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Brain Tumor Detection Using Neural Classification in Machine Learning

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ABSTRACT

Brain cancer classification is a difficult task due to the variety and complexity of tumors shown in magnetic resonance imaging (MRI) pictures. This research presents two neural network approaches for categorizing MRI brain images. The proposed neural network method consists of three steps: feature extraction, dimensionality reduction, and classification. First, we extracted features from MRI images using discrete wavelet transformation (DWT). In this second stage, we reduce the salient features of MRIs using principal component analysis (PCA). For the classification step, two supervised machine learning classifiers have been developed. Artificial neural networks are used by both classifiers; however, the second one employs back propagation (BPN) while the first one uses feed-forward (FF-ANN). Using the classifiers, MRI brain images of the subjects were classified as normal or abnormal. Artificial neural networks have numerous applications, including function approximation, feature extraction, optimization, and classification (ANNs). They are specifically intended to enhance photos, distinguish and categorize items, separate and register objects, and extract features. Among these, object and picture recognition is the most important for complex processing tasks such as classifying brain tumors. Radial basis function (RBF), cellular, multi-layer perceptron (MLP), hop field, and pulse-coupled neural networks have all been used in image segmentation. These networks can be categorized as feed-forward (associative) or feedback (auto-associative).

Keywords : MRI (Magnetic resonance Imaging), discrete wavelet transformation (DWT). Principle component analysis (PCA), feed forward artificial neural network (FF-ANN)

I. INTRODUCTION

It is critical to prioritize the clinical practice of early brain tumor diagnosis and categorization. Using a variety of sources, some academics have presented ways for classifying brain tumors. Here, we present a strategy based on patient data from magnetic resonance imaging (MRI) and magnetic resonance spectroscopy (MRS) for the classification of brain tumors as benign or malignant. Using picture segmentation, feature extraction, and classification, our goal is to accurately distinguish between the two types of tumors. The method could be useful for medical diagnostics. Segmentation and registration must be finished before ROIs are defined and analyzed. ROI placements are confirmed via image registration. Since the tumor location is not incorporated in the classification model, registration is not done in this work. To reliably delineate and detect tumors among participants, image segmentation is needed to set ROI borders. Techniques for segmentation that are manual, automated, or semi-automated are all feasible. The manual technique requires a lot of time and accuracy that depends on the operator's topic knowledge. There are numerous methods for magnetic resonance imaging (MR) brain tumor segmentation. The accuracy with which domain specialists possess the spatial probabilistic information typically determines how effective these strategies are. An automatic segmentation method based on fuzzy connectedness has already been proposed by us. To represent the relationship between each pair of picture voxels (x, y), a real value between 0 and 1 should be assigned. Each voxel is automatically assigned from a large number of seed locations to the structure with the highest connectivity. This method's use of segmentation statistics produces satisfactory results even in situations when ROI boundaries are difficult to determine. Extraction of discriminative features is the next stage in the development of a classification model after the ROI has been divided. The majority of characterization techniques use general visual data that is gathered from the entire image, as opposed to concentrating on particular portions. Feature extraction from medical pictures must focus on certain regions and capture structural, internal volume, and form data in order to train classification algorithms.

We present a method and extract a set of features to help classify MR images. By removing superfluous characteristics, feature selection pre-processing ensures that only the most pertinent features are used in the model's construction [1] and [2]. Statistical data is used in the building of models to determine which MR picture features are most useful. In this study, we also use MRS data to train our classifiers. Classification accuracy has increased. Medical image processing research is essential to improving health.

