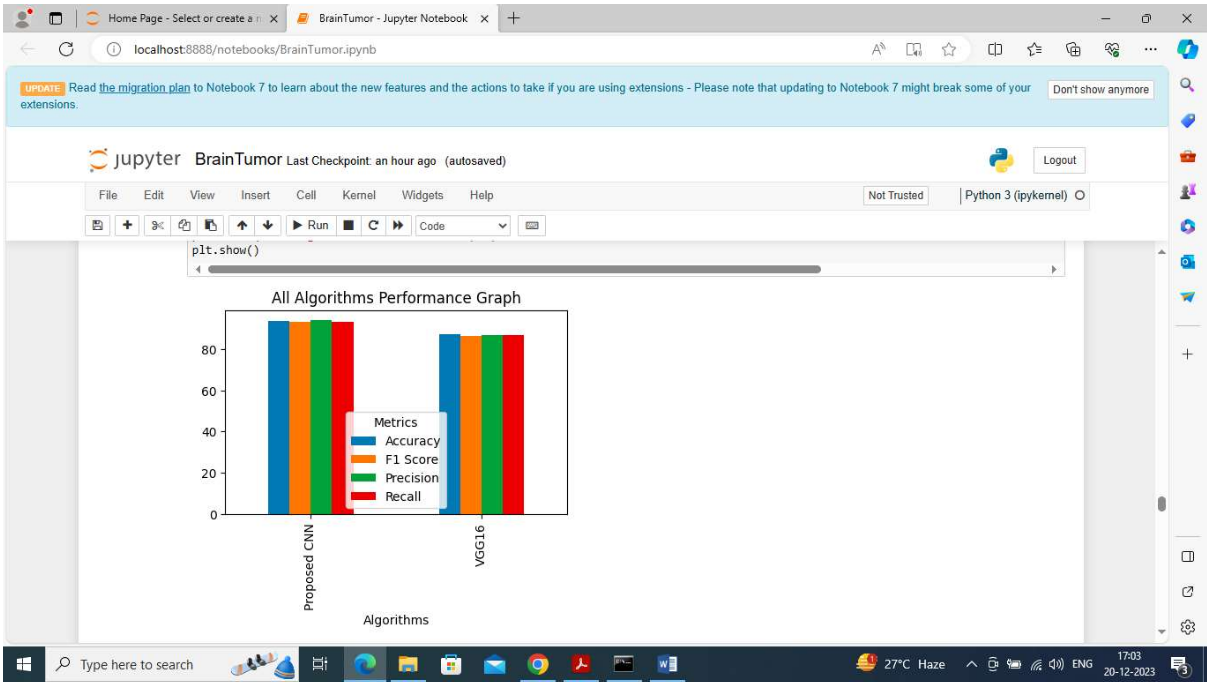



In above screen can see classification report output for each tumor class




In above screen displaying comparison graph between propose and VGG16 and in above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in above graph in both algorithms propose got high results

