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

INDEX

CHAPTER 1

INTRODUCTION

ABSTRACT

Early detection and diagnosis of a brain tumor enhance the medical options and the patient's chance of recovery. Magnetic resonance imaging (MRI) is used to detect and diagnose brain tumors. However, the manual identification of brain tumors from a large number of MRI images in clinical practice solely depends on the time and experience of medical professionals. Presently, computer aided expert systems are booming to facilitate medical diagnosis and treatment recommendations. Numerous machine learning and deep learning based frameworks are employed for brain tumor detection. This paper aims to design an efficient framework for brain tumor segmentation and classification using deep learning techniques. The study employs the 3D-UNet model for the volumetric segmentation of the MRI images, followed by the classification of the tumor using CNNs. The loss and precision diagrams are presented to establish the validity of the models. The performance of proposed models is measured, and the results are compared with those of other approaches reported in the literature. It is found that the proposed work is more efficacious than the state-of-the-art techniques.

1.1 AIM OF THE PROJECT

Segmentation: This refers to the process of identifying and delineating different regions or structures within medical images. In the context of brain tumor analysis, segmentation involves accurately outlining the boundaries of the tumor in 3D space. This step is crucial for understanding the extent and shape of the tumor. Classification: Once the tumor regions are segmented, the next step is to classify the type or nature of the tumor. Brain tumors can be categorized into various types (e.g., gliomas, meningiomas), and their malignancy can also be assessed. Classification involves assigning a label or category to each segmented region based on its characteristics.

1.2 SCOPE OF THE PROJECT

Data Collection and Preprocessing: Identify and collect 3D medical imaging datasets containing brain scans, particularly MRI data. Preprocess the data to ensure consistency, correct artifacts, and normalize intensity values. Model Development: Implement a 3D-UNet deep neural network architecture for the segmentation and classification tasks. Fine-tune or optimize the model to achieve high accuracy and robust performance. Consider transfer learning or pre-training on relevant datasets if applicable.

1.3 OBJECT OF THE PROJECT

Accurate Segmentation of Brain Tumor: Develop a 3D-UNet deep neural network model capable of accurately segmenting brain tumors in three-dimensional medical imaging data, particularly MRI scans. Multi-Class Classification: Extend the model to perform multi-class classification to categorize segmented regions into different types of brain tumors, such as gliomas, meningiomas, and others. High Sensitivity and Specificity: Optimize the model to achieve high sensitivity and specificity, ensuring a low rate of false positives and false negatives in both segmentation and classification tasks.

1.4 INTRODUCTION

Abnormal growth of cells or tissues in the brain can lead to a brain tumor. Neither the exact symptoms of a brain tumor nor the reasons that cause brain tumors are known today. Thus, people may be suffering from brain tumors without realising the gravity of the situation. It is of paramount importance to detect and extract the tumors at their early stages to save the patient's life.

The MRI is an important tool for the detection, diagnosis, and monitoring of brain tumors. However, examining MRI scans is a dexterous, time-consuming, and difficult process. Further, it is very difficult to detect tumors manually, and the results may vary from one clinical expert to another based on their experience.

Effective classification and segmentation of MRI images is quite challenging. The rationale is to build an expert system that would assist in the effective diagnosis of cancerous cells in MRI scans of the brain. Over the years, several researchers from various backgrounds have relied on image recognition techniques for the identification of brain tumor cells (Amin, Sharif, Haldorai, Yasmin, & Sundar Nayak, 2021).

To get the optimum performance, they have used a variety of machine learning techniques to detect cancerous cells. Advanced neural networks and deep learning techniques are also utilized. For instance, advanced neural networks, graph-based CNN, and CNN are employed to improve the detection of malignant lesions in breast mammograms (Zhang, Satapathy, Guttery, Górriz, & Wang, 2021b).

A convolutional neural network with exponential linear units and rank-based weighted pooling is implemented for the early diagnosis of optimal therapeutic intervention (Zhang et al., 2021a). One of the most difficult aspects of dealing with MRI scans is that they are not 2D images like X-ray images. An MRI image is made up of several 3D volumes that show various parts of the brain.

Until image segmentation, these 3D volumes are fused. When merging various channels of an MRI image, certain misalignments can occur, resulting in errors that can be corrected by image registration. Image registration is a technique for aligning images. Various machine learning and deep learning models for brain tumor prediction have been proposed recently.

Many models for detecting, segmenting, and classifying brain tumors have been presented in the literature. For the segmentation of volumetric MRI scans, convolutional neural network architecture has been considered in this study.

This research work focuses on the development of an effective model that can help in the accurate identification of tumors automatically. The proposed model is built on 3D-UNet convolutional neural networks that have been trained for tumor segmentation. The research is based on 3D segmentation of MRI scans.

The volumetric MRI scans' 3D volume is divided into 3D sub-volumes, which are fed into the segmentation model and then recombined into a single 3D volume. The suggested method is useful since it effectively protects all aspects of the image while maintaining the image's volume.

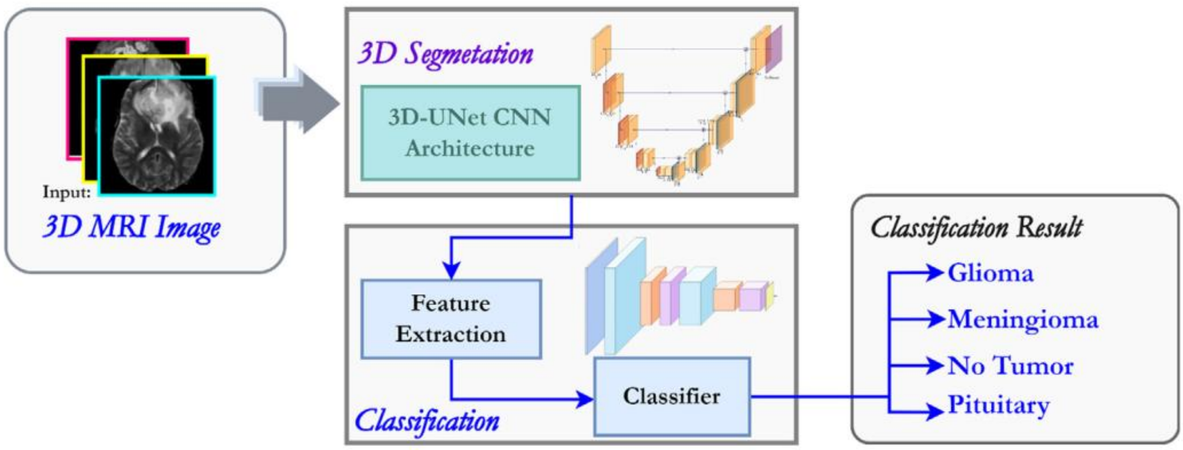

Fig. 1. Abstract view of proposed Brain tumor Detection System.

UNet architecture's effectiveness has also been extensively documented in the biomedical literature.

The proposed work takes into account an image registration model, a 3D U-Net model, and finally a soft dice loss feature, all of which have been combined to form a comprehensive tumor detection model. The first move was to merge 3D image slices from an MRI scan into a single 3D model. Image registration corrects misalignment issues during mixing. The 3D model is divided into subsections after it has been developed.

The subsections are then passed into the U-Net model, and the segmented model is obtained at the output after both down and up convolution cycles. The subsections are then merged once more to create a segmented 3D model, followed by the estimation of the loss function.

After the volumetric segmentation of the tumor the next step is the classification of the brain tumors into meningioma, glioma, and pituitary tumors. Prior to feature extraction and sorting, most traditional brain tumor classification approaches included region-based tumor segmentation.

CNN is made up of a convolutional neural network that performs automated segmentation and feature extraction, supplemented by a classical neural network that performs classification. A Rectified Linear Unit (ReLu), a convolution, and a pooling layer make up CNN's wellknown simple architecture.

The abstract view of the proposed framework is presented in Fig. 1. The MRI images will be used as the input. The main phases of the proposed system are divided into four parts:

i Data Collection

ii Pre-processing

iii Segmentation

iv Classification

Firstly, the collected images are subjected to the pre-processing module. The corrupted and blurred images are filtered in this module. For efficient and enhanced segmentation and classification, better segmentation and classification models are proposed in the research work.

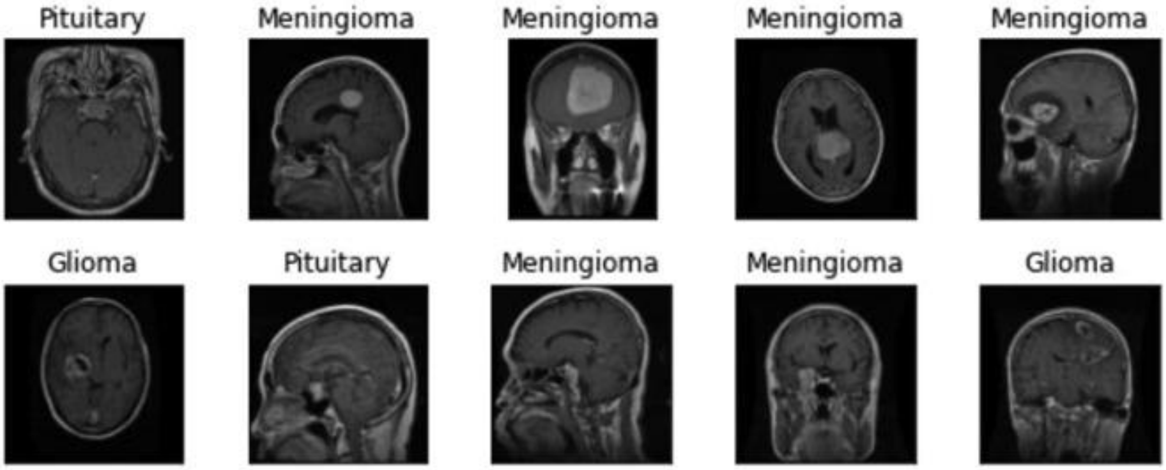

Fig.2 **Types brain tumor**

The major contributions of the paper are as follows:

• The proposed framework incorporated the implementation of an advanced 3D U-Net model for volumetric segmentation and updated CNN for the classification of the MRI images, with the objective of creating an expert system for predicting brain tumors at an early stage.

• The proposed segmentation and classification models are empirically evaluated using various evaluation metrics such as precision, recall, F score, dice similarity co-efficient, and support.

• The loss and precision diagrams have also been used to establish the validity of the models.

• The results are compared with the other approaches reported in the literature, and established as being more efficacious than the state of-the-art techniques.

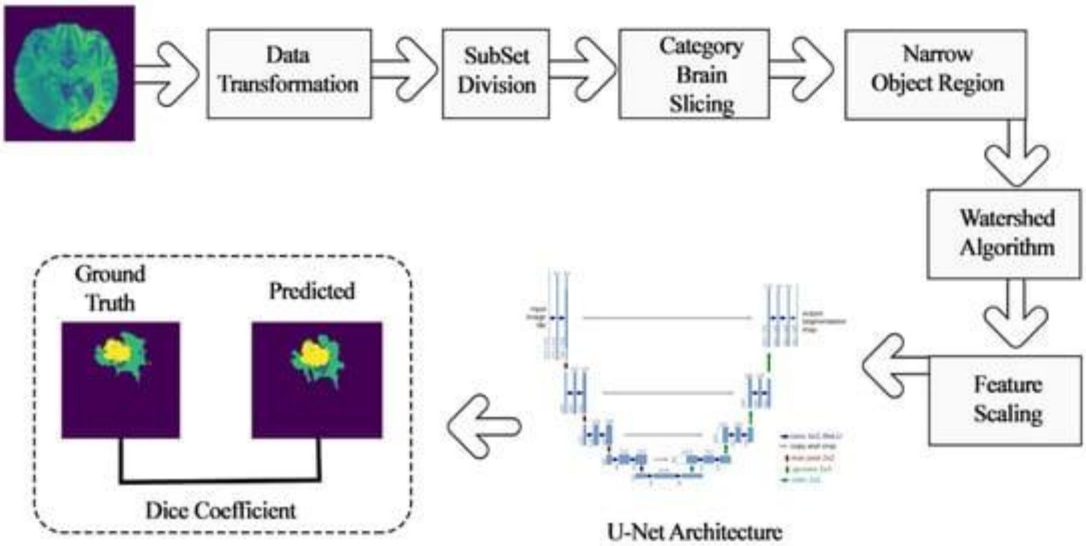

Fig.3. Process of classification of brain tumor

1.4.1 3D-UNet

It is composed of a contractive and an expanding path, that aims at building a bottleneck in its centermost part through a combination of convolution and pooling operations. After this bottleneck, the image is reconstructed through a combination of convolutions and up sampling.

3D U-Net is a type of neural network architecture primarily used for volumetric image segmentation tasks, particularly in medical image analysis. It's an extension of the original 2D U-Net architecture to handle 3D volumes, which are common in medical imaging such as MRI, CT scans, and microscopy.

The "U" in U-Net refers to its U-shaped architecture, which consists of a contracting path (encoder) and an expansive path (decoder), with skip connections between them. These skip connections help to preserve spatial information during the downsampling and upsampling operations, aiding in better localization of features.

Contracting Path (Encoder): This part of the network extracts features from the input volume through a series of convolutional and pooling layers, reducing the spatial dimensions while increasing the number of feature channels.

The decoder upsamples the feature maps back to the original input size using transposed convolutions or upsampling layers. This process gradually recovers spatial information lost during the downsampling, and it typically involves concatenating feature maps from the contracting path at corresponding resolution levels to preserve fine-grained details.

These connections directly link the corresponding feature maps from the contracting path to the expanding path. By doing so, the network can combine low-level features (captured in the early layers) with high-level features (captured in the deeper layers), facilitating precise segmentation.

The 3D U-Net architecture has demonstrated state-of-the-art performance in various medical image segmentation tasks due to its ability to capture spatial dependencies in volumetric data effectively. However, it requires significant computational resources due to the 3D convolutions and larger memory footprint compared to its 2D counterpart. Nonetheless, its benefits in accurately segmenting 3D structures make it invaluable in medical image analysis.

3D-UNet is composed of a contractive and an expanding path, that aims at building a bottleneck in its centermost part through a combination of convolution and pooling operations. After this bottleneck, the image is reconstructed through a combination of convolutions and upsampling.

3D-UNet allows for seamless segmentation of 3D volumes, with high accuracy and performance, and can be adapted to solve many different segmentation problems. The following figure shows the construction of the 3D-UNet model and its different components. 3D U-Net segmentation is an architecture based on the Convolutional Neural Network (CNN), which has typical use to classify labels. However, in medical imaging, the desired output should be more than just classification.

1.5 Related work

Over the years, many specialists from diverse backgrounds have worked and are still working within the domain of image processing, dealing with the detection and classification of various cancerous diseases like brain tumor, kidney tumor etc., and have proposed many novel procedures to generate the best results.

Wadhwa, Bhardwaj and Verma (2019) examined various methods for tumor identification and proposed that combining Conditional Random Field (CRF) with FCNN and CRF with Deep Medic or Ensemble offers better performance than the other approaches for tumor segmentation.

In Özyurt, Sert, Avci and Dogantekin (2019), for segmentation, Fatih Zyurt et al., proposed the use of the neutrosophic set expert maximum fuzzy-sure entropy (NS-EMFSE) process, and SVM and KNN classifiers were used to remove segmented functionality from the CNN architecture.

Recently, CNN has been employed by many researchers for image classification in the domain of medical sciences (Ayadi, Elhamzi, Charfi, & Atri, 2021; Jin, Meng, Sun, Cui & Su, 2020; Kalaiselvi, Padmapriya, Sriramakrishnan & Somasundaram, 2020; Mohsen, El-Dahshan, El-Horbaty & Salem, 2018; Murthy, Koteswararao & Babu, 2022; Rehman et al., 2021; Suganthe, Revathi, Monisha & Pavithran, 2020).

Good performance results are reported using advanced neural network models for MRI scan classification (Liu et al., 2018; Abiwinanda, Hanif, Hesaputra, Handayani & Mengko, 2019; Afshar, Mohammadi & Plataniotis, 2018; Badža & Barjaktarović, 2020; Bedekar, Niharika Prasad, & Revati Hagir, 2018).

Automated classification is very useful in computer-aided diagnosis systems. Ensemble models combining SVMs and neural networks are also implemented for the design of medical diagnosis systems (Deepak & Ameer, 2021). Soft computing techniques like fuzzy logic are also incorporated for better results (Jayachandran & Dhanasekaran, 2013).

Advanced fuzzy methods like adaptive fuzzy C-means clustering are used for segmentation. Results are further improved by the deer hunting optimization algorithm (Murthy et al., 2022). Li, Kuang, Xu and Sha (2019) proposed a multi-CNN approach to tackle the poor performance offered by the conventional methods.

The conventional models have slow training rates and often suffer from overfitting. The proposed method uses 3D-MRI images to train the neural network for volumetric segmentation as compared to 2D-MRI images. The method employs the use of three-dimensional CNNs for this purpose for the volumetric detection of the tumor in the 3D-MRI images.

The work also concludes that instance normalization consumes less time to train the 3D-CNN as compared to batch normalization and group normalization methods, and the proposed 3D-CNN model for the brain tumor detection offers better accuracy and performance.

