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BRAIN TUMOR BASED MRI IMAGE ENHANCEMENT USING ENTROPY AND CLAHE BASED INTUITIONISTIC FUZZY METHOD WITH DEEP LEARNING

Aditya Raj Sahoo, Vaibhav, Dr. Vijayashree J*, Prith Sharma and Shikhar Saxena
School of Electrical Engineering and School of Computer Science, Vellore Institute of Technology, Vellore, India

Abstract
The inner area of the human brain is where abnormal brain cells gather when they become a mass. These are known as brain tumors, and based on the location and size of the tumor, they can produce a wide range of symptoms. Accurate segmentation and classification of brain tumors are critical for effective diagnosis and treatment planning. In this paper, we present a novel approach for the segmentation and classification of brain tumors using Entropy and CLAHE Based Intuitionistic Fuzzy Method with Deep Learning. Entropy and CLAHE (Contrast Limited Adaptive Histogram Equalization) based Intuitionistic Fuzzy Method with Deep Learning is a technique that combines several image processing and machine learning algorithms to enhance the quality of images. By applying entropy-based techniques to an image, we can identify and highlight the most significant features or patterns in the image. Our study provides a thorough evaluation of the proposed technique and its performance compared to other methods, showing its effectiveness and potential for use in real-world applications. Our method separates the tumor regions from the healthy tissue and provides accurate results in comparison with traditional methods. The results of this study demonstrate the potential of this approach to improve the diagnosis and treatment of brain tumors and provide a foundation for future research in this field. The proposed technique holds significant promise for improving the prognosis and quality of life for patients with brain tumors.
Keywords: Brain Tumor, CLAHE, Entropy, CNN, Image Enhancement, CLAHE based Fuzzy Method

I. INTRODUCTION

Brain tumor classification and segmentation are helpful in recent times because they can provide more accurate and detailed information about the tumor with the help of Entropy and CLAHE (Contrast Limited Adaptive Histogram Equalization) based Intuitionistic Fuzzy Method with Deep Learning. Entropy is a measure of randomness or uncertainty in a system, and in image processing, it can be used to quantify the amount of information in an image. By applying entropybased techniques to an image, we can identify and highlight the most significant features or patterns in the image.CLAHE is an image processing method that improves contrast by balancing the histogram of the image's small, overlapping regions.This technique is particularly useful for images with uneven lighting or contrast. Intuitionistic Fuzzy Method is a type of fuzzy logic that considers the chance of halfway participation of a component in a set. This means that an element can have a degree of membership to a set and a degree of non-membership, which allows for a more nuanced representation of uncertainty.Deep learning is a subset of machine learning that uses neural networks to learn from large amounts of data. By training a deep neural network on a large dataset of images, we can develop a model that can accurately classify and enhance images. By combining these techniques, we can develop a powerful image enhancement method that can improve the quality of images with low contrast or uneven lighting. This technique has a wide range of applications, including medical imaging, satellite imaging, and security imaging.

II. BRAIN TUMORS

Brain tumors are complex and complex medical problems that affect many people worldwide. Research on brain tumors is critical to improving our understanding of these tumors, their causes, and possible treatments. Primary brain tumours and secondary brain tumours are the two main categories of brain cancers. Primary brain tumors arise from cells inside the brain, whereas secondary brain tumors arise from cancer cells that spread to the mind from different pieces of the body. Studies have shown that brain tumors can arise from a variety of cell types, including glial cells, neurons, and stem cells. These tumors can be classified based on location, cell type, and genetic profile. Understanding the genetic basis of brain tumors is critical to developing targeted therapies that can improve patient outcomes.

A. Types of Brain Tumors

The type of cell that gave birth to the tumor, its location within the brain, and how closely the tumour cells resemble normal brain cells are just a few of the criteria used to categorise brain tumours. The following are some of the most prevalent kinds of brain tumours:

1) Gliomas: These tumors start in the glial cells, which support and protect the neurons in the brain. Examples include astrocytomas, oligodendrogliomas, and ependymomas.

2) Meningiomas: These tumors start in the cells that line the skull and spinal cord and are generally considered to be benign (not cancerous).

3) Pituitary tumors: These tumours originate in the pituitary gland, which controls hormones and is found at the base of the brain.

