Unsupervised Anomaly Detection in Tumor Detection: A 3D Deep Learning Analysis on Brain MRI

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Abstract: Developing machines that behave in a manner just like humans is the intention of artificial intelligence (AI). Further to sample recognition, making plans, and problem-fixing, laptop sports with synthetic intelligence embody special sports activities. A set of algorithms known as "deep learning" is applied in system learning. With the help of magnetic resonance imaging (MRI), experts use advanced techniques to develop models that can detect and classify brain tumors. This results in the fast and easy identification of such tumors, enabling doctors to provide timely and effective treatment to patients. Thought issues are through and massive as the result of aberrant brain cell proliferation, which could harm the structure of the brain and in the long run, bring about malignant brain maximum cancers. The early identification of brain tumors and the following appropriate remedy may additionally lower the loss of life fee. On this advise generative adversarial community (GAN) architecture for the inexperienced identification of brain tumors through the usage of MRI images. This project discusses numerous methods which include resnet-50, vgg16, and inception v3, and evaluates the proposed structure and those models. To investigate the general performance of the models, we took into consideration unique metrics that incorporate the accuracy, don't forget, loss, and vicinity below the curve (AUC). Due to reading distinct methods with our proposed version and the usage of those metrics, we concluded that the proposed version did better than the others. We may additionally infer that the proposed model is dependable for the early detection of diffusion of thought tumors after evaluating it with the other models. In this project we need to apply extra datasets from 2022. In this architecture will be done by using information collection, Pre-manner with resize and filtering of median, segmentation through thresholding or clustering, and finally using an algorithm with GAN for training and augmentation of the dataset to get more accuracy.

INTRODUCTION:

Cerebrum growths have high bleakness and may prompt profoundly deadly disease. In facilities, precise division of growths is the means for analysis and assurance of resulting treatment choices. Medical image analysis has paid a lot of attention to accurately segmenting tumor lesions because of their irregular and blurry boundaries. Considering what is happening, this paper proposed a cerebrum growth division technique in view of generative ill-disposed networks (GANs). The GAN architecture consists of a classification network for discrimination and a densely connected three-dimensional (3D) U-Net for segmentation. Both of these networks fuse multi-dimensional context information using 3D convolutions. To speed up network convergence and extract more specific information, the densely connected 3D U-Net model introduces a dense connection. The ill-disposed preparing makes the dissemination of division results nearer to that of marked information, which empowers the organization to fragment some unforeseen little cancer subregions. On the other hand, train two organizations lastly accomplish an exceptionally precise grouping of each voxel. The trials directed on BraTS2022 cerebrum cancer X-ray dataset show that the proposed technique has higher precision in mind growth division.

DIFFERENT APPROACHES:

Brain tumor detection is a critical aspect of medical imaging and healthcare. Various approaches are employed for the detection of brain tumors, often utilizing advanced imaging techniques and computational methods. Here are some different approaches for brain tumor detection

i) Medical Imaging Techniques:
ii) Image Segmentation
iii) Machine Learning and Deep Learning

Medical Imaging Techniques:

In the medical imaging approach for brain tumor detection, patients undergo either Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans. These non-invasive procedures use strong magnetic fields (MRI) or X-rays (CT) to create detailed images of the brain. Contrast agents may enhance visibility, and radiologists interpret the images for tumor identification, aiding in accurate diagnosis and treatment planning. Follow-up procedures may be recommended based on the findings.

Image Segmentation:

In image segmentation for brain tumor detection, the process involves dividing medical images into distinct regions or pixels, classifying each based on whether it belongs to a tumor or non-tumor area. Region-based segmentation identifies relevant regions of interest, while pixel-based segmentation focuses on individual pixels within the image. This technique plays a critical role in delineating tumor boundaries, aiding in accurate diagnosis and treatment planning by providing precise information about the tumor's location and size.