An algorithm for 2D MRI scans is also proposed for segmentation and classification of MRI scans. Deep neural network algorithms with different activation functions like SoftMax and sigmoid are also implemented (Chattopadhyay & Maitra, 2022). Some researchers have also deployed a user-friendly computer-aided interface for MRI scan classification (Ucuzal, Yaşar & Çolak, 2019).

Sobhaninia et al. (2018) suggested that medical image recognition relies heavily on image segmentation, because medical photographs are too diverse, and used MRI and CT scan images to segment the brain tumor. The most common use of MRI is for brain tumor segmentation and classification. They proposed the use of fuzzy C-Means clustering for tumor segmentation, which can reliably model tumor cells.

After segmentation, classical classifiers and CNNs were used to classify the data. They implemented and compared the effects of various conventional classifiers such as K-Nearest neighbour, logistic regression, multilayer perceptron, nave bayes, random forest, and support vector machine in the traditional classifier section. SVM had the best precision of 92.42 percent among these conventional ones.

They also introduced CNN, which yielded 97.87 percent accuracy with a split ratio of 80:20 of 217 photographs, and suggested to experiment with 3D brain images in the future to accomplish more effective brain tumor segmentation.

Working with a wider dataset would be more difficult in this regard, and they aspired to create a dataset that emphasizes the abstract in relation to their region, which will help them expand the reach of their research. In Zhou et al. (2020), a web-based application that can identify brain tumor (glioma, meningioma, and pituitary) based on high-precision T1 contrast MRI with CNNs.

It is hoped that the free web-based software would enable medical professionals and other health professionals to identify brain tumors more quickly and accurately. In this regard, the app can be used as a clinical-decision support method for brain tumor classification (i.e., glioma, meningioma, and pituitary).

According to the experimental findings, all of the measured success metrics for classifying the forms of brain tumors on the training dataset were greater than 98%. On the research sample, all performance metrics are greater than 91%, with the exception of the sensitivity and Matthews correlation coefficient (MCC) performance metrics for meningiomas.

When the measured efficiency metrics from the CNN model's training and testing stages are considered, the proposed model is capable of effectively classifying various brain tumor forms. A new research study created the CNN to identify brain tumor on public data sets, with 233 and 73 patients, and 3064 and 516 images on T1-weighted magnetic resonance images.

For the two datasets, the method built in this trial performs significantly better and is able to effectively identify brain tumor multi-classification jobs at the highest overall accuracy levels of 96.13% and 98.7% respectively. A new algorithm for the classification of brain tumor in Grade I, Grade II, Grade III and Grade IV of the CNN profound learning algorithm was also developed.

The proposed algorithm for deep learning consists of three steps: a) tumor segmentation, b) data increase, and c) profound extraction and classification functions. Experimental findings from the other research work were investigated and showed that, when extended to augmented and initial data sets, the proposed algorithm has greater efficiency than the present methods.

The classification and simulation of T1-weighted MRI of brain tumor were well performed during previous experiments in machine learning and deep learning algorithms. But the selection and development of these algorithms may take a lot of time and experience if we consider the machine learning and data mining applications of the studies published over the past few years.

Therefore, in recent years, automated machine learning and various modelling systems have been widely developed. To put it briefly, the current research introduces a novel public web-based program to identify brain tumor types based on CNN's profound learning algorithms for T1-weighted MR images.

Yadav and Sahu (2013) presented a novel approach for the automatic segmentation of the most popular brain tumor, including gliomas, meningiomas, and pituitary. No preprocessing steps are essential for this technique. The findings show that angle-based dividing of photographs increases dividing precision.

The highest score for the dice was 0.79. The tumor segmentation in sagittal view images provided this comparatively high ranking. Other organs are not visible in sagittal images, and the tumor is more pronounced than in other images. The photographs from the axial view of the head received the lowest dice score in their tests, which has been reported as 0.71.

The axial view provides less specificity than the other pictures. It is anticipated that preprocessing this group of images would result in improved tumor pixel classification and an improvement in the dice ranking. The presented approach may be used to segment brain tumor in MRI images as an easy and practical technique for doctors.

In Murthy and Sadashivappa (2014), MRI studies indicate that the cancer-affected region has very high intensity pixels, whereas normal tissue has low intensity pixels. Thresholding is a method of segmentation that uses only the sensitivity parameter. This is one of the most basic types of segmentation, in which the tumor is classified according to its grey level.

Area-based image segmentation (Alqudah, Alquraan, Qasmieh, Alqudah & Al-Sharu, 2020) involves developing regions. Method uses 4-connected neighborhood or 8-connected neighborhood methodology. The amplitude of the same picture is clustered in one area. If the intensity belongs to the same seed, the phase is iterated, and the intensity belongs to one field.

Geometric active contour models focused on regions are more resistant to noise in the MRI, which leads to poor segmentation. T.S. Deepthi Murthy et al. (Kaur & Gandhi, 2019) proposed thresholding and morphological operations that are used to perform effective brain tumor segmentation.

However, since the threshold value used is a global threshold, it is not completely automatic and requires human interference. In Kavita, Alli and Rao (2022), a study has been presented on the multimodal medical image fusion technologies using pulse coupled neural networks with QCSA and SSO optimization techniques.

In Kalaivani and Seetharaman (2022), a three-stage boosted ensemble convolutional neural network has been proposed for the classification of COVID-19 chest x-ray images. The proposes the development of an extended U-Net architecture using ResNet architecture as a backbone. In Muruganantham and Balakrishnan (2021), a survey has been carried out for the various deep learning methodologies used to detect various gastrointestinal tract diseases.

1.6 Deep Learning

1.6.1 Deep Learning:

Deep learning is a subset of machine learning that focuses on training deep neural networks with multiple layers to learn and represent complex patterns in data. Deep neural networks are composed of interconnected layers of artificial neurons that simulate the structure and functioning of the human brain.

Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns and relationships within data. In deep learning, we don't need to explicitly program everything. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Because it is based on artificial neural networks (ANNs) also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain's biological neurons, and they are designed to learn from large amounts of data.

1.6.2 Key aspects of deep learning include:

- Neural Networks: Deep learning relies on neural networks with multiple hidden layers, allowing the network to learn hierarchical representations of the data. Each layer in the network extracts higher-level features from the representations learned in the previous layer. Deep neural networks can automatically learn and extract relevant features from raw data, eliminating the need for manual feature engineering.
- Training Process: Deep learning models are trained through a process called back propagation, where the network adjusts its internal parameters (weights and biases) to minimize the difference between the predicted output and the target output. This process involves propagating errors backward through the network and updating the parameters using gradient descent optimization algorithms.
- Large-Scale Data: Deep learning models typically require a large amount of labeled data for training. The availability of big data and advances in computing power have enabled the success of deep learning models. The large-scale data allows deep neural networks to learn complex representations and generalize well to new, unseen data.
- Applications: Deep learning has shown remarkable performance in various fields, including computer vision, natural language processing, speech recognition, and recommendation systems. It has achieved state-of-the-art results in tasks such as image classification, object detection, machine translation, and speech synthesis.
- Deep learning excels in handling complex and high-dimensional data, capturing intricate patterns, and achieving state-of-the-art performance in many AI tasks. However, it typically requires more computational resources and data compared to traditional machine learning approaches.

In summary, machine learning focuses on training algorithms to learn patterns and make predictions or decisions, while deep learning is a specific approach within machine learning that utilizes deep neural networks to learn complex representations. Deep learning has gained significant attention and has been particularly successful in solving tasks that involve complex data such as images, audio, and text.

Lane detection using deep learning is a popular approach that leverages the power of deep neural networks to detect and track lane markings on the road. Deep learning models excel in learning complex patterns and can effectively capture the distinctive characteristics of lane markings, making them well-suited for this task. Here is a high-level overview of the lane detection process using deep learning:

- Dataset Preparation: The first step is to collect or create a dataset of labeled images or videos, where the lane markings are manually annotated. The annotations typically involve marking the pixels or regions corresponding to the lane markings in the images or videos.
- Data Pre-processing: The collected dataset is pre-processed to prepare it for training. This may involve resizing the images, normalizing pixel values, and splitting the dataset into training and validation sets.
- Model Architecture: A deep learning model architecture needs to be selected or designed for lane detection. Convolutional Neural Networks (CNNs) are commonly used due to their ability to capture spatial dependencies in images. The model architecture may consist of multiple convolutional layers followed by pooling, fully connected layers, and output layers.
- Training: The deep learning model is trained using the labeled dataset. The training process involves feeding the input images into the model, comparing the predicted output (lane markings) with the ground truth annotations, and updating the model's weights through back propagation and gradient descent optimization algorithms. The objective is to minimize the difference between the predicted output and the ground truth annotations.
- Post-processing: Once the model is trained, the lane detection results may undergo post-processing steps to refine the detected lane markings. This may include techniques such as filtering outliers, curve fitting, and extrapolation to extend the detected lanes.
- Evaluation and Testing: The trained model is evaluated on a separate test dataset to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1 score can be used to measure the model's lane detection performance.

- Deployment: The trained lane detection model can be deployed in real-time applications, such as autonomous vehicles or advanced driver-assistance systems (ADAS), to detect and track lane markings in real-world scenarios.

It's worth noting that there are different variations and approaches for lane detection using deep learning, including single-image-based methods and video-based methods. Additionally, techniques like semantic segmentation and instance segmentation can also be employed to precisely detect and differentiate lane markings from other objects on the road.

Deep learning-based lane detection has shown promising results and has been successfully applied in various real-world applications. However, it's important to fine-tune and validate the model on diverse datasets and consider factors such as different weather conditions, road types, and lighting variations to ensure robust and reliable lane detection performance.

1.6.3 Application of Deep learning

Deep learning is a subset of machine learning that uses artificial neural networks (ANNs) to model and solve complex problems. It is based on the idea of building artificial neural networks with multiple layers, called deep neural networks, that can learn hierarchical representations of the data.

Deep learning algorithms use a layered architecture, where the input data is passed through an input layer and then propagated through multiple hidden layers, before reaching the output layer. Each layer applies a set of mathematical operations, called weights and biases, to the input data, and the output of one layer serves as the input to the next.

The process of training a deep learning model involves adjusting the weights and biases of the model to minimize the error between the predicted output and the true output. This is typically done using a variant of gradient descent, an optimization algorithm that adjusts the weights and biases in the direction of the steepest decrease in the error.

Deep learning has a wide range of applications, including image and speech recognition, natural language processing, and computer vision. One of the main advantages of deep learning is that it can automatically learn features from the data, which means that it doesn’t require the features to be hand-engineered. This is particularly useful for tasks where the features are difficult to define, such as image recognition.

1.6.4 Advantages of Deep Learning:

Deep learning has several advantages over traditional machine learning methods, some of the main ones include:

1. **Automatic feature learning:** Deep learning algorithms can automatically learn features from the data, which means that they don't require the features to be hand-engineered. This is particularly useful for tasks where the features are difficult to define, such as image recognition.
2. **Handling large and complex data:** Deep learning algorithms can handle large and complex datasets that would be difficult for traditional machine learning algorithms to process. This makes it a useful tool for extracting insights from big data.
3. **Improved performance:** Deep learning algorithms have been shown to achieve state-of-the-art performance on a wide range of problems, including image and speech recognition, natural language processing, and computer vision.
4. **Handling non-linear relationships:** Deep learning can uncover non-linear relationships in data that would be difficult to detect through traditional methods.
5. **Handling structured and unstructured data:** Deep learning algorithms can handle both structured and unstructured data such as images, text, and audio.
6. **Predictive modeling:** Deep learning can be used to make predictions about future events or trends, which can help organizations plan for the future and make strategic decisions.
7. **Handling missing data:** Deep learning algorithms can handle missing data and still make predictions, which is useful in real-world applications where data is often incomplete.
8. **Handling sequential data:** Deep learning algorithms such as Recurrent Neural Networks (RNNs) and Long Short-term Memory (LSTM) networks are particularly suited to handle sequential data such as time series, speech, and text. These algorithms have the ability to maintain context and memory over time, which allows them to make predictions or decisions based on past inputs.
9. **Scalability:** Deep learning models can be easily scaled to handle an increasing amount of data and can be deployed on cloud platforms and edge devices.
10. **Generalization:** Deep learning models can generalize well to new situations or contexts, as they are able to learn abstract and hierarchical representations of the data.

CHAPTER 2

LITERATURE SURVEY

Principal component analysis is applied for image segmentation but the accuracy is 76.6%. Neural networks works better for image enhancement and image segmentation but the algorithm wont work better in case of noise. The accuracy of basic neural network is less in case of noise.Multiple techniques need prior knowledge for segmentation which is not possible every time. To Design & Implement a technique for Automatic enhancement and segmentation of cardiac region from full cardiac image.

In the paper object segmentation is done with the help of shape driven information.Shape understanding by hierarchical approach gives training to the deep boltzman machine[1].The local as well as global strcture is used to identify shape variations based on learned model of hierarchical architecture.Shape distribution uses the data driven method to extract the object from given corrupted image. Proposed work works better for corrupted data , occulded data as well as noisy data.The CDR(correct detection rate) is not upto the mark for given model.

Exact detection and segmentation for anatomical ultrasound images is one of the important application required[2].Ultrasound images are having many different advantages like portability and low cost.But due to complex structure it is difficult to detect and segment regions exactly.So author designed Deep learning approach for regularization in multi-domain.Results obtained are improved by iterative process which may take more time compared to state of art techniques is the major drawback of proposed work.Compared to human understanding definitely it behave more accurate and also it work for huge image databases.

The author worked with histopathological images to detect and segment the essential part from the image[3].Author showed that the existing methods are having drawbacks of time consuming,error-prone as well as depends on operator.In oder to overcome all the existing challenges DCAN(Deep counter aware network) is proposed by author[3] for better accuracy and perfect segmentation.Also end to end convoltion network is proposed for better accuracy of segmentation.In this auxialary supervision is performed to overcome vanishing gradients while training network.The proposed work by author works on 2015 MICCAI Gland Segmentation Challenge database and show the superior performance of proposed method.

[1] "What regularized auto-encoders learn from the data-generating distribution," Guided by G. Alain and Y. Bengio, by the year of 2014.

assessment, an ordinary strategy intertwine name clinical picture examination assignments. Thusly, getting ready technique progressively significant desires, explicitly in circumstances where the data picture data isn't helpful or unsurprising enough (for instance missing thing limits). Even more essentially, clearly, this is most likely the soonest study displaying the use of convolutional auto encoder frameworks to take fit as a fiddle assortments from clinical pictures. The secluded cardiovascular appraisal up: cardiovascular picture division instead of past.

[2] "A combined deep learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI," Implemented by M. R. Avendi, A. Kheradvar, by the year of May 2016.

Division of the left ventricle (LV) from cardiovascular appealing resounding imaging (MRI) datasets is a fundamental improvement for check of clinical records, for example, ventricular volume and discharge part. Right now, utilize critical learning estimations got along with deformable models to make and study a completely modified LV division mechanical get together from short-turn heart MRI datasets. The technique utilizes huge learning figurings to take in the division task starting from the soonest stage information. Convolutional structures are utilized to ordinarily perceive the LV chamber in MRI dataset. Stacked auto encoders are utilized to gather the LV shape. The discovered shape is consolidated into deformable models to improve the exactness and nature of the division. We asserted our methodology utilizing 45 cardiovascular MR datasets from the MICCAI 2009 LV division challenge and exhibited that it beats the forefront systems. Unimaginable concurrence with the ground truth was developed. Support estimations, level of good shapes, Dice metric, standard converse division and likeness, were taken care of as 96.69%, 0.94, 1.81 mm and 0.86, versus those of 79.2 − 95.62%, 0.87–0.9, 1.76–2.97 mm and 0.67–0.78, secured by different systems, autonomously. In theoretical, a novel strategy for completely altered LV division from cardiovascular MRI datasets is appeared. The method utilizes critical learning figuring's for modified zone and finding the LV shape. The shape was cemented into deformable models and brought more strength and exactness, especially for testing basal and apical cuts. The portrayed procedure is demonstrated to be exact and strong stood apart from the other front line systems. Electrifying understanding and a high relationship with reference structures are picked up. Of course with other robotized approaches, our strategy depends after learning a few degrees of portrayals, relating to a pecking order of administration of highlights and doesn't envision any model or suspicion about the picture or heart. The practicality and execution of this division procedure is enough showed up through taking care of support estimations concerning the best level on the MICCAI 2009 database (Radau et al., 2009). Testing our strategy on a more prominent course of action of clinical information is subject of future research.

[3] "Automatic segmentation of the right ventricle from cardiac MRI using a learning-based approach," Produced by M. R. Avendi, A. Kheradvar, by the year of 2017.

The vast majority of the difficulties for RV division is a consequence of the astonishing life systems of the. join forces like, radiant bow state changes zenith, also arrangement power. Taking into account difficulties, just assessments concentrated division. top level frameworks for RV division experience the underhanded effects of a few hindrances, for example, spillage and shrinkage of structures because of the fluff edges closeness trabeculations. technique vanquished deficiencies and confined shrinkage/spillage by sorting out the collected fittingly conveyed pinnacle. Essentially as different techniques in the synthesis (6), the massive structures can be significantly more precisely apportioned separated and the little structures, and working with picture cuts in territory of the apex especially at ES can be trying an immediate aftereffect of the little size and sporadic shape.