4) Schwannomas: These tumors start in the Schwann cells, which surround the nerve fibers in the brain and spinal cord.

5) Medulloblastomas: These are fast-growing, malignant (cancerous) tumors that start in the cerebellum, the part of the brain that controls movement.

6) Craniopharyngiomas: These tumors start near the pituitary gland and can affect the hypothalamus, which regulates many important functions such as hunger, thirst, and body temperature.

7) Metastatic brain tumors: These tumours develop from cancer that has already moved to another organ of the body.

It’s important to note that brain tumors can be benign (not cancerous) or malignant (cancerous) and can vary in their aggressiveness, symptoms, and treatment options. An accurate diagnosis is important for selecting the best course of treatment.

III. TECHNIQUES USED

A. CNNs

A popular deep learning model for image and video analysis is a convolutional neural network (CNN). Convolutional and pooling layers are used in succession with fully connected layers for classification or regression to automatically learn and extract features from input photos. The main advantage of CNNs is their ability to capture spatial dependencies between pixels, allowing them to detect patterns and features that are important for classification. They can also handle large datasets and learn complex representations of data, making them suitable for a wide range of computer vision tasks such as object detection, segmentation, and recognition. CNNs have become a popular choice for image recognition and classification tasks, with notable applications in fields such as medical diagnosis, autonomous driving, and surveillance. However, they require a large amount of labeled data for training and may be computationally expensive to train and deploy.

B. Types of CNN used

1) Resnet 50: ResNet-50 is a deep convolutional neural network (CNN) architecture developed by Microsoft Research. It is a residual network, which means that instead of learning an end-to-end mapping from input to output, it instead learns residual functions, with the goal of making it easier to train very deep networks. The ImageNet dataset, which includes more than 1 million photos from 1000 different classifications, was used to train ResNet-50, which has 50 weight layers. This makes it a powerful feature extractor for a wide range of image classification tasks, and It has been extensively employed in numerous applications, including transfer learning, semantic segmentation, and object detection. In addition, ResNet-50 is computationally efficient and can be easily implemented using popular deep learning frameworks such as TensorFlow and PyTorch. This makes it an accessible and popular choice for researchers and practitioners working on computer vision problems.

2) Densenet 169: DenseNet-169 is a deep convolutional neural network (CNN) architecture developed by researchers at UC Berkeley. It is a dense network, meaning that each layer is connected to every other layer in a feed-forward manner. This connectivity pattern is designed to encourage feature reuse and reduce the number of parameters required to train the network, making it more computationally efficient.DenseNet-169 has 169 weight layers and is trained on the ImageNet dataset, which contains over 1 million images from 1000 different classes. This makes it a powerful feature extractor for a wide range of image classification tasks.DenseNet-169 has been shown to outperform other popular CNN architectures on a variety of benchmarks and is widely used in various applications, including object detection, semantic segmentation, and transfer learning.

3) InceptionV3: InceptionV3 is a deep convolutional neural network (CNN) architecture developed by Google.It is renowned for making effective use of computational resources and delivering cutting-edge results on a range of image classification applications. InceptionV3 uses an innovative architecture known as an ”Inception module,” which allows the network to learn features at multiple scales and from multiple perspectives, improving its ability to capture complex patterns in the data. This makes InceptionV3 well-suited to handle a wide range of image classification tasks. The ImageNet dataset, which includes more than a million images from a thousand different classifications, was used to train InceptionV3. This makes it a powerful feature extractor for a wide range of image classification tasks. InceptionV3 is an accessible and well-liked option for researchers and practitioners working on computer vision problems since it can be simply deployed using well-known deep learning frameworks like TensorFlow and PyTorch, similar to ResNet-50 and DenseNet169.

4) Resnet 101: ResNet-101 is a deep convolutional neural network architecture which is made up of 101 layers. The model consists of repeating blocks of layers, where each block contains several convolutional and batch normalization layers followed by a ReLU activation function. The key innovation in ResNet was the introduction of residual connections between the layers, which allow for the propagation of information through the network even when the

model is very deep. The residual connections are designed to allow for the skip connection of the activations from one layer to another, bypassing several layers in between. This allows for the network to learn residuals or shortcuts, which enable the network to learn the identity function and maintain low-level feature representations through the depth of the network. As a result, the vanishing gradient problem is mitigated and the network is able to learn and perform well even when it is very deep. In terms of performance, ResNet-101 has achieved state-of-theart results on several benchmark datasets, including ImageNet.