Tumors grow and push out healthy tissue. Brain cancer develops when brain cells divide uncontrolled. The characteristics of brain tumors might vary widely. Brain tumors may be benign or malignant. Precise brain tumor detection is critical for various medical imaging studies. [3]. This helps with treatment planning, therapy evaluation, and other tasks. Doctors' inability to deliver fast diagnosis is a big issue that can endanger patients and cause a variety of difficulties. To identify brain tumors, physicians rely on precise maging. [4]. Problem solving may necessitate a thorough analysis. Radiology professionals rely on X-rays. It takes photos with ionized X-rays. The physicians struggled to identify the patient's body. To obtain more precise information, more costly CT scans or MRIs are performed. X-rays cannot see through tissues, organs, or nerves. MRI and CT scans of the brain are able to pick up on features that X-rays are not as good at [5]. [6]. CT scans provide three-dimensional views of the brain as opposed to X-rays, which only provide two-dimensional images. CT and MRI scans are too expensive for patients. As such, the three-dimensional digital image structure is provided by the digital x-ray technique. In digital radiography, X-rays are described. Numerous diseases can be identified with X-rays. Physicians depend on precise diagnoses for brain traumas. Digital x-rays are therefore helpful in therapeutic procedures. When looking at brain fractures, X-rays are typically utilized [7].

The purpose of this project is to create an image processing system that employs digital x-rays to accurately and quickly categorize diseases in jpeg, png, and other comparable image formats. Research into medical image processing is critical to improving health. A tumor is an abnormal growth of tissue. Tumors grow and push out healthy tissue. Brain cancer develops when brain cells divide uncontrolled [8]. The characteristics of brain tumors might vary widely. Precise brain tumor identification is critical for many medical imaging applications. This helps with therapeutic evaluations, early treatment planning, and other tasks. Patients face a genuine risk of death and a slew of other issues when doctors spend their time detecting illnesses. As a result, reliable imaging studies are required for the diagnosis of brain tumors. Some critical components for precise analysis may encounter difficulties. Radiology professionals rely on X-rays.

Characteristics of Brain Tumors

Brain tumors are characterized by aberrant and uncontrolled cell growth. Several of them are referred to as "primary" since they first arise in the brain. Some of them have spread to this location from other sections of the body, becoming secondary tumors. At this point, the brain tumour has not spread to other regions of the body; yet, it may grow malignant or remain benign. Both benign and malignant tumours cause serious health risks. When malignant regions develop within the narrow skull space, the risk to human life rises [7]. Edoema develops when blood cannot reach certain areas of the brain due to high intracranial pressure, resulting in normal tissue functions and cell death. Brain tumors are the second leading cause of cancer-related fatalities among people under the age of 30. The Central Brain Tumor Registry of the United States (CBTRUS) predicts 64,530 additional cases of primary brain and central nervous system tumors by the end of 2011. Currently, the global case count is close to 600,000. [8].

There are two basic types of brain tumors: primary and secondary. The aberrant cells in the main brain tumour develop slowly, thus it is safe to ignore them. At this point in the tumor treatment procedure, it is critical to take your medication exactly as prescribed. Failure to cure primary brain tumors causes the development of secondary tumours. When brain tumours reach the second stage, which is malignant, aberrant cells begin to proliferate at a rapid pace. Because medicine and surgery are no longer effective in controlling malignant brain tumors, radiation therapy is recommended for patients with these cancers [9]. The aberrant brain cells are surgically removed, followed by a vigorous course of treatment. A brain tumor is described as an abnormal growth of tissue [10-14]. Brain tumors, unlike malignancies in other regions of the body, can only spread within the brain. The origins of the rapid development of brain tumor cells remain unknown. Some tumors, known as gliomas, form in the glial tissues that allow the brain to connect with the rest of the body. Mixed gliomas, ependymomas, and astrocytoma's can develop from gliomas, the most common primary brain tumors. [15]

Benign and Malignant Brain Tumors

If a tumor is small, has not spread, and only affects a small number of cells, it is not malignant. They are completely reversible because they can be surgically removed and do not spread to neighboring tissues [16–18]. Malignant tumors have progressed to a later stage when they have metastasized, or invaded nearby healthy tissue. Hurts are excruciatingly painful and take a long time to heal. The cells in this type of tumor practically dissolve and lose their borders. An indication of a malignant tumor is a sharp rise in intracranial pressure. A tumor in the brain or spinal cord is an illustration of a primary tumor [19]. These rarely happen and travel from the brain to the peripheral branches of the central nervous system.