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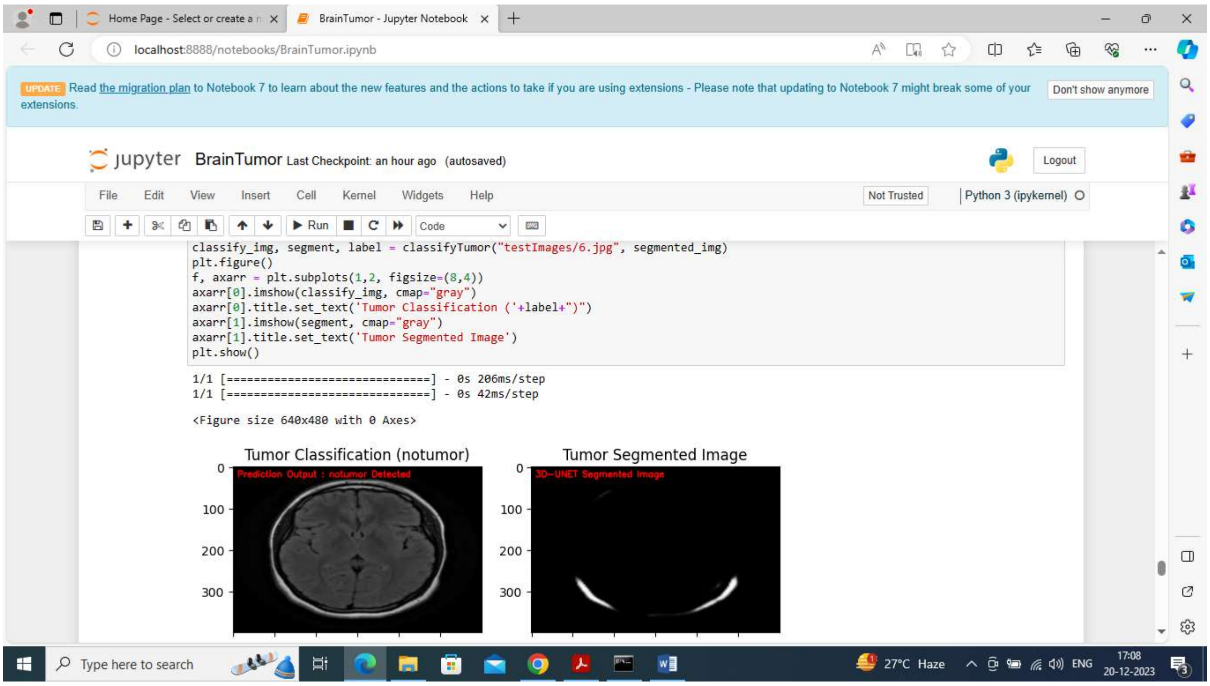
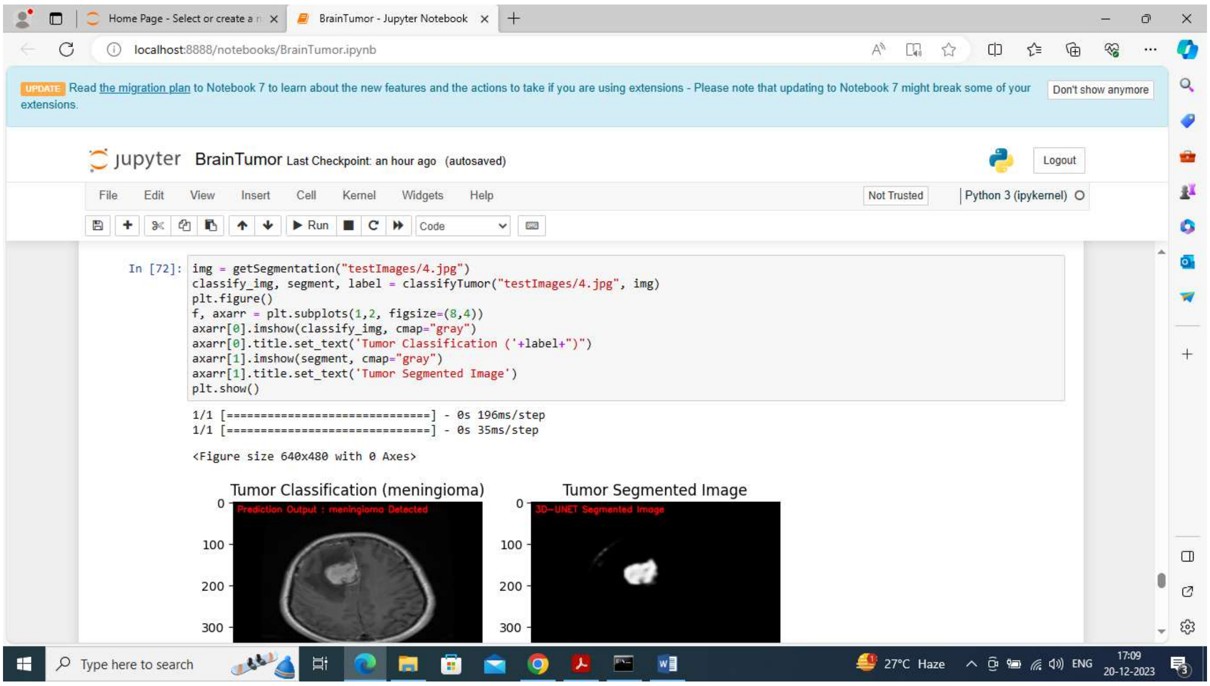