5) InceptionResnetV2: InceptionResnetV2 is the combination of both the Inception and ResNet architectures ideas. The idea behind Inception is to use multiple parallel convolutional layers with different filter sizes and pooling operations, and concatenate their outputs to form a rich representation of the input image. This approach allows the network to capture both local and global features of the image at different scales. InceptionResNetV2 combines the strengths of both architectures by using the Inception module with a ResNetstyle loopback connection. In particular, the initial module of InceptionResNetV2 has been modified to include remaining connections that add inputs to the module's outputs. This helps to reduce the vanishing gradient problem and allows the network to be trained very deep. It is also used in various application fields such as face recognition, medical image analysis, and natural language processing. Because of its design features and performance, it is widely used in a wide range of image classification and object recognition applications.

6) VGG 16: The VGG16 architecture is characterized by simplicity and depth. It consists of 16 convolutional layers and fully connected layers. The first 13 layers are convolutional layers and the last 3 are fully connected layers. The convolutional layer uses a 3x3 filter with a stride of 1 and a padding of 1. The pooling layer uses a 2x2 filter with a stride of 2. The main idea of VGG16 is to use a very deep network with small filters to capture rich and detailed features of the input image. The VGG16 can use small filters to capture fine image details such as edges and textures that larger filters miss. This approach has been shown to be effective for image recognition problems. The VGG16 also uses several other design features to improve performance. For example, batch normalization is used to speed up the learning process and improve generalization. It also uses dropout regularization to prevent overfitting.

IV. RELATED WORK

A. Entropy

In order to calculate how much information is included in an image, image processing professionals employ entropy, a measure of unpredictability or uncertainty in a system.

By applying entropy-based techniques to an image, we can identify and highlight the most significant features or patterns in the image.

B. Diagnosis

Diagnosis of brain tumors involves the identification and characterization of abnormal growths or masses within the brain. The following are the key steps involved in the diagnostic process:

1) Medical history: Collection of the patient's medical history, including symptoms and any prior medical conditions.

2) Neurological exam: A thorough examination of the patient's neurological function, including assessments of muscle strength, sensation, coordination, and reflexes.

3) Medical imaging: Using medical imaging methods to view the brain and spot any anomalies, such tumours, such as MRIs or CT scans.

4) Biopsy: In some cases, a biopsy may be performed to obtain a sample of the tumor tissue for further analysis and classification.

5) Pathological analysis: Analysis of the biopsy sample to determine the type and grade of the tumor, as well as to identify any genetic or molecular markers that may inform treatment decisions.

6) Consultation with specialists: Consultation with a team of specialists, including neurosurgeons, neurologists, and medical oncologists, to determine the most appropriate course of action for the patient.

In order to help with the creation of a successful treatment strategy, the diagnostic process aims to precisely identify the presence and kind of brain tumours as well as their extent and location.

C. Treatment Planning

Treatment planning for brain tumors involves a multidisciplinary approach that takes into account the type and location of the tumor, as well as the overall health and medical history of the patient. There are some steps involved in the treatment planning process, firstly confirmation of the presence of a brain tumor through medical imaging techniques, such as MRI or CT scans, and the classification of the tumor based on its characteristics, such as size, shape, and location. The assessment of the extent of the tumor, including its size and the involvement of surrounding tissue and analysis of the molecular and genetic characteristics of the tumor to help determine the most appropriate treatment for that specific type of tumor. Consultation with a group of experts to decide on the best course of treatment for the patient, including neurosurgeons, radiation oncologists, and medical oncologists .Consideration of various treatment options, including surgery, radiation therapy, chemotherapy, or a combination of these treatments. The choice of treatment will depend on the specific characteristics of the tumor and the overall health and medical history of the patient. Development of a comprehensive treatment plan, including the type and duration of treatment, as well as any supportive care that may be required, such as physical therapy or rehabilitation.Planning a patient's course of therapy for a brain tumour should aim to deliver the most suitable and effective care possible while reducing the likelihood of adverse effects and maximising the likelihood of favourable patient outcomes.