Arranged estimations in Table 1 show that the structures at ED were significantly more precisely isolated the degree that DM separated and the shapes general considering the way that shapes at ES are more prominent and increasingly direct to segment. Once more, this is in like way an attribute of other division frameworks as organized in petit jean et al (6). Table 2 solidifies the enrolled quantitative estimations appeared at the midpoint of strategy beats top level strategies. Mean DM updates separated and different frameworks run assessment uncovered unimportant tendencies and a dominating degree of perception separated and that of different techniques. For instance, the Bland Altman follows identified with EF displayed a propensity near zero with the 95% farthest reaches of appreciation (6 1.96 SD) very nearly 6 0.10. This presentation takes after what organized.

Manuals encode noteworthy anatomical and significant data from a mass. Right now, biventricular cardiovascular chart book was worked from a stand-apart instructive grouping, which incorporates critical guidelines heart MR pictures of 1000+ standard subjects. Considering the outline book, genuine methods were utilized to take a gander at the collection of cardiovascular shapes and the dissipating of heart improvement over the spatio-transient district. indicated honest gotten along straight think about effect sexual bearing territorial divider. At long last, in like way broke down the impact of the individual's size on map book improvement and layout book based assessment. The huge principles map book, the genuine models and the SPM framework will profit more evaluations on heart life structures and breaking point assessment later on. As of now, developed the graph book pictures must seen solid. Thusly, manual quantifiable data sound addresses average life structures improvement. Regardless, give beginning stage to pondering the sporadic life structures and improvement. For instance, the picture work changed as per setup separated and normal.

In like way, the improvement of the patient can in like way be accustomed to the setup space, with the target that remarkable advancement models might be perceived utilizing the bona fide advancement model of the normal's, for example, the. Disclosure remarkable divider impossible to miss improvement design is a dazzling bearing. Investigated all-inclusive masses outcomes genuine force, significant assessments, instance, considers appraisals. Specific point of view, a test that we face in managing a colossal instructive record is the all-encompassing extent of manual intercession. As of now, spots of intrigue are utilized to introduce the picture choice. Future work is depended upon to dislodge this part with solid and motorized picture enlistment by strategies for accomplishment divulgence or organ restraint.

Besides, fused outline picture division significant coming about genuine assessment since the myocardial divider thickness is figured from the division. Once more, a computerized quality control system is required if this or comparable procedures are to be sent for much more noteworthy educational records, for instance, for experiences, for example, the UK Biobank4, which is proposing to look over to 100,000 subjects.

As of now, enlistment is performed going before assessing the game plan picture. An elective course for map book progression is to join picture selection and arrangement structure Leem put, methodology pack smart picture enrollment and diagram book update. Regardless, GroupWise picture determination can be computationally over the top for a gigantic enlightening record. Right now, perform subject-wise picture choice and check the graph book some time later. For building a sensible graph book, we figure the mean of the nonrigid changes utilizing dealing with figures clearing.

Precisely enormous clearings open, in any case, ceaselessly suitable process utilizing structure, for example speed proposed Ash burner choice expected unimaginably enormous distortion might be thought of. Illuminating record, photographs solid . discovered in wake of evacuating the relative parts, the extra non-unbending changes between solid subjects are near nothing. Right now, the Euclidean mean can be a middle of the road theory. There are various systems for pre-managing before quantifiable appraisal cross sections. instance, bearing contrasts cross areas.

[5] W. Bai et al., “A probabilistic patch-based label fusion model for multiatlas segmentation with registration refinement: Application to cardiac MR images,” IEEE Trans. Med. Imag., vol. 32, no. 7, pp. 1302–1315, Jul. 2013.

The appraisal of ventricular limit is noteworthy for the investigation of cardiovascular afflictions. It normally incorporates estimation pit. layout structures repetitive the enthusiastic experience of the ace map book strategy heart alluring resonation picture division. procedure perspectives. In the place, characterizes fix name mix picture selection precision name information, prompts division surveyed heart picture typical spread measurement division wretchedness, benefit pit strategy can give exact information to clinical investigation. In the examinations, we have found that selection precision significantly influences division execution. With enrollment refinement, mark blend. Besides, enlistment qualification between name blend procedures gets unnoticeable. Without a doubt, even lion's offer throwing a voting form can perform very well for this circumstance. Regardless, if the enlistment isn't amazingly exact, for example when relative selection is used, refined name blend frameworks, for instance, the fix based technique accept a huge activity in improving division execution. a guide book fix are resolved, the spread can achieve smooth assortment of the heaps and in like manner smooth assortment of the name map measure.

[7] “Topology aware fully convolutional networks for histology gland segmentation,” Produced by A. BenTaieb and G. Hamarneh, by the year 2016.

The progressing achievement of significant learning techniques all together and article distinguishing proof assignments has been used for division tasks. Regardless, a weakness of these significant division models is their limited ability to encode raised level shape priors, for instance, flawlessness and assurance of complex relationship between object territories, which can realize fantastical divisions. In this work, by characterizing and smoothing out another setback, we present the principle significant framework arranged to encode geometric and topological priors of control and partition. Our results on the division of histology organs from a dataset of 165 pictures display the upside of our novel disaster terms and show how our topology careful plan pounds fighting systems by to 10% in both pixel-level accuracy and article level Dice.

We guessed that the thought of before data in the readiness of significant totally convolutional frameworks for the division of histology organs can achieve progressively exact divisions. To test our theory, we presented a novel adversity work inspired by essentialness based models for multi-area checking and balanced for significant frameworks. Our revelations show that our system yields on a very basic level dynamically exact and possible divisions while being even more computationally profitable at test-time. We plan to furthermore investigate the effect of furnishing significant learning models with huge prior data for getting ready more regularized sorts out on different clinical division applications.

[8] "Segmentation algorithms in 3D Standardized evaluation system for left ventricular echocardiography," Authorized by O. Bernard, By the year of Apr. 2016.

Steady shown exact gadget. Regardless, conspicuous verification troublesome endeavor, essentially separation photos got together regular antiquated rarities. A couple of semi and totally modified figuring's dividing evacuate records, yet methodical sensible connection strategies incomprehensible on account of the nonappearance of a straightforwardly open essential database. Here, we familiarize a standardized evaluation structure with constantly survey and break down the introduction of the figuring's made edge involving heart narratives concentrations relating estimations figuring's bundles surveyed taken a gander at stage. concerning pros' estimations records, incredible division regards to partition botch with respect to the masters' irregularity run. The stage remains open for new sections.

A straightforwardly open standardized evaluation framework to consider the introduction of endocardial division methodology in RT3DE was presented in this article. The results exhibited current figuring's in regards authorities' estimations records, extraordinary division exactness to the extent mean partition botch with respect to the pros' change pursue accord understanding. In spite of the way that these results are enabling, they also reveal that there still exists chance to improve.

[9] "Deep learning shape priors for object segmentation," Produced by F. Chen, and X. Zeng, by the year of Jun. 2013.

This paper were present another system as the object division. readiness initially significant pick up capability with the different leveled designing of shape priors. This informed different leveled building show assortments as well as worldwide or neighborhood enthusiastic structure. Assessments display abstract adjust to picture upheaval and wreckage, similarly as fragmentary obstacles. Our strategy involves significant Boltzmann machine to isolate as the different leveled planning structure. That different leveled structure can reasonably get worldwide and close by structures of prior shapes. During the second stage a shape-driven variational structure is manufactured genuinely on the space of shape probabilistic depiction. This dynamic structure of shape prior is familiar in an eager structure with regularize the target shape in variational picture division. We show the practicality of the ensuing figuring in segmenting pictures that incorporate low-quality data and hindrances.

[10] "DCAN: Deep contour-aware networks for object instance segmentation from histology images," Produced by H. Chen, and P.-A. Heng, by the year Feb. 2017.

The morphology of organs has been used routinely by pathologists to study the danger level of adenocarcinomas. Exact division of organs from histology pictures is a crucial development to get reliable morphological estimations for quantitative examination. In this paper, we proposed a compelling significant structure careful framework (DCAN) to deal with this troublesome issue under a bound together perform different assignments learning structure. In the proposed orchestrate, amazed intelligent features from the different leveled configuration are examined with right hand the executives for exact organ division. Right when united with perform different assignments regularization during the arrangement, the discriminative capacity of midway features can be furthermore improved. Moreover, our framework can yield exact probability maps of organs, yet furthermore depict clear structures simultaneously for secluding grouped articles, which further lifts the organ division execution.

This united structure can be powerful when applied to colossal extension histopathological data without relying upon additional steps to make structures reliant on low-level finishes paperwork for post-secluding. Our methodology won the 2015 MICCAI Gland Segmentation Challenge out of 13 genuine gatherings, beating the different systems by a critical edge. In this paper, we have presented a significant structure careful framework that consolidates amazed consistent features to absolutely part organs from histology pictures. As opposed to learning organ division in withdrawal, we figured it as a united play out various assignments learning process by handling the corresponding information, which helps with advancing separate the gathered organ questions beneficially. Wide test results on the benchmark dataset with rich connection results showed the exceptional execution of our procedure. Later on work, we will upgrade the strategy and research its ability for huge extension histopathological dataset.

[12] “3D U-Net: Learning dense volumetric segmentation from sparse annotation,” Produced by A. Abdulkadir, and O. Ronneberger, by the year of 2016.

This paper presents a framework for volumetric division that gains from meagerly remarked on volumetric pictures. We plot two engaging use examples of this procedure: (1) In a semi-modernized plan, the customer remarks on specific slices in the volume to be segmented. The framework gains from these sparse remarks and gives a thick 3D division. (2) In a totally modernized course of action, we acknowledge that a representative, inadequately remarked on planning set exists. Arranged on this educational assortment, the framework thickly pieces new volumetric pictures.

[13] “Combining point distribution models with shape models based on finite element analysis,” Developed by T. F. Cootes and C. J. Taylor, By the year 1995.

This paper depicts a method for joining two different ways to manage exhibiting versatile articles. Measured Analysis using Finite Element Methods (FEMs) makes a great deal of vibrational modes for a Éêëèíî shape. Point Distribution Models (PDMs) make a genuine model of shape and shape assortment from a Éîï of model shapes. Another strategy is depicted which makes vibrational modes when barely any model shapes are open and changes effectively to using progressively quantifiable techniques for assortment when a colossal enlightening record is presented. Results are given for both made and authentic models. Tests using the models for picture search show that the solidified variation performs better than either the PDM or FEM models alone. The system depicted above licenses us to solidify the shape variability chose detail istically from a planning set with that delivered erroneously by building a 'physical' model of the objects of interest. Exactly when only a singular model is open just FEM modes are used. As more models are incorporated, the quantifiable depiction of the shape assortment.

[14] C. Davatzikos, X. Tao, and D. Shen, “Hierarchical active shape models, using the wavelet transform,” IEEE Trans. Med. Imag., vol. 22, no. 3, pp. 414–423, Mar. 2003.

Dynamic shape models (ASMs) are much of the time weaknesses reasonably get extent natural capriciousness. Methodology dynamic specifying dynamic change. Quantifiable change shape penniless somewhere near methods for head part assessment, and used as priors in the structure's misshapening. A part of respectably overall as far as possible, however, some of them get close by and high-repeat shape traits and, as such, fill in as neighborhood flawlessness necessities. This arrangement achieves two goals. In the first place, it is solid when only a foreordained number of getting ready tests is available. Second, by using close by bits of knowledge as flawlessness constraints, it forgoes the necessity for getting uncommonly designated physical models, for instance, adaptability or distinctive flawlessness models, which don't generally reflect authentic normal vacillation. Models on alluring resonation photos of the corpus callosum and hand structures show that incredible and totally electronic divisions can be cultivated, even with as very few as five getting ready tests. We presented a different leveled plan of dynamic quantifiable going before have the alternative to get fine similarly massacres hindrances past reliant arrange.

Different leveled depiction with respect to change trailed explanation technique though for the most part humble number of getting ready tests can't generally get the high-dimensional probability thickness. . The realities affirm that if certain assortment of the shape isn't presented in the readiness tests. By then paying little heed to what number of tests set up it incredibly improbable assortment. Legitimate unique yet. In any case, techniques offer deal with all more probable depicts the assortments readiness tests. Furthermore depicted continuously relies upon grungy depiction. As gives as well as nature twist depiction some degree distorted way to deal with amass different leveled dynamic shape model. Procedure 2 relies upon the wavelet rot. It has an exhaustive logical establishment, and the multiresolution chain of significance noteworthy

CHAPTER 3

1. Convolutional Neural Networks (CNNs)

- **Overview**: CNNs are one of the most commonly used deep learning techniques in image recognition tasks. They work by detecting patterns, edges, textures, and higher-level features in images.
- **Application in Brain Tumor Detection**: CNNs are trained on large datasets of brain MRI images to distinguish between normal and abnormal brain scans. They are particularly effective in automatically extracting spatial features relevant to identifying tumors.
- **Examples**:
  - **U-Net**: A popular architecture used in medical image segmentation. U-Net is used to segment tumors in MRI scans into various regions (e.g., enhancing, non-enhancing tumor regions, edema).
  - **3D CNNs**: To better capture volumetric information in MRI or CT scan images, 3D CNNs process 3D data, improving performance over traditional 2D CNNs.

2. Transfer Learning

- **Overview**: Transfer learning involves using pre-trained deep learning models (trained on large datasets like ImageNet) and fine-tuning them for the specific task of brain tumor detection.
- **Application in Brain Tumor Detection**: Popular models such as ResNet, InceptionV3, and VGG16 can be fine-tuned with a dataset of brain images. These models learn general features from large datasets and are then adapted to classify brain tumor images.
- **Advantages**: Reduces the need for large labeled datasets and speeds up the training process.

3. Recurrent Neural Networks (RNNs)

- **Overview**: While CNNs are primarily used for static images, RNNs can be employed when temporal data or sequences (e.g., multiple MRI scans over time) are involved. In brain tumor detection, RNNs can track tumor progression.

- **Application in Brain Tumor Detection**: If temporal information (such as changes in tumor size across different scans) is available, RNNs can be used for dynamic prediction, providing insights into tumor growth.

4. Generative Adversarial Networks (GANs)

- **Overview**: GANs consist of two neural networks, a generator, and a discriminator, that compete with each other. They have been used for generating synthetic data, data augmentation, and even improving image quality.
- **Application in Brain Tumor Detection**: GANs can be used for data augmentation, creating new synthetic MRI images that improve model robustness. Additionally, GANs can help with image segmentation tasks by refining the boundaries of tumors.

5. Hybrid Approaches

- **Overview**: Hybrid approaches combine multiple models or techniques to improve accuracy.
- **Example**:
  - **CNN + LSTM**: Combining CNNs for feature extraction and Long Short-Term Memory (LSTM) networks for time-series prediction has shown promise for tumor classification and tracking tumor progression over time.

6. Segmentation Models

- **Overview**: Segmentation is a crucial task in brain tumor detection, where the goal is to delineate the tumor from the surrounding tissue. Common methods include U-Net, Mask R-CNN, and fully convolutional networks (FCNs).
- **Applications**:
  - **Tumor Region Detection**: Identifying regions affected by tumors for further analysis.
  - **Segmentation of Tumor Types**: Differentiating between tumor types (e.g., glioma, meningioma) through pixel-wise segmentation.

7. Preprocessing and Data Augmentation

- **Preprocessing**: Raw MRI or CT scans are often noisy, so preprocessing steps like normalization, contrast adjustment, and skull stripping (removal of non-brain regions) are performed.
- **Data Augmentation**: Techniques such as rotation, flipping, zooming, and adding noise are used to artificially increase the size of the training dataset, making models more robust.

8. Ensemble Learning

- **Overview**: Ensemble methods combine the predictions of several models to improve the overall accuracy and reduce overfitting.
- **Application in Brain Tumor Detection**: Multiple deep learning models (e.g., different CNN architectures) can be trained and combined to improve tumor detection accuracy.

9. Evaluation Metrics

- **Accuracy**: Measures the overall correctness of the model.
- **Dice Coefficient/IoU (Intersection over Union)**: Measures the overlap between predicted and actual tumor regions, used for segmentation tasks.
- **Precision and Recall**: These metrics are particularly important for imbalanced datasets, where the number of positive cases (tumors) may be small compared to the negative cases (healthy scans).
- **ROC Curve & AUC**: To evaluate classification performance, especially in distinguishing between benign and malignant tumors.

Key Datasets for Brain Tumor Detection:

- **BRATS (Brain Tumor Segmentation Challenge)**: A widely used dataset with MRI scans of brain tumor patients, categorized by tumor types and segmentation masks.
- **ISLES (Ischemic Stroke Lesion Segmentation)**: Though focused on stroke lesions, it is also used for studying brain imaging segmentation techniques that could apply to tumor detection.

- **LiTS (Liver Tumor Segmentation)**: While focused on liver tumors, the methodologies for segmentation are applicable to brain tumor detection.

Challenges:

- **Data Imbalance**: Many datasets have far fewer tumor cases than healthy brain images, making it hard for models to learn to identify rare conditions.
- **Complexity of Tumor Types**: Brain tumors can vary greatly in shape, size, and location, making accurate detection and classification difficult.
- **Interpretability**: Deep learning models, especially CNNs, are often seen as "black boxes." Clinicians may need interpretable results to trust and use these models in practice.