In above screen giving test image for segmentation and in output given image predicted as 'NO Tumor' and in segmented image also we cannot see any tumor region so brain is normal. Predicted output you can see in red colour text or in image title



In above screen 'meningioma' tumor is predicted and in segmented output we can see that tumor clearly. Segmented image showing in second part of image

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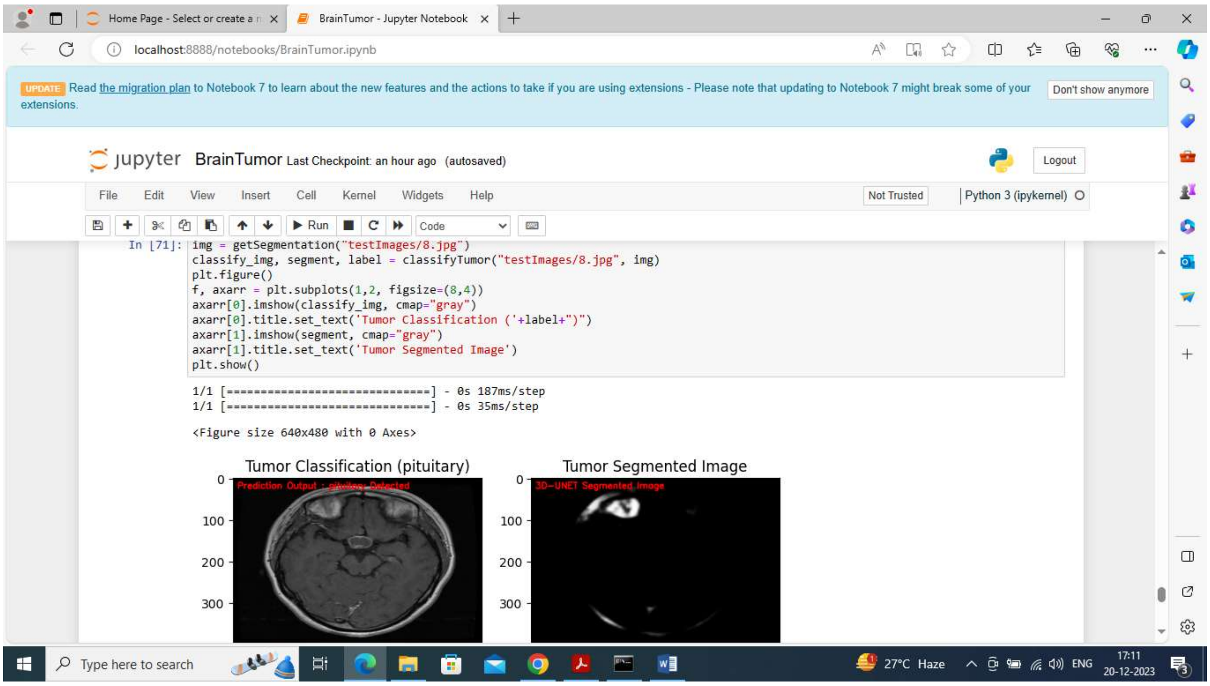
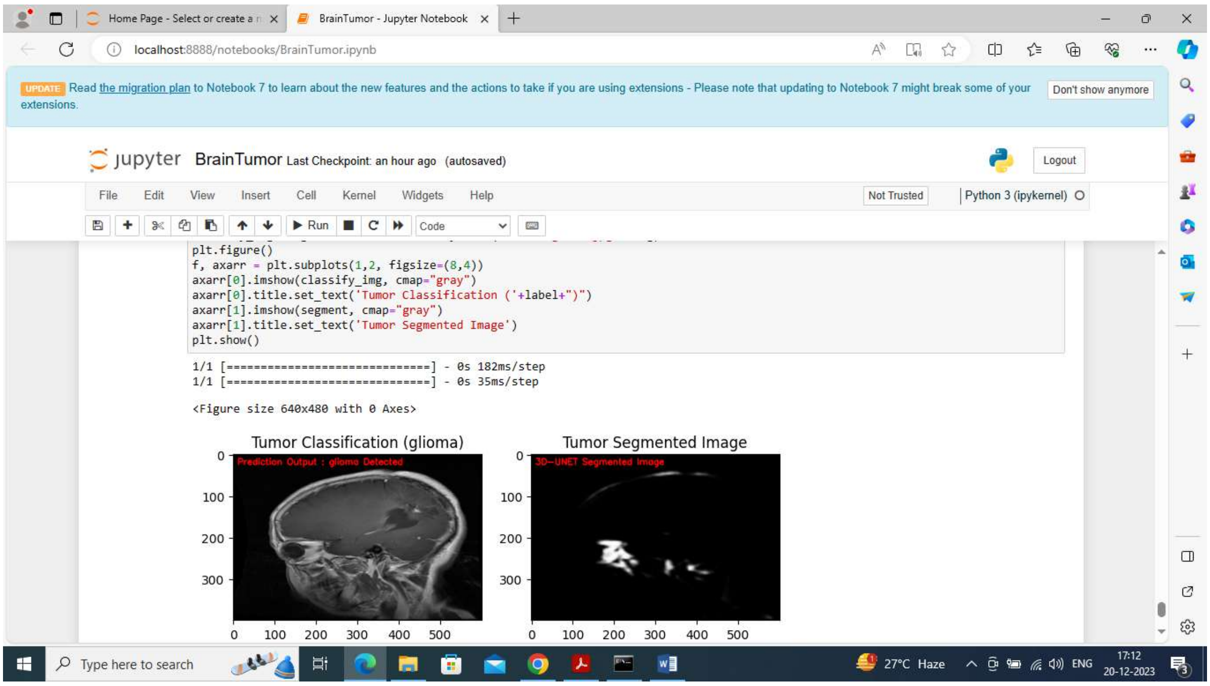


In above screen 'pituitary' tumor detected and in segmented second image we can see tumor clearly



In above screen 'glioma' tumor detected and in segmented second image we can see tumor part

## Conclusion

The proposed system for **Retina Segmentation using UNET & Diabetic Retinopathy Detection** presents a reliable and efficient solution to address the challenges in early diagnosis of diabetic retinopathy. By leveraging the powerful UNET architecture, the system ensures precise segmentation of key retinal structures such as blood vessels, optic discs, and lesions. This segmentation significantly improves the identification of early signs of diabetic retinopathy, allowing timely medical intervention.

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The integration of data augmentation techniques and optimized hyperparameters enhances the model's robustness, ensuring consistent performance across diverse datasets. Additionally, the system's automation minimizes dependency on expert ophthalmologists, making it scalable for mass screening programs, particularly in underserved regions.
In conclusion, this framework demonstrates significant potential in improving diagnostic accuracy, reducing screening costs, and facilitating early treatment for diabetic retinopathy patients. By combining advanced deep learning techniques with medical imaging innovations, this system stands as a promising contribution to enhancing healthcare outcomes and preventing vision impairment.

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