D. Monitoring

Brain tumor classification and segmentation is a process of identifying and outlining the regions of the brain that contain a tumor and determining the type of tumor present. Medical imaging methods including computed tomography (CT) scans and magnetic resonance imaging (MRI) are frequently used to do this. The process can involve manual review by radiologists or medical professionals or can be assisted by computer algorithms. The goal of brain tumor classification and segmentation is to accurately diagnose the presence and type of brain tumor and to guide treatment planning. Regular monitoring of the brain tumor is important to track the progression and effectiveness of treatment.

E. Personalized Medicine

Customized medicine is the practise of designing a patient's medical care to meet their unique needs while taking into consideration their genetics, lifestyle, and environmental factors. In the context of brain tumor classification and segmentation, personalized medicine can involve the use of molecular and genetic profiling to help determine the most appropriate treatment for a specific patient. This can lead to more effective and targeted treatment, as well as reducing the risk of side effects and improving overall patient outcomes. For example, molecular profiling can be used to identify specific genetic mutations present in a patient's tumor, which can then inform treatment decisions, such as selecting a targeted therapy that is more likely to be effective for that patient's specific type of tumor. Personalized medicine has the potential to greatly improve the accuracy and effectiveness of brain tumor classification and treatment, leading to better patient outcomes.

F. Research

Brain tumor research can be improved by accurate classification and segmentation of tumors. This is especially important for studying the disease, as it allows for the development of new treatments. Brain tumor classification and segmentation is a complex and challenging area of research, requiring a multi-disciplinary approach that combines medical imaging, computer science, and machine learning. Some of the most important fields of study in this domain are as follows:

1) Medical imaging: Development of new and improved medical imaging techniques that can provide high-quality, detailed images of the brain, allowing for more accurate identification and classification of tumors.

2) Computer algorithms: Development of computer algorithms that can automate the process of brain tumor classification and segmentation, reducing the time and effort required by medical professionals and increasing the accuracy of results. 3) Machine learning: Use of machine learning algorithms, such as deep learning networks, to analyze medical images and classify brain tumors with high accuracy.

4) Clinical trials: Conducting clinical trials to validate the effectiveness and safety of new treatments for brain tumors, including the use of targeted therapies and personalized medicine.

5) Combination therapies: Investigation of combination therapies, such as the use of surgery, radiation therapy, and chemotherapy, to improve patient outcomes and reduce the risk of treatment-related side effects.

Overall, the goal of research in brain tumor classification and segmentation is to improve the accuracy and effectiveness of diagnosis and treatment, leading to better patient outcomes and a reduction in mortality rates.

V. IMAGE PRE-PROCESSING

A. Contrast Limited Adaptive Histogram Equalization(CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a technique used to improve the contrast of images. The goal of CLAHE is to enhance the contrast of the image in a way that is both visually appealing and biologically relevant.The basic idea of CLAHE is to divide the image into small, overlapping tiles, and then perform histogram equalization on each of these tiles. The resulting enhancement is then limited to a maximum slope, to prevent over-amplification of noise and other image artifacts. CLAHE is widely used in medical imaging, especially for CT and MRI images, where it can improve the visibility of small structures and help to highlight important features. It can also be useful in other domains, such as astronomy, where it can help to reveal details in images with low contrast. Overall, CLAHE is a powerful tool for image enhancement that can help to reveal important features in images with poor contrast, while avoiding the introduction of unwanted artifacts.

B. CLAHE based Fuzzy Method

CLAHE (Contrast Limited Adaptive Histogram Equalization) is an image processing technique used to improve the contrast of an image while preserving its local details. Fuzzy logic, on the other hand, is a mathematical framework that allows for reasoning with uncertainty and imprecision.