Example of Existing Systems:

1. **Deep Brain**: A system based on deep learning that can automatically detect and segment brain tumors from MRI scans.
2. **BrainTumorNet**: A deep learning model that uses a combination of CNN and fully connected layers for detecting and classifying brain tumors from MRI scans.
3. **SegNet**: A deep learning-based model for pixel-wise segmentation of brain tumors in MRI scans.

CHAPTER 4

PROPOSED METHOD

(The proposed segmentation and classification models are explained in this section).

3.1. Segmentation model

i. Dataset

In multimodal magnetic resonance imaging (MRI) scans, BraTS has always concentrated on evaluating cutting-edge techniques for brain tumor segmentation. BraTS 2020 segments intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, such as gliomas, using multi-institutional pre-operative MRI scans.

BraTS'20 also uses integrative analyzes of radiomic features and machine learning algorithms to pinpoint the clinical validity of this segmentation task, as well as estimate patient overall survival and the discrepancy between faux progression and actual tumor recurrence. Finally, BraTS'20 attempts to evaluate the algorithmic sophistication of tumor segmentation.

i 3D-Unet U-Net is one of the most popular architectures used for segmentation. It was designed for image segmentation in the biomedical field. It produced great results for cell tracking. It can work with hundreds of examples and produce good results. As it is U-shape so it is called the U-net model.

It consists of two paths: the contracting path and the expanding path. Both paths perform opposite results. The contracting path involves down sampling and down convolution. Expanding paths involves up-sampling and up-convolution. In contracting path feature maps get spatially smaller, whereas in an expanding path, the feature maps are expanded back to their original size.

This model was basically built for 2D images, but by replacing 2D convolutional networks with 3D networks the model can be used for 3D convolution as well. Fig. 2 shows the architecture of the 3D-Unet deep neural network architecture.

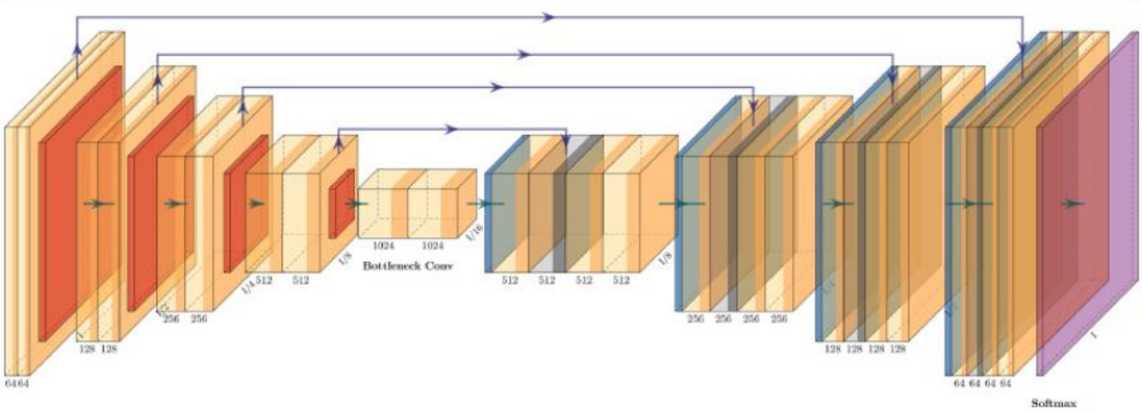

Fig. 4. 3D-UNet structure.

The 3D U-Net model is the model introduced in this paper. The models that make up the full tumor detection platform are an image registry model, a 3D U-Net model, and soft dice failure. The first step was to combine 3D image slices from an MRI scan into a single 3D model. Image registration is used to solve misalignment issues during combination.

Following the formation of the 3D model, the 3D model is divided into subsections, each of which is coded in the appendix. The subsections are then fed into the U-Net model, which produces the segmented model after all of the down and up convolution cycles. The subsections are then merged once more to create a segmented 3D model. The next move is to calculate the damage. 3.2. Classification model

3.1.1. Dataset

The classification model is based on the Brain tumor Classification (MRI) Kaggle dataset. This dataset is split into training and research sets, accumulating 3264 files categorized as glioma, meningioma, pituitary, and no tumor photographs. Since this is a classification model, this dataset aids in the accurate and precise training and testing of the model.

3.1.2. Convolutional neural network

Neural network architecture is inspired by the biological human brain. Neural networks are primarily used to quantify vectors, approximate data, cluster data, align patterns, optimize, and classify functions.

Based on their links, the neural network is categorized into three groups, viz., (a) feedback, (b) feedforward, and (c) recurrent networks. Further, a neural network can be classified as a single-layer network or a multilayer neural network.

The picture cannot be scaled in the standard neural network. However, in the convolution of the neural network, pictures can be scaled (i.e. in length, width, and height). The Convolution Neural Network (CNN) consists of an input layer, a convolution layer, and a rectified linear unit (ReLu).

The provided input picture is divided into several small regions of the convolution sheet. In the ReLu layer, element-wise feature activation is performed, and an optional pooling layer could be used. The pooling layer is used primarily for sampling purposes.

A class score or mark score value dependent on chance between 0 and 1, is used in the last layer (i.e., to produce the completely connected layer). Fig. 3 shows the block diagram of the grouping of brain tumor based on the neuronal network. The classification of brain tumor based on CNN is split into two stages: (a) preparation and (b) research.

The number of photographs is categorized by naming the marks (tumor, non-tumor images, etc.) into various categories. In the training step, pre-processing, functional extraction and loss function classification are carried out to produce a prediction model.

First, the picture collection is marked for the instruction, and then the image is resized to adjust the image size in the pre-processing process. Finally, for the automated detection of brain tumor the neural convolution network is used.

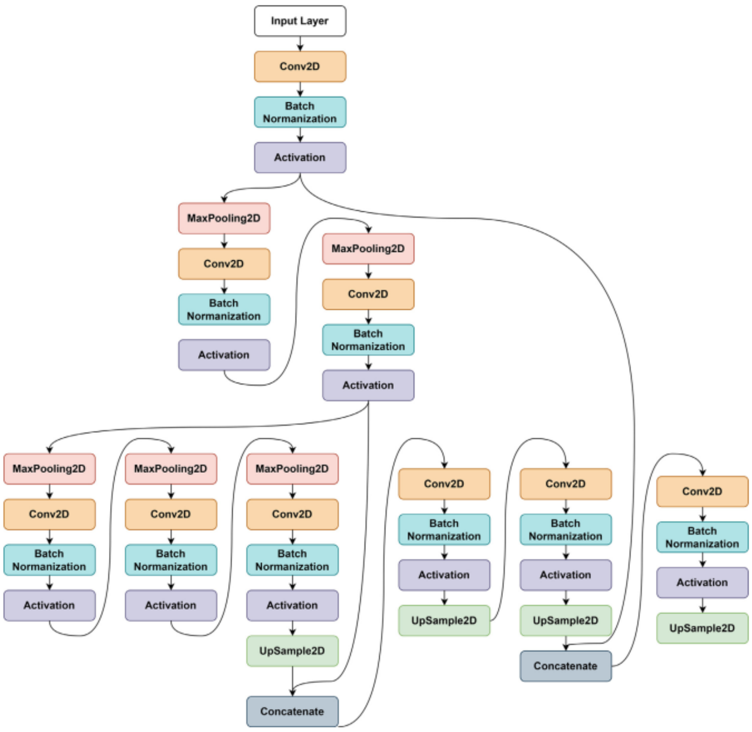

Fig. 5. Segmentation and Detection model.

The brain image dataset used for this model is taken from Kaggle. To use the untrained dataset, the model is trained from layer one until the end layer. This can be very time-consuming and will also affect the outcome. So, for classification measures, a pre-trained model-based brain dataset is used to prevent this issue.

In the proposed model, only the last layer is trained during implementation. As a result, the proposed model has a short computing period with higher efficiency. The loss function is determined by the gradient descent algorithm. The raw pixel image is mapped using a score feature to achieve class results. Quality is calculated by the loss function of a particular set of parameters.

It is dependent on the way induced results are accepted in the training data with the ground truth marks. In order to increase the precision, calculating the loss function is extremely necessary. When there is a high loss function, the precision will be very poor. Similarly, when the loss function is minimal, the precision will be high. The value for the loss function is determined to estimate the downward gradient algorithm, and it accesses the gradient value to calculate the loss function gradient repeatedly.

4.1.3. Proposed segmentation model

The proposed model in this paper is a newly developed CNN architecture. The proposed architecture is novel because it is updated. The design has 16 layers to enable the classifier to efficiently classify the brain tumor images. The configuration of the implemented CNN architecture is presented in Fig. 4.

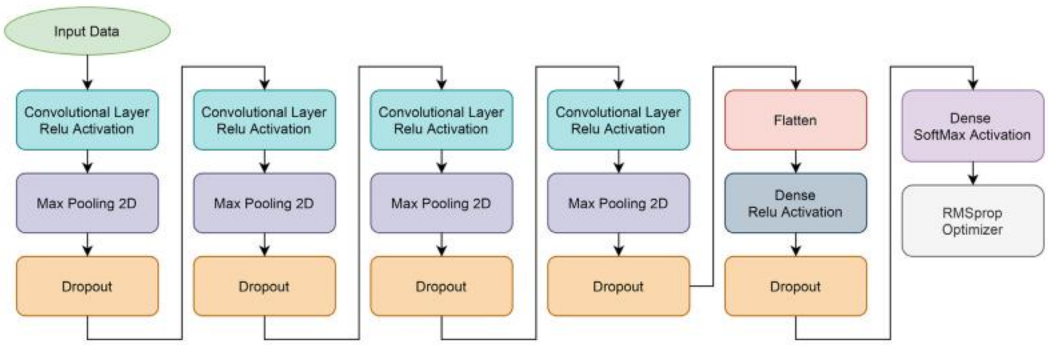

Fig. 6. Proposed Classification Model.

4.3 Flowchart for proposed method

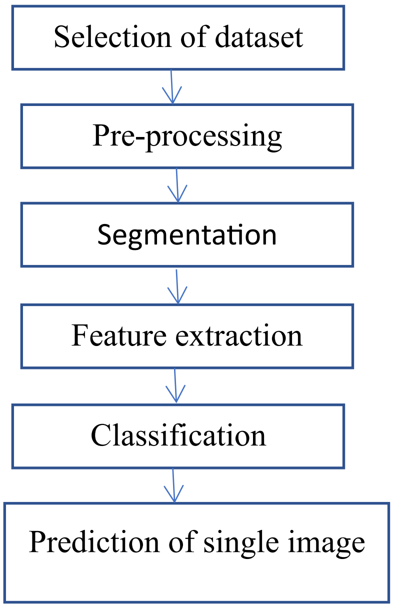

Fig. 7 Flowchart of proposed method

4.4 FEASIBILITY STUDY

Feasibility Study of Brain Tumor Detection Using Deep Learning (DL)

A feasibility study for implementing **Deep Learning (DL)** in brain tumor detection involves evaluating its technical, operational, and financial aspects. The objective is to understand whether using DL models for brain tumor detection is viable in real-world clinical settings. Below is a comprehensive study that includes the technical feasibility, operational feasibility, financial considerations, and challenges.

1. Technical Feasibility

This aspect examines the hardware, software, and algorithmic requirements for implementing a DL-based brain tumor detection system.

- **MRI/CT Scan Data**: Large annotated datasets of brain images (such as BRATS, LiTS) are crucial for training DL models. These datasets should be diverse in terms of tumor types, sizes, and locations.
    - **Challenge**: Data might not be uniformly available or may require extensive preprocessing to ensure quality (e.g., normalization, skull stripping).
    - **Solution**: Data augmentation techniques (rotation, flipping, zooming) can help increase the size and diversity of the dataset.

b. Hardware Requirements

- **GPU (Graphics Processing Unit)**: Deep learning models, especially CNNs, require substantial computational resources. Training models on large datasets necessitates powerful GPUs (e.g., NVIDIA Tesla V100 or A100) to accelerate the training process.
- **Storage**: Medical image data requires significant storage space due to the large size of 3D MRI scans or high-resolution images.
- **Processing Power**: High-performance CPUs and GPUs are required for training models in a reasonable time frame, with cloud computing platforms (e.g., AWS, Google Cloud) providing scalable resources.

c. Model Development & Architecture

- **CNNs & Advanced Architectures**: Convolutional Neural Networks (CNNs), particularly U-Net and 3D CNNs, have been shown to work well for tumor detection and segmentation. For classification, a hybrid approach combining CNNs with Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) models could be used if there is temporal data (sequences of MRI scans).
    - **Challenge**: Choosing the right architecture is key. For example, 3D CNNs are better suited for volumetric data but require more processing power and training time.
    - **Solution**: Pre-trained models (transfer learning) can be used to reduce training time and improve performance with limited data.

d. Model Training & Evaluation

- **Accuracy & Performance Metrics**: The model's performance should be evaluated using metrics like accuracy, Dice coefficient, sensitivity, specificity, and Area Under the Curve (AUC) for classification.
    - **Challenge**: Imbalanced datasets (where healthy scans are much more common than tumor scans) can affect model performance, resulting in a higher rate of false negatives.
    - **Solution**: Data augmentation, oversampling techniques, or cost-sensitive learning algorithms can address these issues.

2. Operational Feasibility

This aspect evaluates the practical aspects of deploying a DL-based brain tumor detection system in real-world clinical environments.

a. Integration with Existing Systems

- **Electronic Health Records (EHR)**: The DL system must integrate seamlessly with existing hospital infrastructure, such as PACS (Picture Archiving and Communication Systems) and EHR systems, to automatically retrieve MRI/CT images and store the results of the detection process.
    - **Challenge**: Integration with legacy systems can be complex and may require custom interfaces.

- **Solution**: Developing APIs or using standards like DICOM (Digital Imaging and Communications in Medicine) will simplify integration.

b. Model Deployment

- **Cloud-Based vs. On-Premise**: The deployment can either be on cloud platforms for scalability or on-premise for greater control over data security. Both have their trade-offs in terms of cost, data privacy, and computing power.
    - **Challenge**: Ensuring fast and reliable performance of the system during clinical use, where doctors need to quickly access results.
    - **Solution**: Hybrid models (edge computing combined with cloud storage) could be considered, where initial processing occurs locally, and more intensive computations are offloaded to the cloud.

c. Real-Time Detection

- **Intraoperative or Postoperative Use**: For real-time detection (e.g., during surgery), the model needs to provide fast predictions, requiring optimized models and fast computation.
    - **Challenge**: DL models, especially complex ones like 3D CNNs, may require optimization techniques such as model pruning, quantization, or using smaller architectures to meet the speed requirements.

d. Clinician Acceptance & Usability

- **User Interface**: The system must provide intuitive user interfaces that integrate with existing hospital workflows.
    - **Challenge**: DL-based models can sometimes be seen as "black boxes," making it hard for clinicians to trust the results.
    - **Solution**: Interpretability techniques like Grad-CAM or attention mechanisms can be implemented to highlight which parts of the image contributed to the detection, improving clinician trust.

3. Financial Feasibility

The financial feasibility considers the costs associated with implementing and maintaining a brain tumor detection system.

a. Initial Investment

- **Hardware Costs**: High-performance GPUs, data storage systems, and server infrastructure for training and deployment can be expensive.
    - **Estimated Costs**: GPUs can cost anywhere between $5,000 to $10,000 per unit, and server infrastructure could cost $50,000 or more, depending on the scale of the system.

b. Development and Maintenance Costs

- **Software Development**: Building a custom DL solution requires skilled data scientists, software developers, and engineers. This could involve an initial investment of $100,000 to $500,000 depending on the team size and project scope.
- **Model Maintenance**: Continuous model updates, retraining with new data, and system maintenance are ongoing costs that need to be factored into long-term budgeting.

c. Cost of Cloud vs. On-Premise Deployment

- **Cloud Costs**: Cloud computing can incur costs based on usage (compute time, storage), potentially making it more cost-effective for smaller hospitals or practices that don't have high upfront budgets.
    - **Cost Estimate**: Cloud services typically charge on a per-hour basis for compute, which can range from $0.50 to $10/hour depending on the resources used.
- **On-Premise Costs**: On-premise solutions require a larger initial investment but may have lower ongoing operational costs.

d. Potential Revenue & Return on Investment (ROI)

- **Cost Savings**: By automating brain tumor detection, healthcare providers can reduce the time required for diagnosis, increase throughput, and potentially improve patient outcomes by detecting tumors earlier.
- **Market Demand**: As healthcare systems increasingly embrace AI, the demand for automated diagnostic systems in radiology is expected to grow, providing a return on investment (ROI) over time.

4. Challenges and Risks

a. Data Privacy & Security

- Medical data is highly sensitive. Ensuring compliance with regulations such as HIPAA (Health Insurance Portability and Accountability Act) in the U.S. and GDPR (General Data Protection Regulation) in the EU is critical.
    - **Challenge**: Secure data transmission and storage must be guaranteed, especially in cloud-based systems.

b. Model Interpretability

- Lack of interpretability could limit the adoption of DL models in clinical settings. Healthcare professionals need to understand why a model makes a particular diagnosis, especially in high-stakes situations like brain tumor detection.

c. Regulatory Approval

- The system must undergo regulatory scrutiny from bodies such as the FDA (U.S. Food and Drug Administration) or EMA (European Medicines Agency) before it can be deployed for clinical use.
    - **Challenge**: Regulatory approval can be time-consuming and costly.

d. Bias and Fairness

- DL models might develop biases if the training data is not sufficiently diverse (e.g., lacking representation from different demographic groups), leading to inaccurate results for certain populations.