Machine Learning and Deep Learning:

In machine learning and deep learning approaches for brain tumor detection, algorithms are trained on labeled datasets to distinguish normal and abnormal brain images. Supervised learning involves using predefined features, while unsupervised learning discovers patterns without labeled examples. Deep learning networks, such as Convolutional Neural Networks (CNNs), directly learn complex features from medical images. These techniques enhance automated tumor detection, providing efficient and accurate assistance to healthcare professionals in the diagnostic process.

LITERATURE SURVEY:

In this section we studied previous researches works about brain tumor detection using different approaches.

Ahmed Abdelgawad et al.[3]evaluated their proposed model on a dataset of 3264 MRI images, including both healthy and tumor-affected images. In this paper they ave proposed a CNN model for detection of brain tumor. The proposed system is trained with pre-processed MRI brain images that classifies newly input image as tumorous or normal based on features extracted during training. Back propagation is used while training to minimize the error and generate more accurate results. Autoencoders are used to generate image which removes irrelevant features and further tumor region is segmented using KMeans algorithm which is a unsupervised learning method.

Shahzad Ahmad Qureshi et al.[5] have developed an Ultra-Light Deep Learning Architecture for feature extraction and combine it with textural features to improve the performance of brain tumor detection. The introduction sets the stage for the research, highlighting the importance of accurate and efficient brain tumor detection and introduces the proposed method for achieving this goal. The article suggests that this approach can be valuable for real-time surgical applications. T1-weighted CE-MRI dataset is used.

Mircea Gurbina et al.[7] proposed a system which is efficient and accurate method for tumor detection and classification of MRI brain images. Wavelets based transform are mathematical tools which are used to extract information from images. The system uses SVM, a powerful machine learning algorithm, to extract features from the MRI image and to segment and classify the tumor. The system was evaluated on a dataset of 100 MRI brain images.

Ashfaq Hussain et al.[8] proposed a method for semantic segmentation of brain tumors from MRI images using a support vector machine (SVM) classifier and gray level co-occurrence matrix (GLCM) features.The proposed method consists of the following steps:Preprocessing , Segmentation , Feature Extraction ,Classification.The proposed method was evaluated on a dataset of 62 MRI images, including 31 tumorous images and 31 normal images.

Gajendra Raut et al [9] proposed a deep learning-based method for detecting and segmenting brain tumors in magnetic resonance imaging (MRI) scans. The method consists of two phases: Detection (CNN) , Segmentation (FCN).The proposed method was evaluated on the BraTS 2018 dataset, which is a publicly available dataset of MRI scans from patients with brain tumors.

R. Tamilselvi et al[10]purposed development of a new database called BRAMSIT, which focuses on MRI images for brain tumor diagnosis and detection.The database consists of 319 MRI images collected from various subjects, each labeled with a reference number, age, and axial position .The BRAMSIT database is structured through several stages, including providing detailed information about the subjects, labeling the images for easy understanding and interpretation, and manual annotation of each MRI scan image, including unique subject ID, age, gender, and axial position. Emphasizes the simplicity and accessibility of BRAMSIT, comparing its access time and processing time favorably against other existing datasets like BRATS, Figshare, and Kaggle

PROPOSED METHODOLOGY:

Image Acquisition:

Image acquisition is the first step in image processing. This step is also referred to as pre-processing in image processing. It involves retrieving the image from a source, usually a hardware-based source. This can be done via hardware systems such as cameras, encoders, sensors, etc.

Data Pre-Processing:

The main goal of pre-processing is to enhance the quality of the image so that we can analyze it better. With the aid of preprocessing, we can suppress undesired distortions and enhance some features that are necessary for the particular application we are working for. Data preprocessing is an important step in the data mining process. It refers to the cleaning, transforming, and integrating of data to make it geared up for analysis. The goal of data preprocessing is to improve the quality of data and to make it extra appropriate for the specific statistics mining undertaking.

Median Filter:

The median filter is a technique used for noise removal from images and signals. The median filter is very crucial in the image processing field as it is well known for the preservation of edges during noise removal.