Segmentation of Brain Images

Segmentation, which analyzes the similarities and differences between individual pixels in a brain image, can be used to generate smaller representations of the brain. The use of an image's functional components enables segmentation, which isolates the region of interest from the rest of the image [20]. Most segmentation criteria are based on how similar or distinct the item's intensity levels are. To this goal, we deconstructed the provided image. In theory, segmentation can be used to any digital image type. Using this technology for medical imaging purposes, such as CT scans and MRIs, necessitates knowledge of both biology and computer science to achieve the desired result autonomously [21]. Medical imaging methods obtain an image that encompasses not only the object (organ) being examined, but also the immediate environment around it. The difficult but necessary task of choosing the discussion topic falls on you. This is made possible by segmentation techniques used in digital picture processing. Picture segmentation techniques can be broadly categorized into four groups: region-growing approaches, clustering methods, edge detection methods, and thresholding methods. These broad categories include knowledge-based methods such as graph, pixon, clustering, intensity, discontinuity, similarity, and hybrid approaches [22, 23].

Clustering methods

In an image, similar pixels are grouped together. Maybe this is an image of a portion of the picture. Subsequently, sets of pixels with comparable values are recognized and distinguished. This technique can be used during human dissection to separate specific organs. In situations where segmentation inside an organ is necessary, clustering might not yield discernible differences in pixels. [24]

Threshold based techniques

Using these methods, images are categorized as high- or low-intensity based on how each pixel compares to a predetermined threshold. There are, to put it simply, zones of brightness and parts of darkness. The primary drawback of this method is that object coherency cannot be ensured. There may be picture features like excess pixels or blank regions [25].

Rationale for MRI

Magnetic resonance imaging (MRI) has been primarily used in the research of neurological diseases; however, it has also proven to be an efficient tool in the diagnosis of musculoskeletal ailments. The diagnostic application of magnetic resonance imaging (MRI) for illnesses affecting the human body's internal organs has become commonplace due to recent advancements in both technology and MRI technology. Medical imaging techniques such as CT, PET, MRI, and X-rays have expanded into new fields thanks to a wealth of research and applications. Neuro imaging has both positive and negative aspects. Despite its monochrome output, magnetic resonance imaging (MRI) is a vital tool for medical diagnostics, especially in the early identification of cancer. The sharpness of the image is primarily to blame for this.

Because MRI produces higher-quality images, it is able to better distinguish between the object's hard surfaces and its soft tissues. This facilitates tumour localization and cancer staging. When it comes to determining the local stage of cancer, researchers have found that MRI, specifically brain cancer, is the gold standard among radiologic modalities. The axial plane will get the most of the radiology specialist's focus, but don't disregard the coronal and sagittal planes either. When it comes to sagittal and coronal plane imaging, MRI is second to none. Using magnetic resonance imaging (MRI), several views of the brain in cross-sectional form are possible.

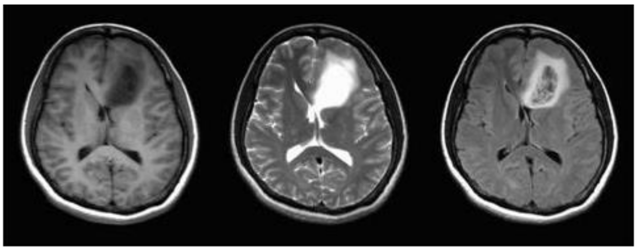

Figure 1. Examples of MRI weighted images (From left to right: T1- weighted, T2 weighted and FLAIR-weighted images)

II. LITERATURE REVIEW

Geethanjali N et.al (2023) A brain tumour is a collection of abnormal cells. There are two main types of brain tumours: malignant and benign. Brain tumours are very dangerous if not detected in their early stages; they are among the most common types of cancer. After a brain cancer has been diagnosed, the first step in creating an effective treatment plan is to classify the tumour. Thus, earlier detection helps create better therapies and might potentially save lives. Neuroimaging studies of humans were used as a basis for this investigation. Brain MRIs that reveal both tumours and healthy tissue are part of it. The next step is data pre-processing, which involves applying various image processing techniques including blurring, cropping, filtering, etc. Both the "training" and "testing" datasets exist inside the larger collection. A number of haphazard procedures are used to augment them with new information. With the pre-trained dataset in hand, a CNN model is created. Next, the model checks for the presence of the tumour. It is possible to identify three different kinds of tumours if they are present. Tumours of the pituitary gland, meningioma, and gliomaare the three most common kinds.