CHAPTER 4

SOFTWARE AND HARDWARE REQUIRMENT

4.1 HARDWARE REQUIREMENTS:

- System : Pentium Dual Core.
- Hard Disk : 120 GB.
- Monitor : 15’’ LED
- Input Devices : Keyboard, Mouse
- Ram : 4 GB

4.2 SOFTWARE REQUIREMENTS:

- Operating system : Windows 10
- Coding Language : python
- Tool : Python
- Database : dataset
- Server : Flask

4.3 Hardware Interfaces

Intel Core i5 2.00GHz Processor or each and every other processor and 200 GB min RAM 20GB Hard plate, and mouse is required.

Software Interfaces

The Python IDLE is an open-supply web utility that allows you to make and charge records that be essential for stay code, circumstances, portrayals, and story-printed content. Uses encompass realities cleansing and exchange, numerical re-establishment, quantifiable illustrating, realities conviction, framework examining, and divides

4.4 SOURCE CODE

4.4.1 Frontend code

```
import tkinter as tk
from tkinter import filedialog, messagebox
import os
def load_dataset():
    folder_selected = filedialog.askdirectory()
    if folder_selected:
        dataset_path.set(folder_selected)
        messagebox.showinfo("Success", "Dataset loaded successfully!")
def train_model():
    messagebox.showinfo("Training", "Model training started...")
    # Call the training script or function here
    messagebox.showinfo("Training", "Model training completed!")
def segment_image():
    file_selected = filedialog.askopenfilename(filetypes=[("NIfTI files", "*.nii *.nii.gz")])
    if file_selected:
        messagebox.showinfo("Segmentation", "Segmentation process started...")
        # Call the segmentation function here
        messagebox.showinfo("Segmentation", "Segmentation completed!")
def classify_image():
    file_selected = filedialog.askopenfilename(filetypes=[("Image files", "*.png *.jpg *.jpeg")])
    if file_selected:
        messagebox.showinfo("Classification", "Classification process started...")
        # Call the classification function here
        messagebox.showinfo("Classification", "Classification completed!")
```

```
root = tk.Tk()

root.title("Brain Tumor Segmentation & Classification")

root.geometry("400x300")

dataset_path = tk.StringVar()


tk.Label(root, text="Brain Tumor Segmentation & Classification", font=("Arial", 14)).pack(pady=10)


tk.Button(root, text="Load Dataset", command=load_dataset).pack(pady=5)

tk.Button(root, text="Train Model", command=train_model).pack(pady=5)

tk.Button(root, text="Segment Image", command=segment_image).pack(pady=5)

tk.Button(root, text="Classify Image", command=classify_image).pack(pady=5)

tk.Label(root, textvariable=dataset_path, wraplength=350).pack(pady=5)

root.mainloop()
```

4.4.2 Backend code

```
import cv2

import numpy as np

import tensorflow as tf

from tensorflow.keras.models import load_model

def load_and_preprocess_image(image_path):

    image = cv2.imread(image_path)

    image = cv2.resize(image, (128, 128))  # Resize to match model input

    image = image / 255.0  # Normalize

    return np.expand_dims(image, axis=0)


def train_model(training_data, labels):

    model = tf.keras.Sequential([

        tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(128, 128, 3)),

        tf.keras.layers.MaxPooling2D(2,2),

        tf.keras.layers.Conv2D(64, (3,3), activation='relu'),

        tf.keras.layers.MaxPooling2D(2,2),

        tf.keras.layers.Flatten(),

        tf.keras.layers.Dense(128, activation='relu'),

        tf.keras.layers.Dense(2, activation='softmax')  # Binary classification

    ])

    model.compile(optimizer='adam',                         loss='sparse_categorical_crossentropy',
metrics=['accuracy'])

    model.fit(training_data, labels, epochs=10, batch_size=32)

    model.save("image_model.h5")

    return model

def segment_image(image_path, model_path):
```

```
    model = load_model(model_path)
    image = load_and_preprocess_image(image_path)
    prediction = model.predict(image)
    segmented_image = (prediction > 0.5).astype(np.uint8)  # Basic thresholding
    return segmented_image
def classify_image(image_path, model_path):
    model = load_model(model_path)
    image = load_and_preprocess_image(image_path)
    prediction = model.predict(image)
    class_index = np.argmax(prediction)   return class_index
```

CHAPTER 6

RESULT

RESULT

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

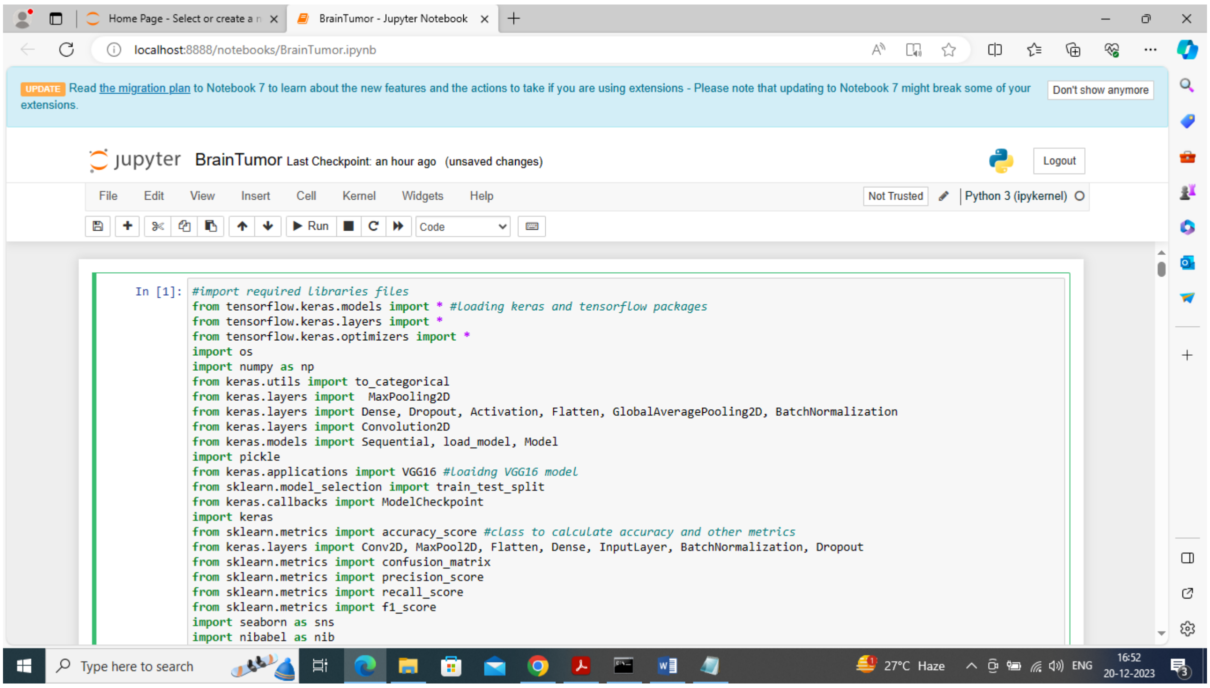

Fig.8. Importing python classes

In above screen importing required classes and packages

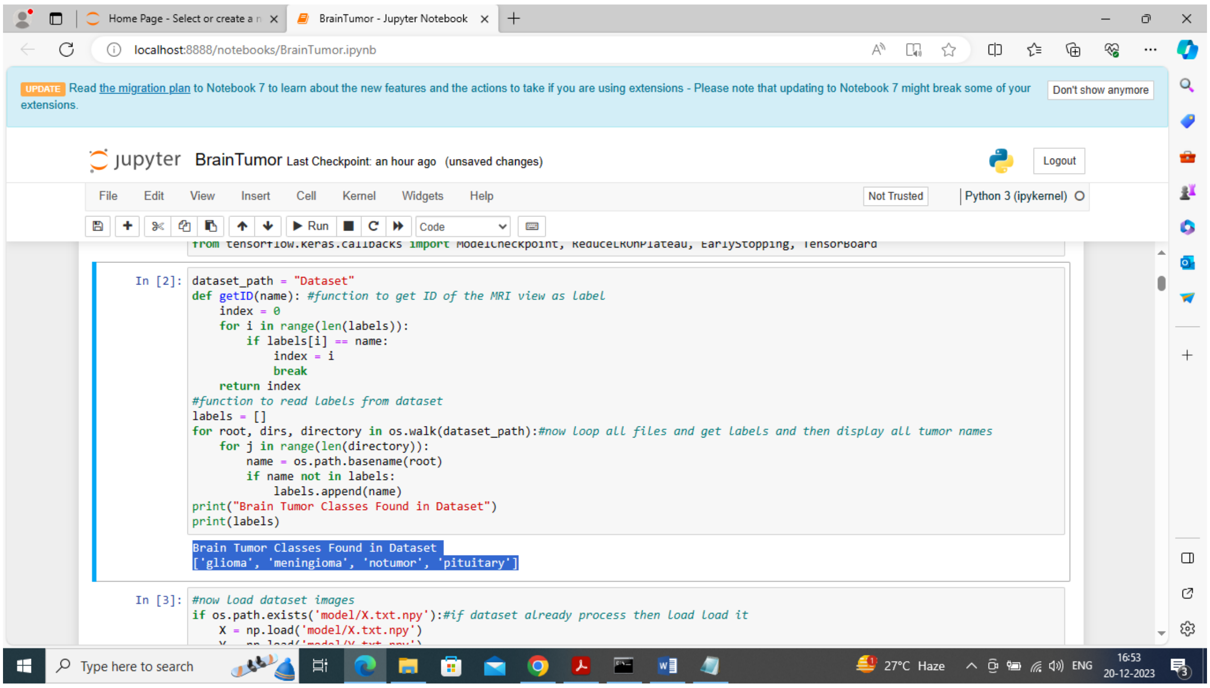

Fig.9 loading dataset

In above screen loading dataset to identify different tumor or class labels found in dataset and all tumor names we can see in blue colour text

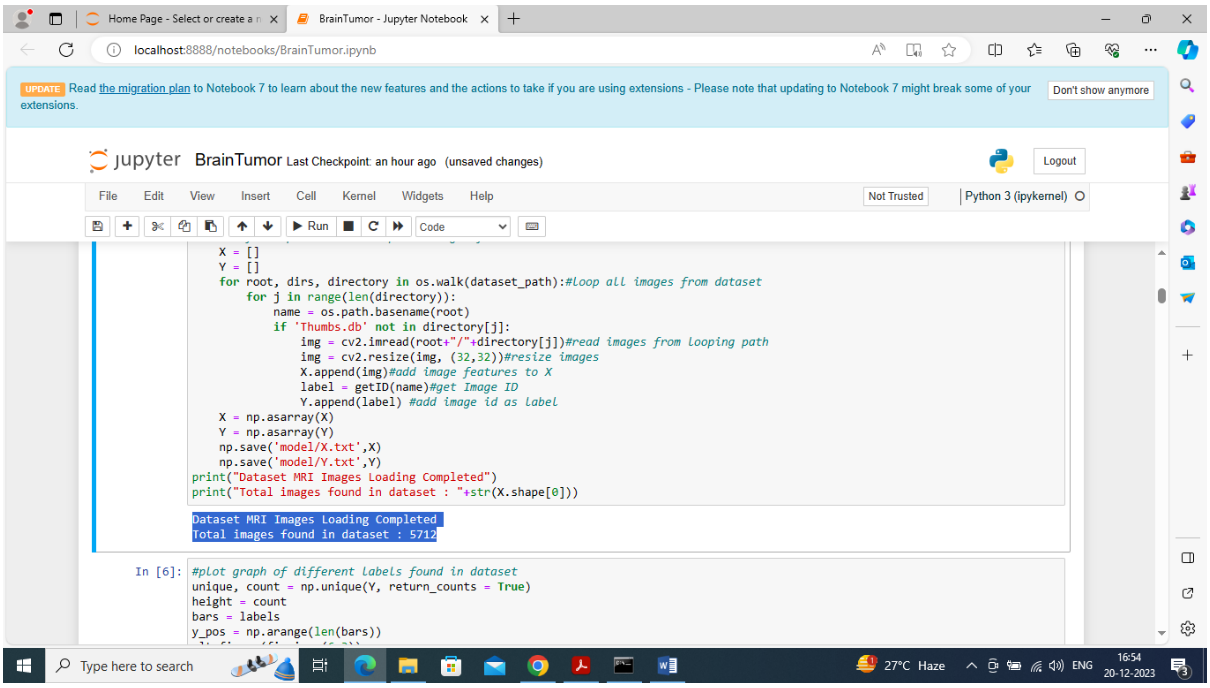

Fig.10 looping and reading all images

In above screen looping and reading all images from dataset and then resizing all images to equal size and then adding to X and Y training arrays and then in blue colour text can see total number of images loaded