The CLAHE based fuzzy method combines these two techniques to enhance the contrast of an image and segment it using fuzzy logic. The method works by applying CLAHE to the input image to enhance its contrast. Then dividing the enhanced image into non-overlapping blocks. Followed by computing the mean and variance of each block, use the mean and variance as inputs to a fuzzy system that performs image segmentation, assigning a membership grade to each pixel in the image based on its similarity to the segmented regions and finally generating a binary image by thresholding the membership grades. The fuzzy system used in this method typically consists of a set of fuzzy rules that relate the mean and variance of a block to its class membership. These rules can be manually defined or learned from training data. Once the fuzzy system is defined, it can be used to segment any image that has been enhanced using CLAHE. The CLAHE based fuzzy method has been shown to be effective in a wide range of image processing applications, including medical image analysis, remote sensing, and industrial inspection. However, like any image processing technique, its performance depends on the specific characteristics of the input image and the parameters used in the method.

VI. PROPOSED ALGORITHM - INTUITIONISTIC FUZZY ENTROPY AND CLAHE

The intuitionistic fuzzification scheme is a method used to convert crisp data into intuitionistic fuzzy sets, which can better handle uncertainty and imprecision in data. Intuitionistic fuzzy sets are a generalization of classical fuzzy sets, where each element is characterized by a degree of membership and a degree of non-membership. The intuitionistic fuzzy entropy measures the uncertainty and fuzziness of an intuitionistic fuzzy set. The optimization of intuitionistic fuzzy entropy involves finding the optimal values of the membership and non-membership degrees for each element in the set. Entropy calculation in the bounds of 1-5 (0.2 step) is done.

$$\mu_1 = \frac{d - d_{min}}{d_{max} - d_{min}}$$

For membership degree computation

$$\mu_{I1} = 1-(1-((1-\mu_1)(k-1))))^{(k(k-1)}$$

For non-membership degree computation $\nu_{I1} = 1-(1-((1-\mu_1)(k-1))))^{(k(k-1)}$

For hesitation degree compute function $\pi_{I1} = 1-(1-((1-\mu_1)(k-1))))^{(k(k-1)} -\nu$

VII. PROPOSED ARCHITECTURE - CNN

A Convolutional Neural Network (CNN) is a type of neural network that is commonly used for image and video recognition tasks. The architecture of a CNN typically consists of several layers, including:

Convolutional layers: These layers perform convolution operations on the input image, which involve applying a set of filters to the image to extract features. The filters are learned during the training process, and they are used to detect specific features in the image, such as edges or textures.

Pooling layers: These layers perform down-sampling operations on the feature maps produced by the convolutional layers. Pooling layers are often used to reduce the spatial dimensionality of the feature maps, which can help to reduce the computational complexity of the network and make it more robust to small translations of the input image.

Fully connected layers: These layers connect all the neurons of the previous layers, and are used for the final classification of the input image.

Activation functions such as ReLU or Sigmoid can be used in the layers to introduce non-linearity to the system.

Dropout regularization can be used to prevent overfitting of the model by randomly switching off neurons during training. As loss decreases, accuracy increases.

Finally, the output layer of the CNN typically uses a softmax activation function to produce a probability distribution over the different classes of the image, which can be used to predict the input image's class.

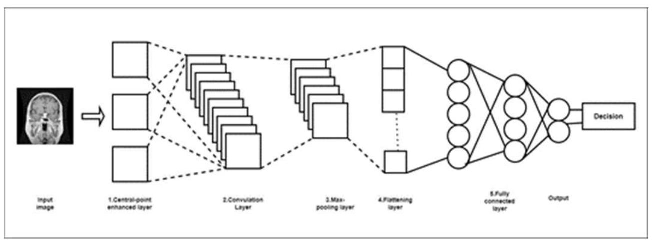

Fig. 1. CNN architecture

VIII. RESULTS

We evaluated the performance of two different image enhancement techniques, namely fuzzified CLAHE and CLAHE, on a dataset of MRI images including glioma, meningioma, and pituitary tumors. Our results show that both methods are effective in improving image contrast and enhancing the visibility of tumor features. Specifically, we found that the fuzzified CLAHE method produced images with higher contrast and sharper edges than the original images, while also preserving the important features of the tumors. On the other hand, the CLAHE method also improved image contrast but tended to produce images with more noise and artifacts.