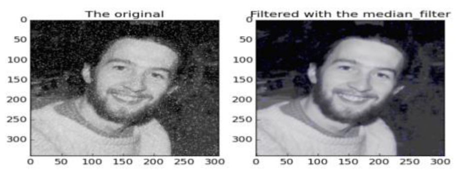
GAN:

Generative adversarial networks (GANs) are an exciting recent innovation in machine learning. GANs are generative models: they create new data instances that resemble your training data. For example, GANs can create images that look like photographs of human faces, even though the faces don't belong to any real person.

Segmentation:

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels).

CONCLUSION:



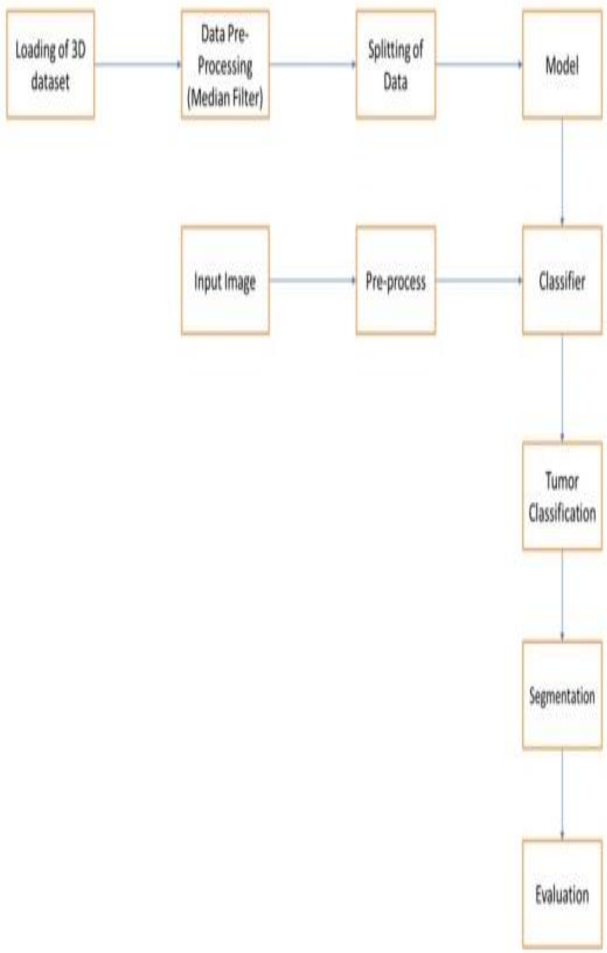
In conclusion, this survey paper comprehensively explores the use of Generative Adversarial Networks (GANs) in brain tumor detection, highlighting the significance of this innovative approach in the realm of medical imaging and healthcare. The integration of GANs into brain tumor detection processes represents a paradigm shift, leveraging the power of adversarial networks for generating realistic and informative medical images.The survey covers a range of methodologies and architectures, including the combination of GANs with deep learning models such as ResNet-50, VGG16, and Inception V3. Through an analysis of various metrics such as accuracy, recall, loss, and area under the curve (AUC), the survey underscores the potential of GAN-based approaches in achieving superior performance compared to traditional methods.The versatility of GANs in handling diverse

The purpose of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

Evaluation:

Evaluation is a wider concept than testing & measurement. Evaluation is the combination of quantitative estimation and qualitative judgment of one's behavior

SYSTEM ARCHITECTURE:



datasets and generating synthetic images for training purposes is a key strength discussed in this survey. Additionally, the paper addresses the critical importance of early detection of brain tumors, emphasizing how GANs contribute to enhancing the accuracy and efficiency of diagnostic processes.Looking forward, the survey suggests future directions for research, including the incorporation of additional datasets from recent years to further train and validate GAN-based models. The paper also advocates for continued exploration of advanced techniques in data pre-processing, segmentation, and GAN-based augmentation to improve the overall robustness and reliability of brain tumor detection systems.In summary, this survey paper provides a comprehensive overview of the current landscape of brain tumor detection using GANs. It serves as a valuable resource for researchers, practitioners, and healthcare professionals seeking insights into the evolving methodologies and technologies that have the potential to revolutionize medical imaging and diagnostics in the context of brain tumor detection.

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