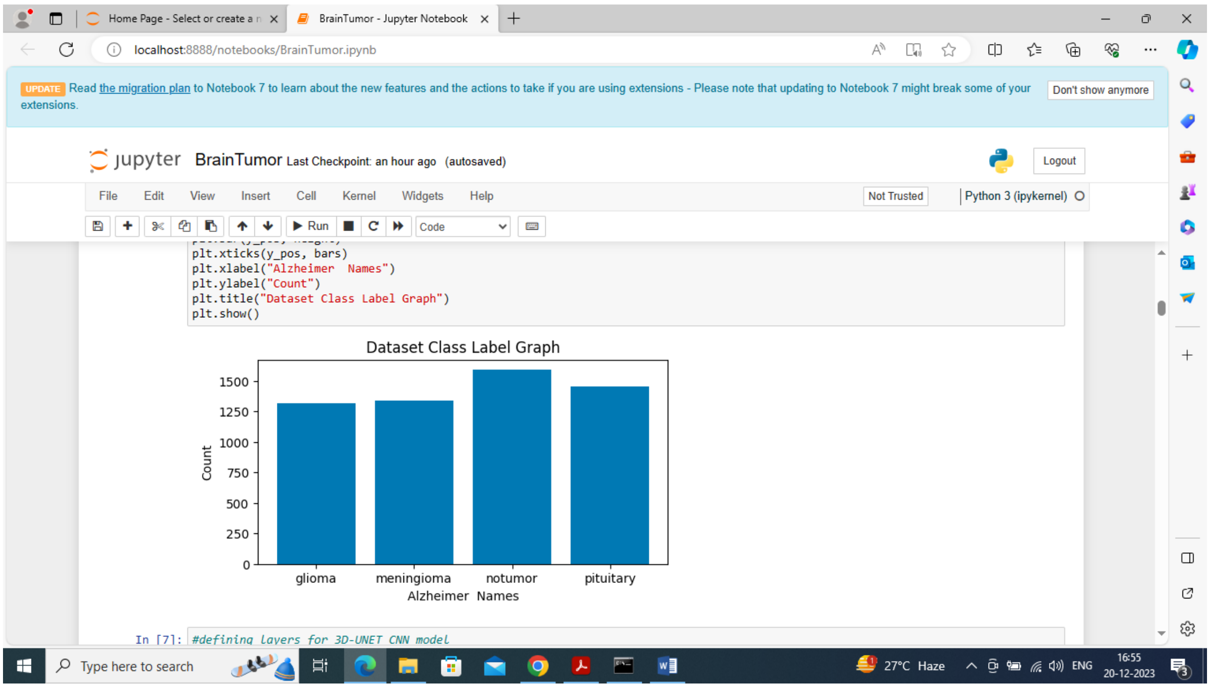

Fig.11 Graphical representation

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

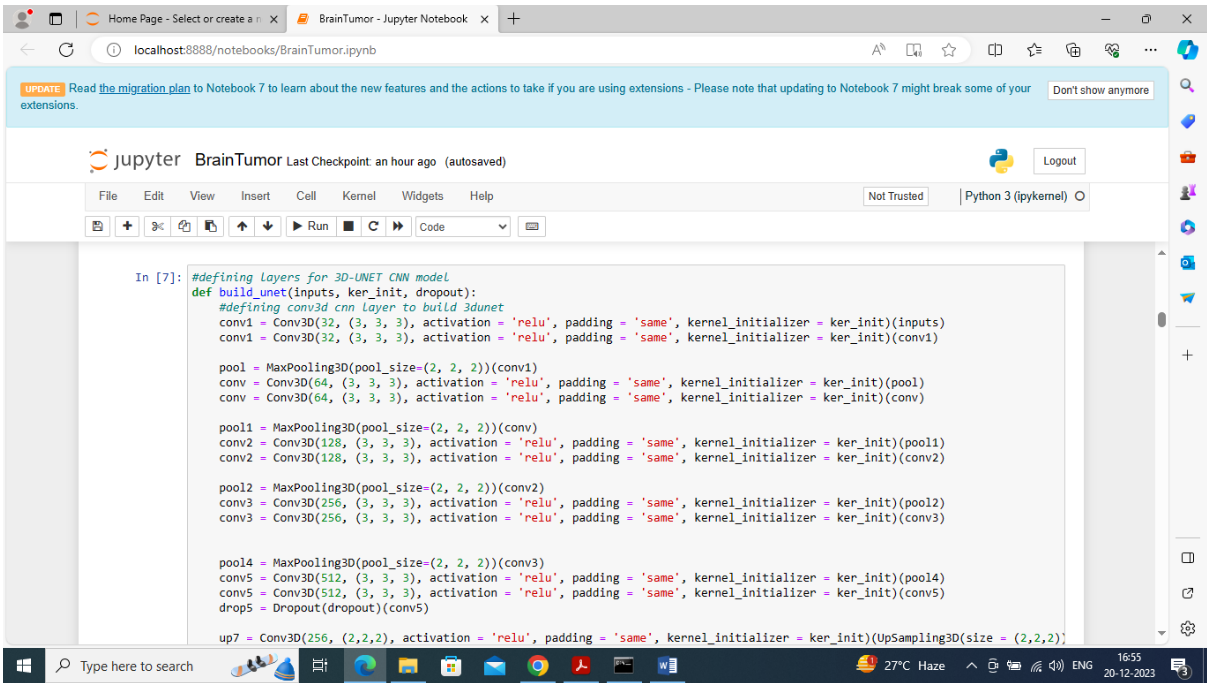

Fig.12 defining 3D-UNET model

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

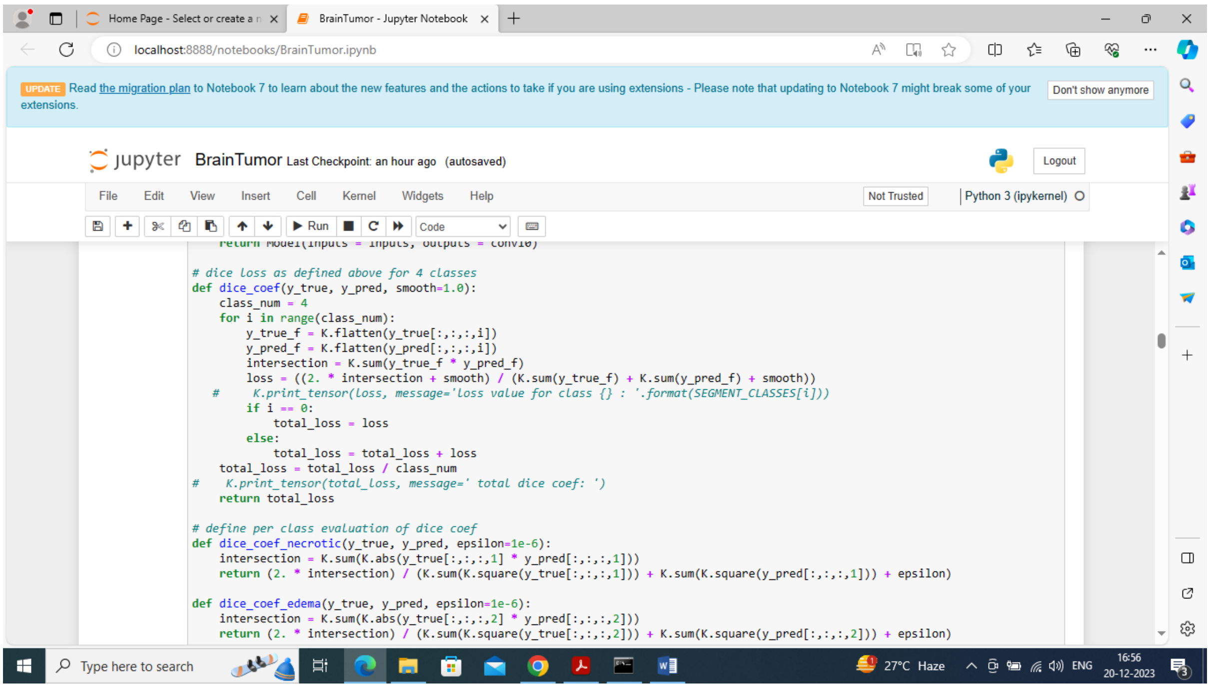

Fig.13 defining dice score function

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

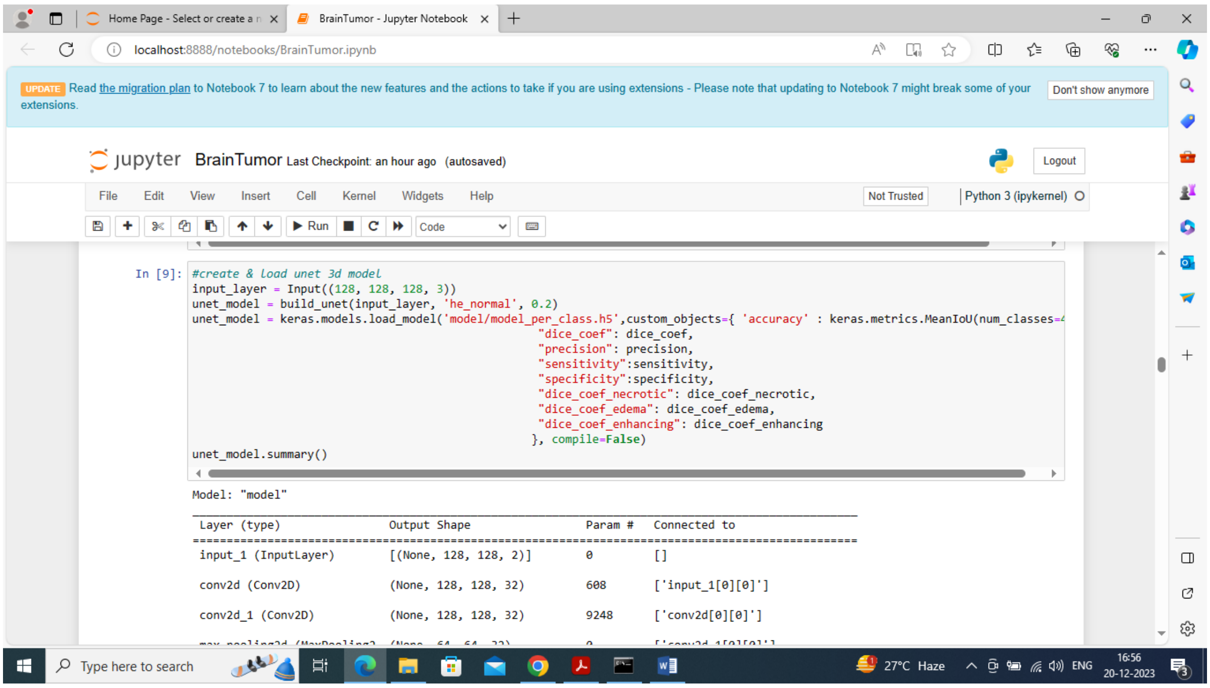

Fig.14 creating and loading 3DUNET

In above screen creating and loading 3DUNET model with all metrics like Precision, dice and many more and then displaying loaded model details

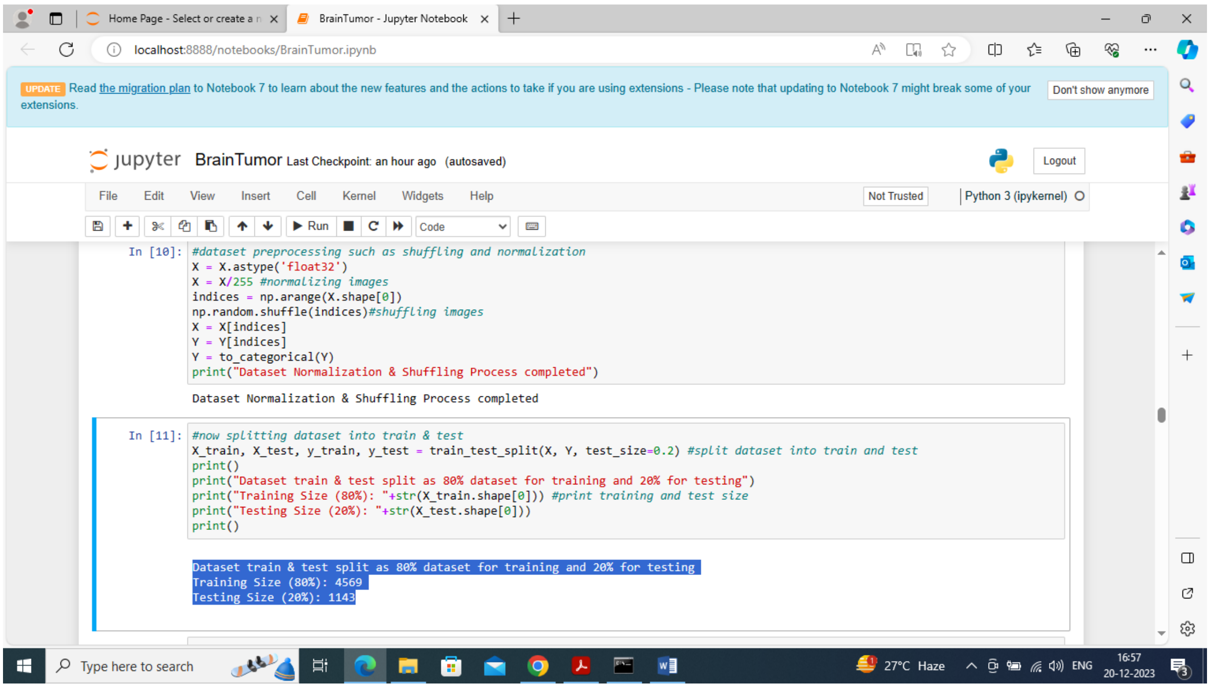

Fig.15 defining code to shuffle, normalize images

In above screen defining code to shuffle, normalize images and then split images into train and test where application using 80% images for training and 20% for testing

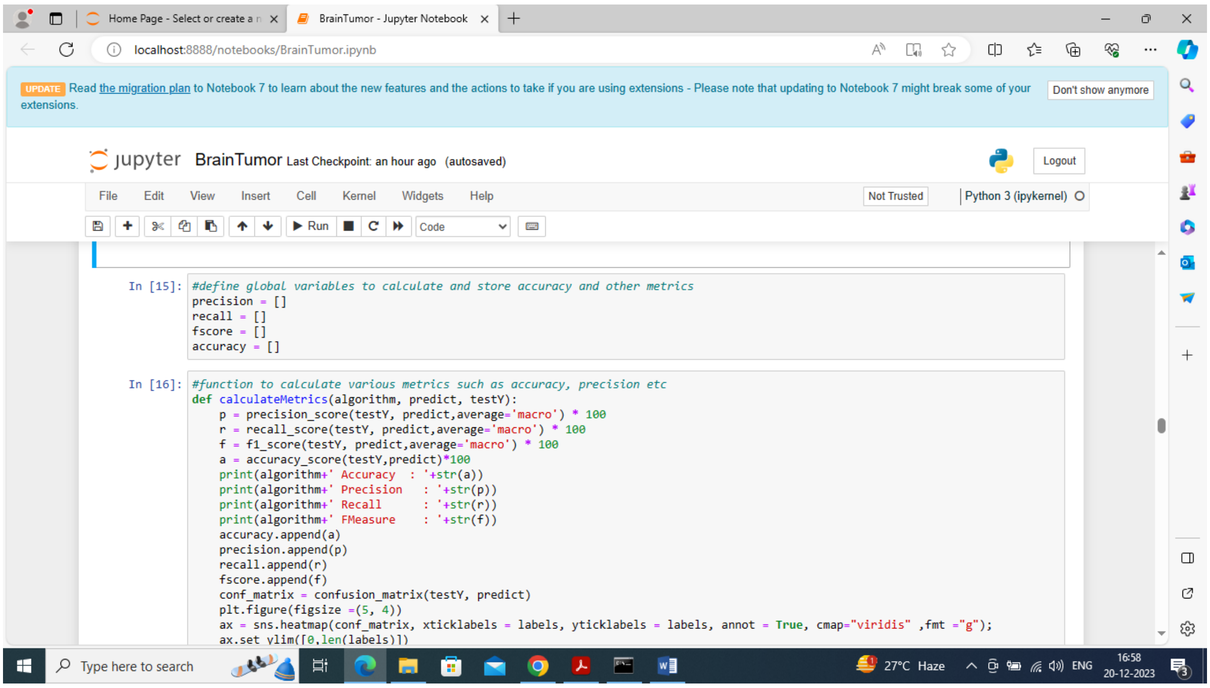

Fig.16 defining function to calculate accuracy

In above screen defining function to calculate accuracy and other metrics

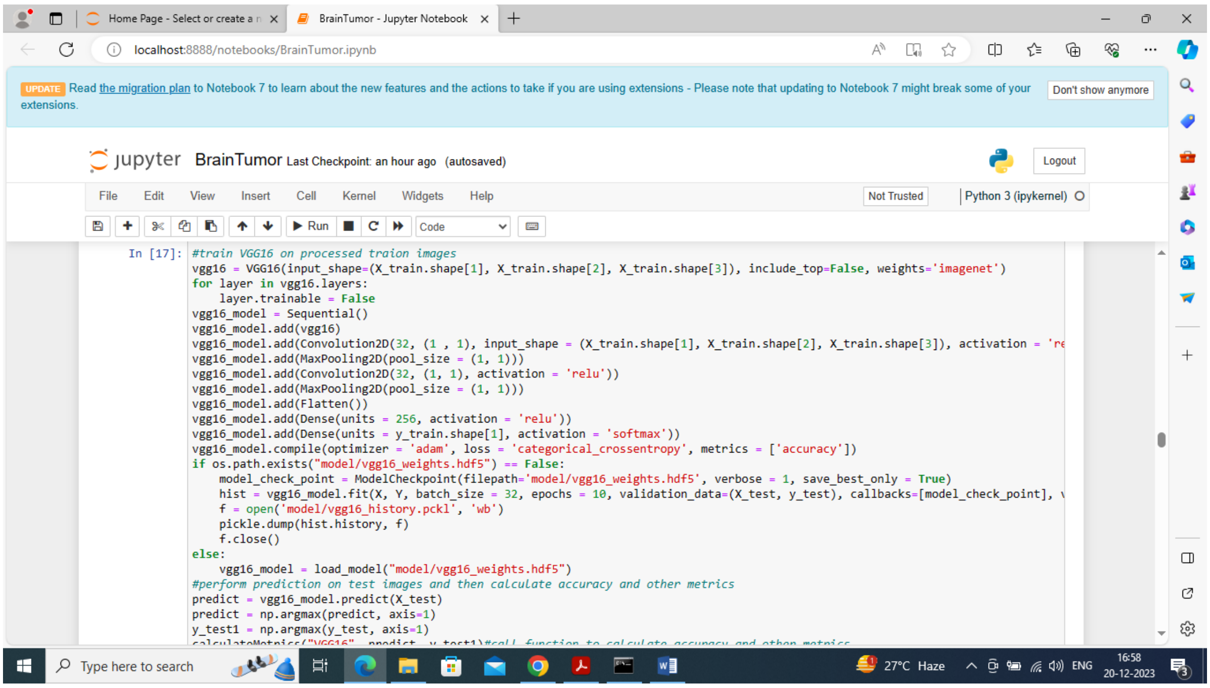

Fig.17 training VGG16 existing algorithm

In above screen training VGG16 existing algorithm and after executing above model on 20% test images will get below output