Sumit Hassan Eshan et.al (2023) An antenna for brain tumour detection using the novel material Kapton polyimide is detailed in this article. Because it may trigger the metastasis of cancer to other organs, a brain tumour is among the most lethal illnesses. In order to identify brain cancers, this research mainly focuses on using a novel material and tracking variations in the S1,1 parameter. A brain phantom model with three different sized cancers and a K-band on-body microstrip patch antenna were used by the researchers to identify the existence of a brain tumour. Specifically, this antenna is usable between 4 and 14 GHz. The proposed antenna's resonance frequency in free space was determined to be 12.96 GHz. Also, the S1,1 level was 92.06 dB, and the VSWR was 1.00. While S1,1 is 49.93 dB at 8.58 GHz in a healthy brain, it drops to 40.51 dB at 11.87 GHz in a brain affected by a tumour.

Hanming Hu et.al (2021) Brain tumours may be first detected with the use of magnetic resonance imaging (MRI) by both researchers and doctors. In order to further understand the tumor's nature, a biopsy or surgical resection is often conducted after an MRI scan detects its presence. But experts in brain tumours need time to go through tissue samples to find out what type of malignancy they are. If the neurosurgeon operating on the tumour lacks expertise, a misdiagnosis might potentially occur. Consequently, we set out to solve the challenge of identifying and detecting brain cancers using MRI scans by using deep learning techniques. This research put many deep learning models to the test in an effort to find the best one. Our use of a YOLO model for targeted tumour extraction from MRI images substantially improved classification accuracy. It seems that the accuracy of categorization is diminished when YOLO detection and visual augmentation are used. In the future, deep learning models may be used to treat brain tumours and other complex conditions, since our findings demonstrate that they may significantly improve the accuracy and speed of brain cancer identification.

Deependra Rastogi et.al (2021) It is well-known that brain tumour segmentation is very difficult since gliomas may vary greatly in size and intensity. There is a significant death rate and a morbidity rate of over 3% for glioma tumours, the most frequent kind of malignant brain tumours. When it comes to identifying brain tumours, magnetic resonance imaging (MRI) is considered the gold standard by hospitals. Edoema, healthy, enhancing, and non-enhancing regions all have similar intensity distributions, which make automated segmentation a difficult task. Brain cancer areas can be better identified and monitored using multi-modal MRI scans. This might help with patient impact assessments, post-diagnosis monitoring, and treatment monitoring. Still used extensively in clinical settings, manual segmentation of brain tumours is laborious, error-prone, and subject to large individual variances in performance. For this reason, studies aimed at developing trustworthy automated segmentation systems are crucial. Segmentation of brain tumours has shown potential using convolutional neural networks' (CNNs) remarkable learning capabilities. A 2D-VNet model is suggested by the authors of this study to enhance brain cancer segmentation and prediction. The offered model not only properly diagnosed brain cancers, but it also predicted the fate of both hypothetical and real enhancing tumours. The following outcomes were achieved from our studies carried out on the BRATS2020 benchmarks dataset: Results in training:.0025 for loss,.9974 for dice coefficient, and.9971 for accuracy; in testing:0032,.9967, and.9968, respectively; and in validation.9971 for accuracy.