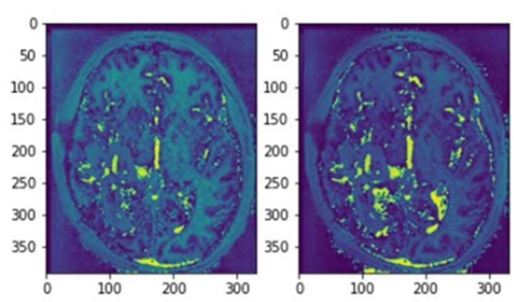

Fig. 2. Fuzzified Clahe and Clahe - Glioma tumor images

Specifically, for glioma images, we found that the fuzzified CLAHE method produced images with higher contrast and sharper edges, which facilitated better visualization of tumor boundaries and infiltration. This enhanced visibility can be critical for preoperative planning and monitoring treatment response.

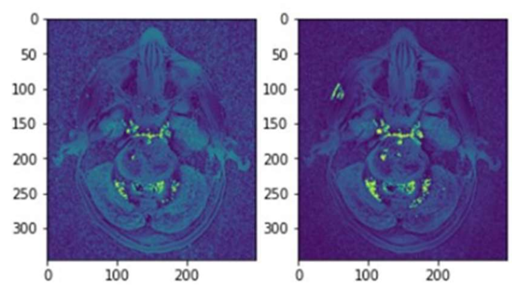

Fig. 3. Fuzzified Clahe and Clahe - Meningioma tumor images

For meningioma images, both fuzzified CLAHE and CLAHE methods produced images with improved contrast and reduced noise, which facilitated better visualization of the tumor's relationship to surrounding structures.

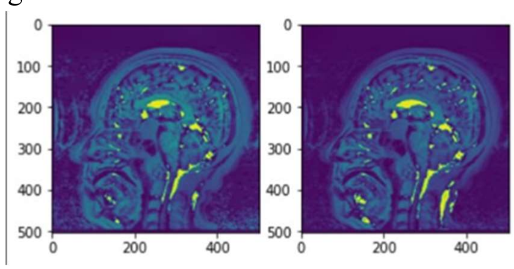

Fig. 4. Fuzzified Clahe and Clahe - Pituitary tumor images

For pituitary tumors, both methods were effective in enhancing the visibility of tumor features, such as the size and location of the tumor, which can aid in the diagnosis and management of these tumors.

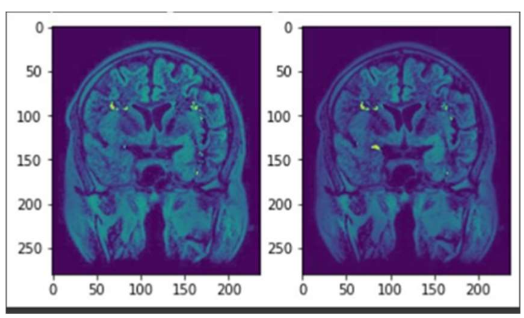

Fig. 5. Fuzzified Clahe and Clahe - No Brain tumor images

These findings suggest that image enhancement techniques such as fuzzified CLAHE and CLAHE can be useful tools for improving the visualization of normal brain structures in cases where no tumor is found.

CNN Models	Classification Accuracy %	
	CLAHE	FUZZIFIED CLAHE
RESNET 50	91.67	94.01
DENSENET201	94.5	97.01
DENSENET 169	95.6	98.05
RESNET 101	92.4	94.9
INCEPTION V3	93.7	96.2
INCEPTION RESNET V2	94.3	96.8
VGG16	95.01	97.6

Fig. 6. CLASSIFICATION ACCURACY RESULTS

Overall, our findings suggest that the fuzzified CLAHE method may be a more suitable choice for enhancing tumor images, as it produces images with better contrast and fewer artifacts. This is important for surgical planning, as meningiomas are often located near critical structures such as blood vessels and nerves. However, further studies are needed to confirm these findings and to explore other image enhancement methods that may be more effective in different clinical settings.

IX. CHALLENGES FACED

The challenges faced in the field of brain tumor classification and segmentation are:

A. High variability in imaging modalities and acquisition protocols, leading to difficulties in developing generalizable models.

B. The limited availability of annotated data, especially for rarer types of tumors, makes it difficult to train robust models.

C. The high variability and complexity of brain anatomy and tumor shapes pose challenges for accurate segmentation.

D. The presence of additional lesions and the overlap in the appearance of tumours and normal tissue on imaging might provide results that are either falsely positive or falsely negative.