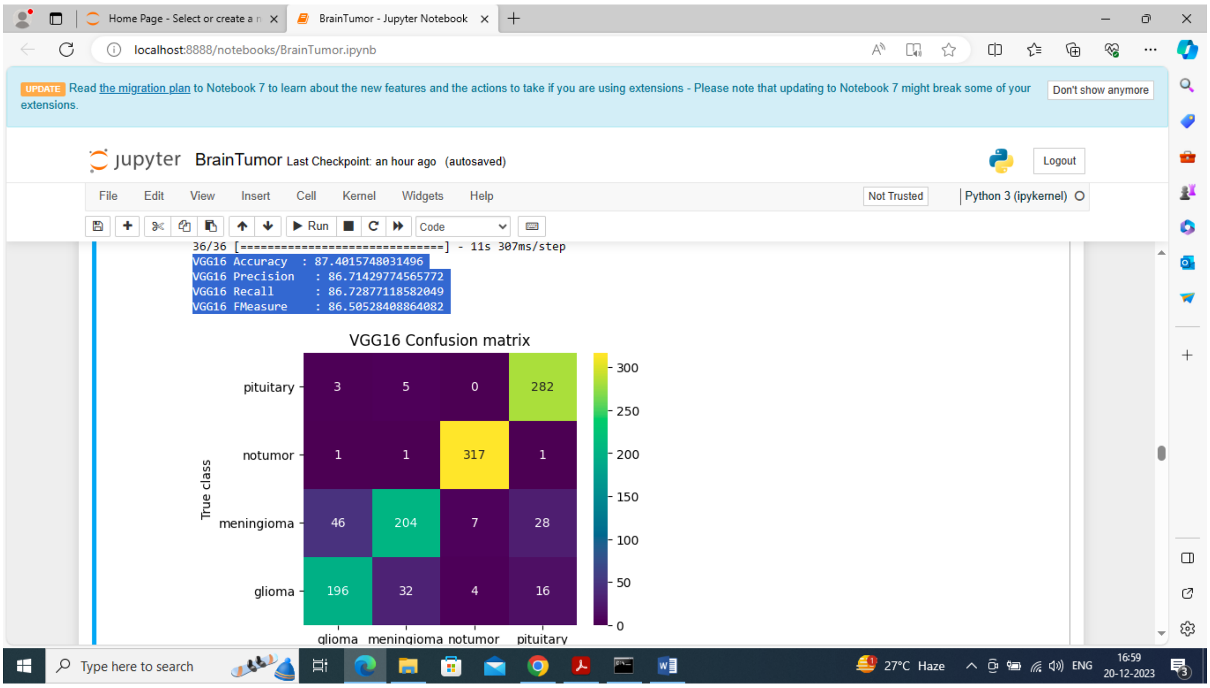

Fig.18 VGG16 Confusion matrix

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

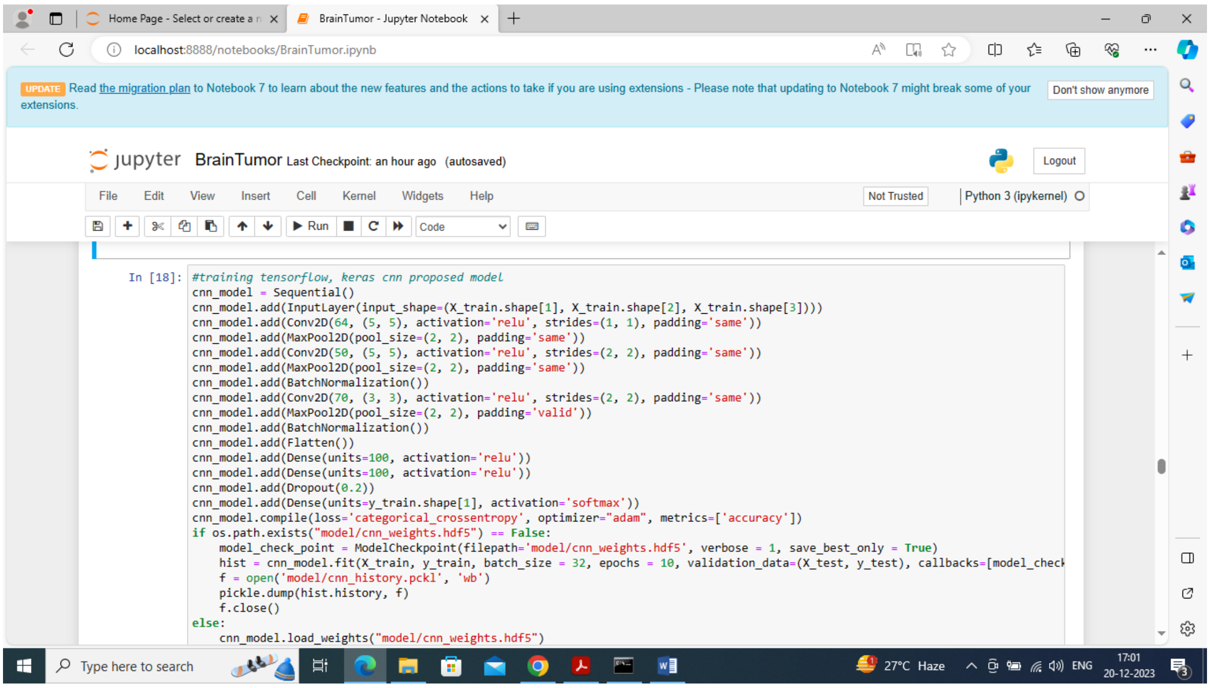

Fig.19 defining propose 16 layers CNN model

In above screen defining propose 16 layers CNN model and in above code each line will represents one layer and after executing above model will get below output

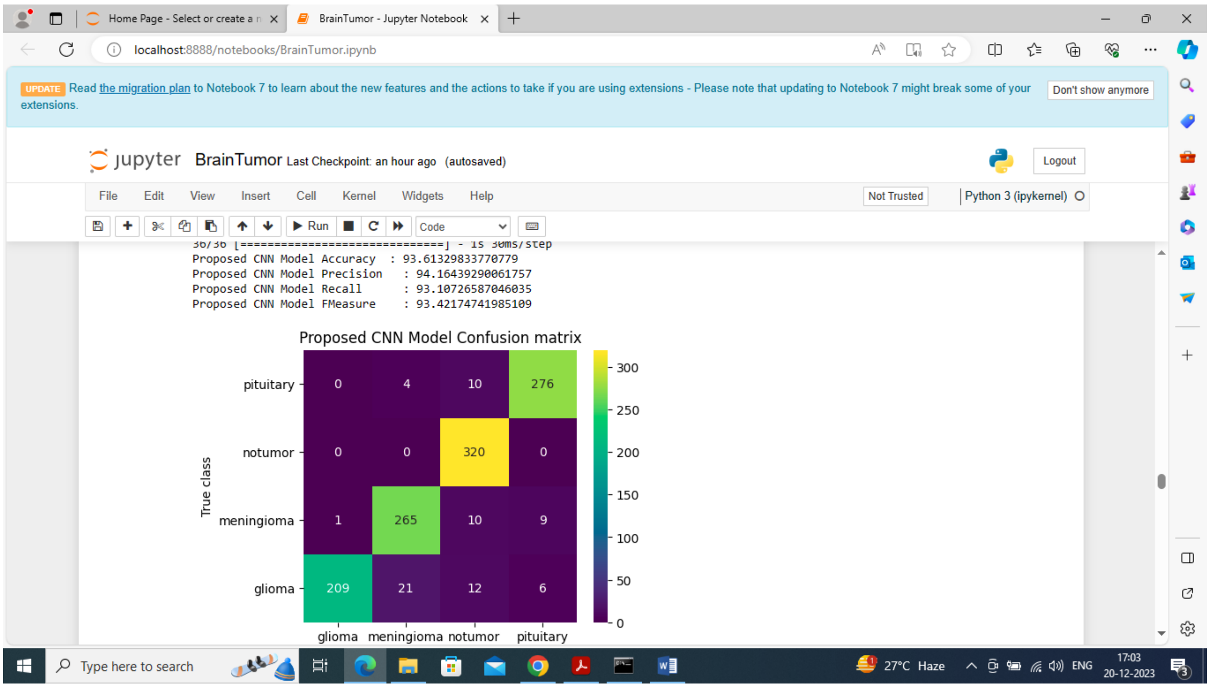

Fig.20. Proposed CNN Mode confusion matrix

In above screen propose CNN model got 93% accuracy and can see other results also

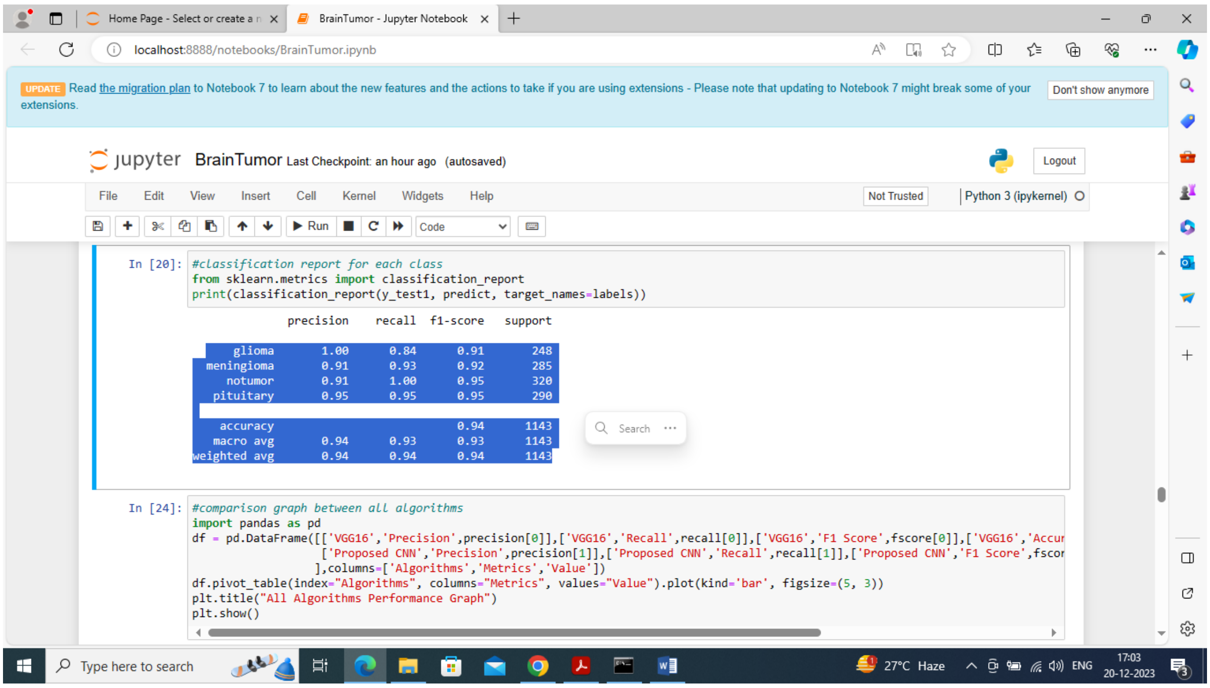

Fig.21 defining propose 16 layers CNN model

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

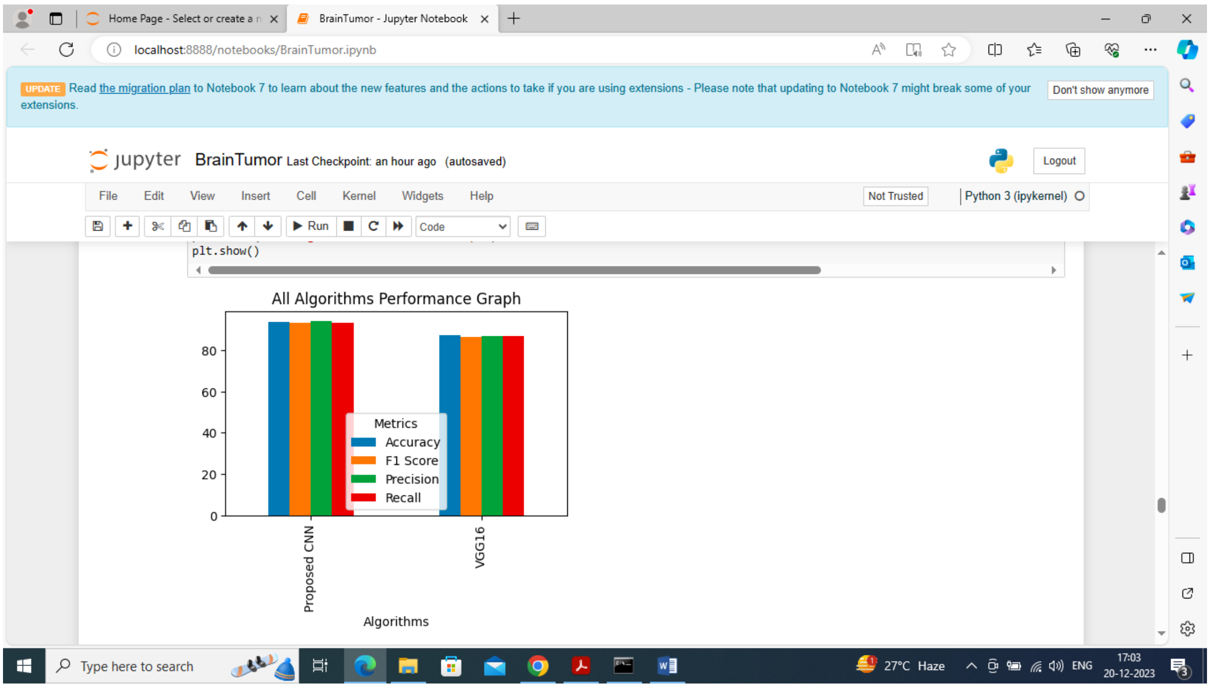

Fig.22 comparison graph

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

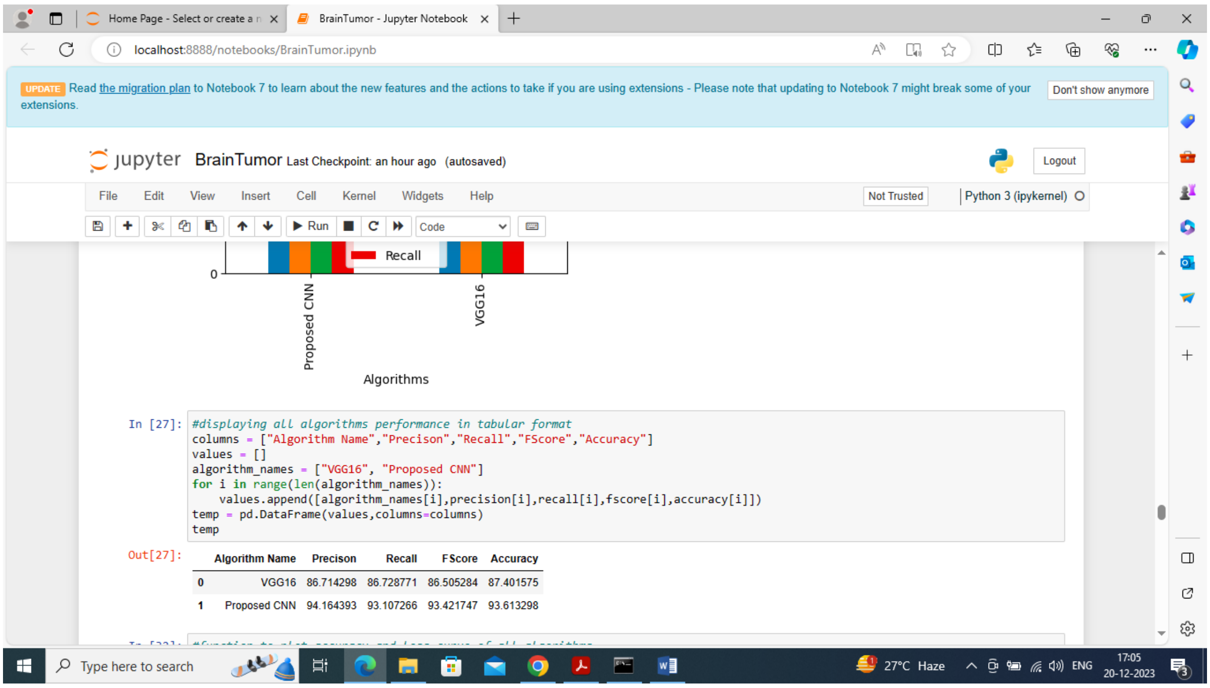

Fig.23. algorithm results in tabular format

In above screen can see both algorithm results in tabular format

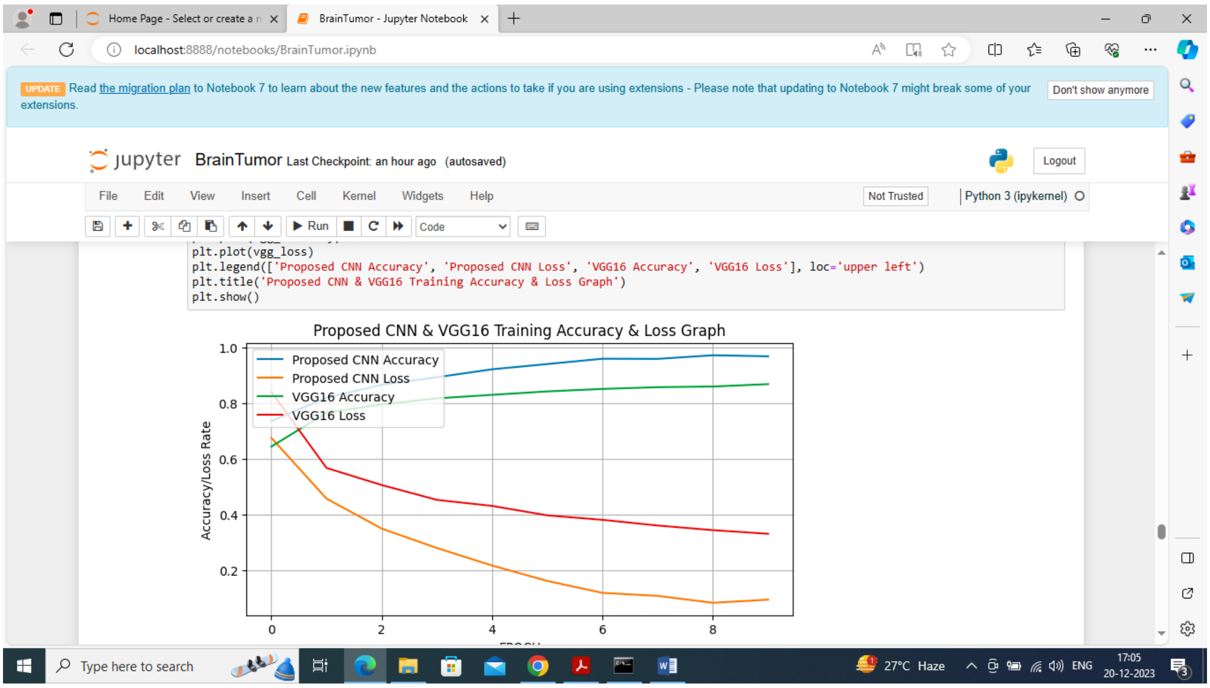

Fig.24 Proposed CNN and VGG16 training accuracy and loss graph

In above graph displaying VGG and propose CNN training and loss graph and in graph x-axis represents training epochs and y-axis represents accuracy/loss values and then blue line is for propose CNN accuracy and green line for VGG16 accuracy and red line for VGG16 loss and orange line for propose CNN loss. In above graph we can see with each increasing epoch accuracy got increase and loss got decrease for both algorithms but propose got high training accuracy and less loss.