Sakshi Ahuja et.al (2021) Disease analysis using various medical imaging modalities is a big challenge for medical professionals. A computer-aided design (CAD) tool for deep learning-based brain tumor diagnosis and classification is presented by the proposed research. The CAD tool is trained with the CA-MRI brain dataset in axial, sagittal, and coronal views in order to localize and categorize tumors. The input brain MRI dataset is preprocessed and then split into three parts: a training set that makes up 70% of the total, a testing set that makes up 15% of the total, and a validation set that makes up 15% of the total. The ineeption-ResNet-v2 deep learning model was trained using a larger dataset. Several statistical metrics are used to assess the efficacy of the pre-trained deep learning model. The training set yielded an AUC of 1, a recall rate of 99.56%, and an accuracy rate of 98.72%. To locate the tumour in multiple-angle photos, a CAD application is created utilizing a pre-trained deep learning model and a set of feature maps.

Brain tumor segmentation

Neoplasm segmentation is the first and most crucial step in creating an AI-based diagnostic system for glioma characterization and treatment management. Gliomas have intricate pathology on the inside, which includes necrosis, edoema, an enhancing core, and a non-enhancing tumor area. They spread randomly and infiltratingly. Tumor segmentation aims to separate the malignant elements of the tumor (e.g., active, necrotic, and edematous tissues) from the surrounding healthy tissues. The ROI or VOI, specified in two or three dimensions, is the final product. Internal properties of gliomas, such as necrosis, edoema, and enhancing and non-enhancing traits, are displayed in a 2D segmented picture. Neuroradiologists and other specialists in the field frequently employ MR imaging to locate and identify brain tumors. While manual segmentation is technically possible, it is laborious and frequently yields imprecise results. Thus, developing reliable algorithms for automatic segmentation has been a major research topic in recent years. The degree of human input required to classify manual, semi-automated, and fully-automated segmentation procedures is determined.

1. Manual segmentation: Using this technique, the ROI of the tumor is manually annotated by a qualified neuro radiologist. Slice by slice, specialists analyze multimodal MRI data, applying their expertise to identify tumor features and painstakingly manually labeling tumor sub regions. This is a labor-and time-intensive process that is prone to rating discrepancies amongst raters. However, skilled radiologists continue to use manual segmentation

on a regular basis to assess the effectiveness of fully-automatic or semi-automatic techniques.

2. Semi-automatic segmentation: Nevertheless, few strategies integrate the benefits of fully automated and semi-automatic segmentation. They could be able to manually fix a segmented tumor mask with minimal assistance from humans. Certain settings may require human intervention, such as choosing a ROI starting point, thresholds, pre-processing parameter modifications, getting feedback on automated process performance, and making necessary revisions. Semi-automatic techniques use conventional image segmentation techniques like thresholding or image expansion. Inaccurate ROI definitions can still result from human mistake, even if these techniques can save time and effort in comparison to manual operations. Thus, the focus of the majority of current segmentation research has been on fully automated techniques.
3. Automatic segmentation: The foundation of these techniques is formed by deep learning, machine learning, and artificial intelligence algorithms. A wide range of tumor changes in terms of size, shape, location, texture, and intensity are visible on glioma MRIs [15]. An additional concern is that tumor boundaries are not always clearly defined. The 3D representation significantly increases the complexity of multimodal MRI data. Correct management of these problems is necessary for strong, repeatable, fully autonomous segmentation. Automatic methods can be broadly classified into two categories: generative and discriminative processes.

In order to obtain the feature, discriminative algorithms employ supervised learning techniques, which aid in their comprehension of the connection between the input and the actual image. Generative algorithms generate probabilistic models in place of employing data such as geographic locations, maps of normal brain structure, and tumor area.

Pre-processing, segmentation, classification, post-processing, and feature extraction (or reduction of features) are frequently standard processes in the processing pipeline of an automated technique. Since the BRATS benchmark was initially introduced in 2012, a yearly public benchmarked database has been made accessible in conjunction with the brain tumor segmentation challenge. Ever since, several segmentation strategies have been put to the test in a global competition. The deep learning paradigm has been the source of the most recent advancements in tumor segmentation [14], notwithstanding the success that these conventional automated methods have had. These days, deep learning techniques like stacked auto encoders, restricted boltzman machines (RBMs), convolutional neural networks (CNNs), deep belief networks (DBNs), etc., constitute the foundation of many cutting-edge solutions for pattern recognition and computer vision problems. Studies show that these methods have been heavily utilized in medical imaging segmentation in the last few years.