X. WEBSITE IMPLEMENTATION

Implementing a website for brain tumor classification and segmentation involves several steps, including:

1) Data collection: The first step is to gather a dataset of brain scans, which can include CT scans, MRI scans, or other types of medical images. The images should be annotated with ground-truth labels indicating the presence and location of tumors.

2) Model development: Next, a deep learning model can be developed and trained on the collected data to perform brain tumor classification and segmentation. Common neural network architectures used for this task include U-Net, Mask R-CNN, and ResNet.

3) Model deployment: The trained model can then be deployed on a web server, where it can be accessed through a web API. This API can take an input image, run the image through the model, and return the predicted tumor class and segmentation masks.

4) Website design and development: A website can be built to interface with the API and allow users to upload images for analysis. The website should have a user-friendly interface and allow users to easily upload images and view the results.

5) Quality assurance: Finally, the website should be tested and validated to ensure that it provides accurate and reliable results. This can include testing the model on additional data, as well as conducting user testing to assess the usability and user experience of the website.

The portal would enable the hospital administrative staff to upload the MRI scans, test reports and prescriptions for the patients to take a look at. The files will be added to the database record for the relevant patient and are accessible at any time.

A. Security Features

While signing up for the first time, OTP verification has been put to ensure security. Md5 or Message Process 5 has been used to encrypt passwords within the database. Proper security measures have been taken, while writing the code, to prevent the website from attacks like Cross Site Scripting (XSS), SQL injection, Cross-site request forgery. The portal has been placed on the cloud with SSL certification to add security and thwart DDOS, Brute force, and phishing assaults. The gateway would make it easier for patients to use the Razorpay PHP SDK to make online payments.

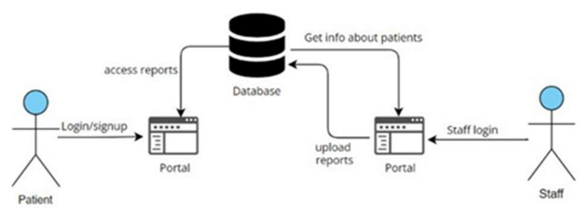

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Fig. 7. Website Flowchart

1) Secure Passwords: Enforcing strong passwords that include a mix of uppercase and lowercase letters, numbers, and special characters can help to prevent unauthorized access to user accounts.

2) Regular Backups: In the event of a security breach or other major catastrophe, regular backups of a website’s data can ensure that the website can be rapidly restored.

3) One-Time Password: One-Time Password (OTP) can be used as a security feature for websites. OTP is a unique password that is generated for a single use and typically has a short validity period. It adds an additional degree of security by requiring the user to provide a code in addition to their password to access their account.

XI. CONCLUSION

In conclusion, brain tumor classification and segmentation are important problems in medical imaging, with the potential to significantly improve diagnosis and treatment planning for patients with brain tumors. Despite the numerous challenges, including variability in imaging modalities and acquisition protocols, limited annotated data, and complex anatomy, advances in machine learning, deep learning and computer vision have led to significant progress in this field. However, there is still much work to be done to develop robust, generalizable, and clinically relevant algorithms for brain tumor classification and segmentation. Future research should focus on improving accuracy, robustness, and interpretability, as well as addressing the challenges faced in this field, to make these techniques more widely available and accessible to patients in need.

XII. FUTURE WORK

Future work in the field of brain tumor classification and segmentation could focus on the following areas:

A. Developing models that can handle a large variability of imaging modalities, image acquisition protocols and brain anatomies.

B. Integration of additional clinical and demographic information, such as patient history, to improve diagnosis and treatment planning.

C. Incorporating novel imaging modalities and techniques, such as molecular imaging and multi-modal imaging, to improve diagnosis and treatment.

D. Building models that can handle sparse or limited annotated data, to make the techniques more accessible in resourcelimited settings.

E. Development of real-time, online, and interactive segmentation methods for clinical use to help with surgical planning and intervention.

F. Improving the interpretability ,accuracy and robustness of algorithms and developing methods to explain the decisionmaking process of the models.

These are some of the promising directions for future work in the field of brain tumor classification and segmentation.

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