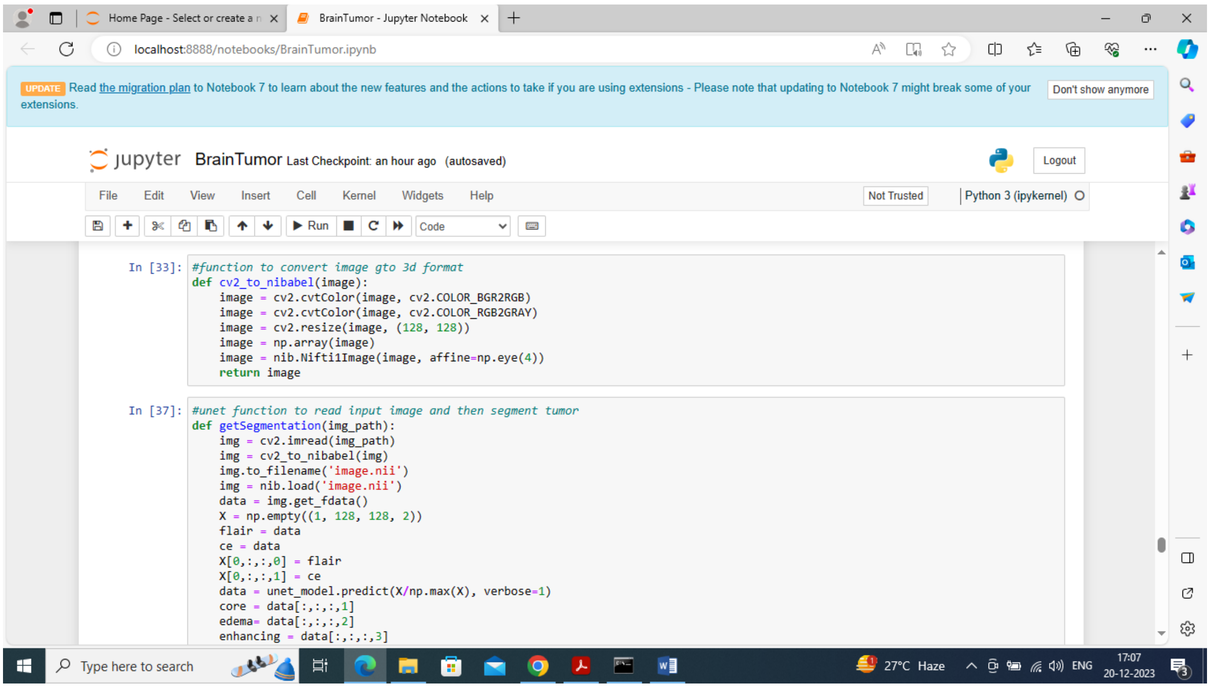

Fig.25 segment test image using UNET

In above screen defining function to segment test image using UNET

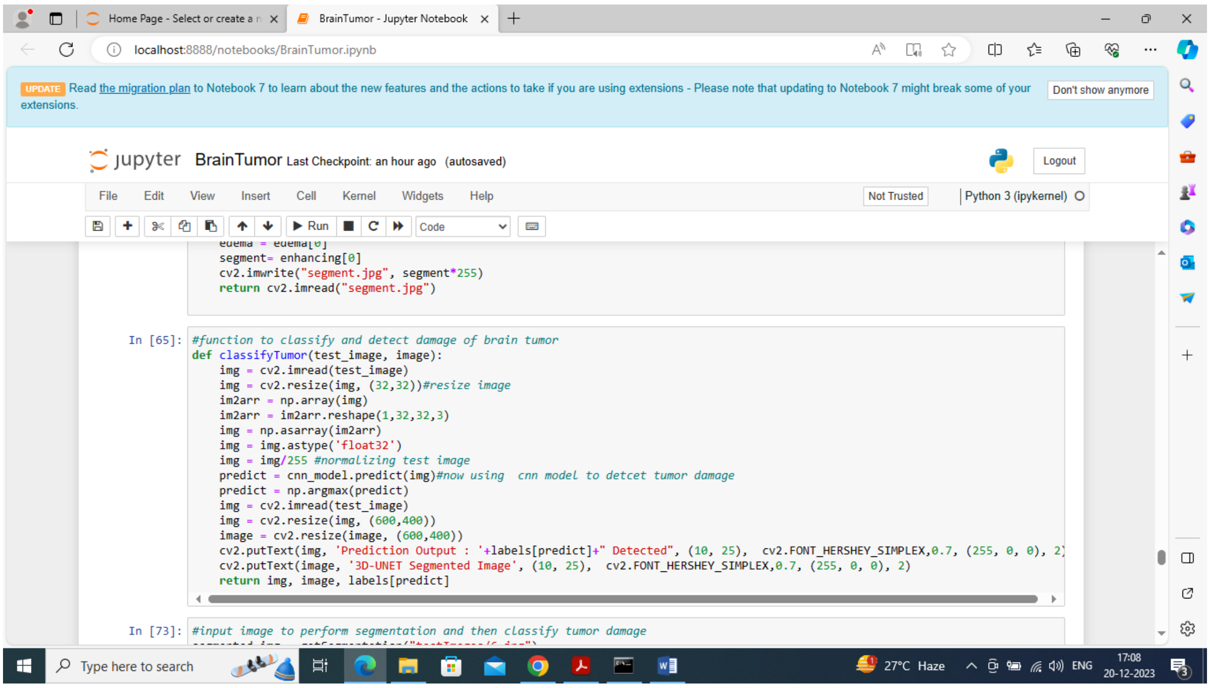

Fig.26 classify tumor or predict damage

In above screen defining function to classify tumor or predict damage

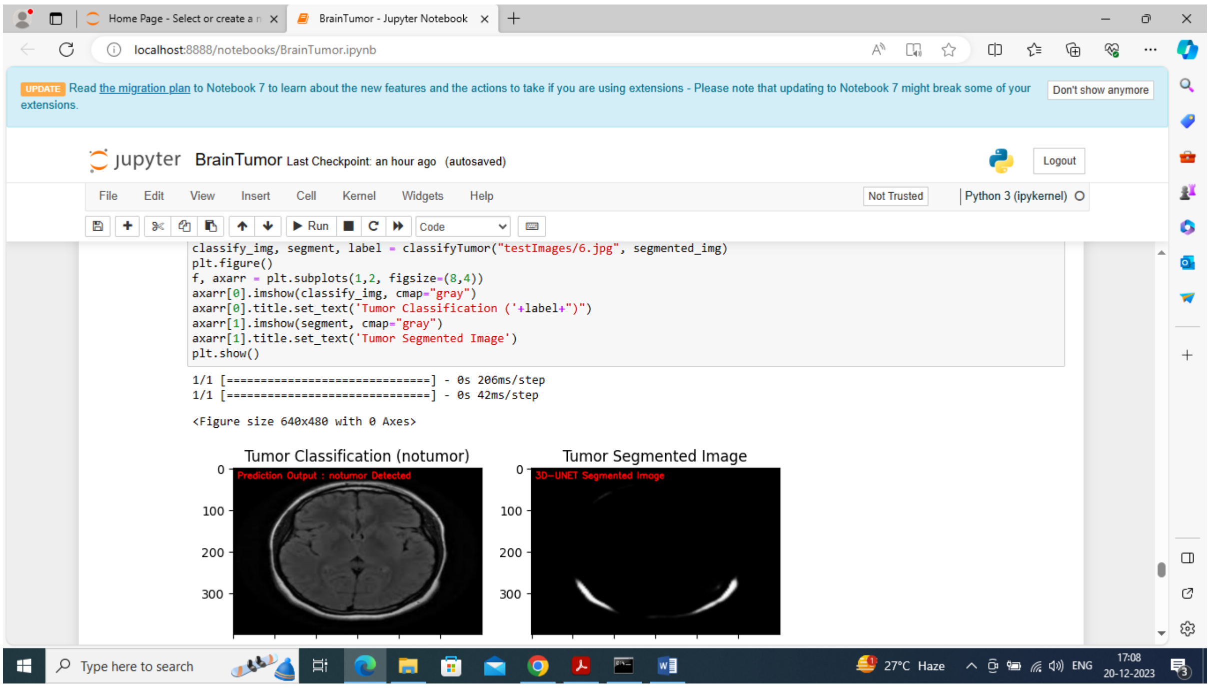

Fig.27 test image for segmentation

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

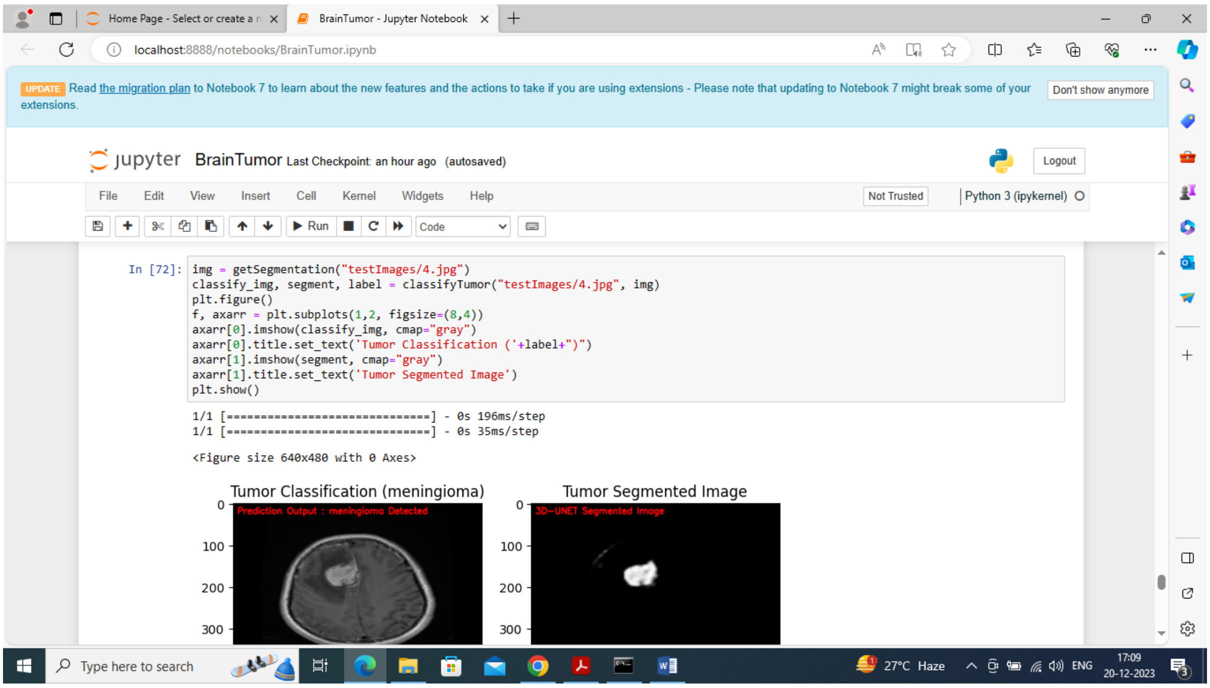

Fig.28‘meningioma’ tumor is predicted

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

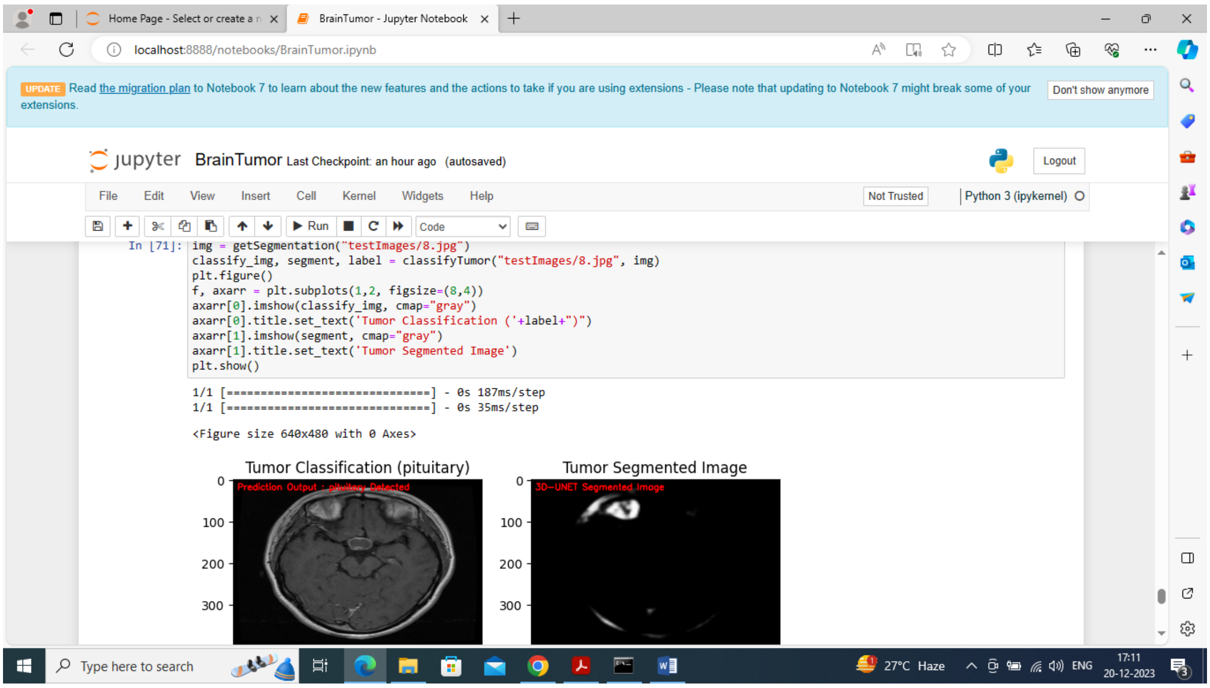

Fig.29 pituitary' tumor detected

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

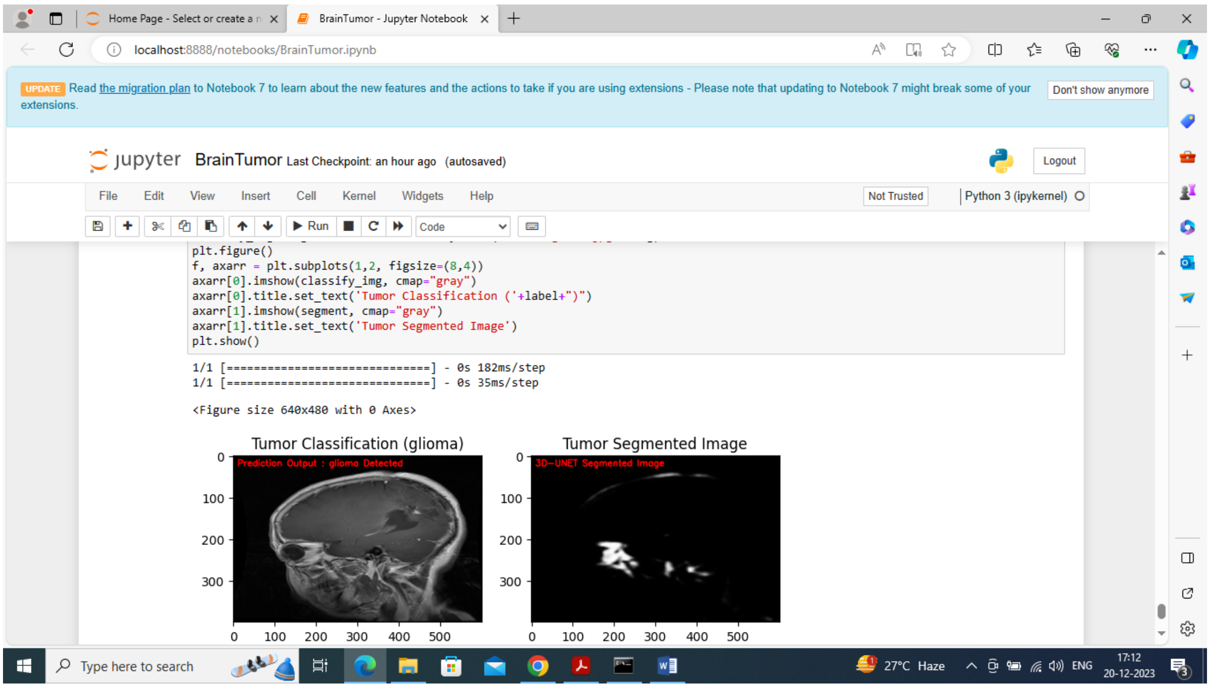

Fig.30'glioma' tumor detected

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

CHAPTER 7

CONCLUSION

In this study, segmentation and detection of brain tumor have been done using deep neural networks. In the present study, the MRI image dataset is used to train the neural network, and then soft dice loss is used to detect losses in the segmented model. Later, the model is trained, rectifying those losses and giving the segmented image as output. Initially, the 3D MRI model is divided into 3D sub-models to pass through the segmentation model. There are two datasets used for the CNN models. Every dataset is taken from different patients from different parts of the world to conquer the problem of generalization. Secondly, the CNN model is implemented in particular for the three most popular kinds of brain tumor, i.e., glioma, meningioma, and pituitary, to be classified immediately without involving the use of area-based pre-processing procedures. The results obtained establish the efficacy of the proposed work when compared to the models already proposed in the literature.

CHAPTER 8

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