Two-Dimensional Discrete Wavelet Transform (2D DWT)

Wavelet Transform's ability to analyze data at many resolutions makes it easier to identify features from brain scans obtained through magnetic resonance imaging (MRI). The multi-resolution representation might offer a simple way to increase the amount of image data. The 2D discrete wavelet transform can be used to split an image into four distinct sub bands: the vertical, which is for horizontally low-frequency details; the horizontal, which is for horizontally high-frequency details; the approximation images, which is for images with shorter wavelengths in both directions; and the vertical, which is for vertically high-frequency details. [12, 13]

Principal Component Analysis (PCA)

Simplifying tumor classification requires reducing the amount of memory storage and superfluous characteristic computations. Principal component analysis (PCA) effectively decreases the dimensionality of new data, allowing for analysis with fewer processing resources. When a dataset has multiple connected variables, principal component analysis (PCA) is a great method to reduce the dimensionality of the dataset while maintaining a high degree of variability. The information is rearranged into a collection of variables, and the significance levels or variances of each are utilized to establish the order of importance for each variable. This method accomplishes three goals at once: it firstly makes the components of the input vector orthogonal and uncorrelated. It then arranges the generated orthogonal components according to how much they contribute to the variability of the data. Ultimately, the person with the least contribution is eliminated. [14]

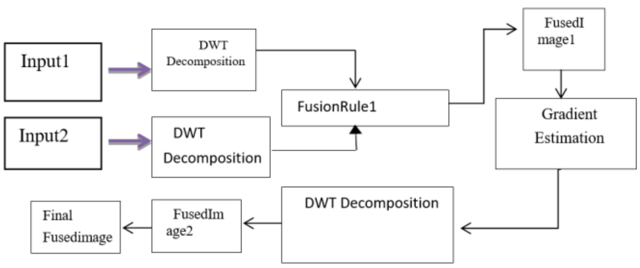

Fig.2 Flow diagram of proposed method

Pre-processing

- When given an image as input, the proposed system should do the following:
- Adjust the image's size to fit the input.
- De-colorize the given image while preserving its contrast and brightness. It is necessary to compute a global threshold before converting the gray scale image to a binary image. Once changed, this threshold takes on an intensity value between 0 and 1.
- The image may be converted to a binary format with the help of this threshold.
- In the final image, each pixel with brightness greater than the threshold will be shown as white, while every other pixel will be displayed as black.

Segmentation

Segmentation is a crucial stage in picture analysis. At the moment, segmentation is done using eight different methods: atlas guidance, Markov random field models, region growth, classifiers, clustering, artificial neural networks, deformable models, and thresholding. In this specific system, we employed the K-means clustering algorithm for tumor segmentation. This method requires that the distance in geometric units between each pixel and the centroid of k clusters be determined before it can be used.

Feature Extraction

The goal of feature extraction is to minimize the amount of information required to accurately represent data. It can take longer and require more processing resources to classify the entire photo dataset. By extracting all the pertinent information from the original image, we can accurately identify it with the assistance of a feature extraction procedure. The classification model is trained using the features. Comparing the feature sets of images can help identify which ones belong to the same category. Topology and geometry: regional and global aspects [20]. Here, the image is modified in a way that makes it possible to identify its key characteristics. Brain MRIs are primarily classed using four criteria: texture, form, statistics, and intensity-based criteria.

Texture Analysis

Texture analysis is the process of labeling areas of a picture according to their texture characteristics. Surface textures are intricate patterns in the visual domain that are composed of multiple layers of smaller patterns, each with unique characteristics including color, brightness, slope, size, hue, and so forth. Texture analysis is primarily concerned with quantifying intensity and grey scale range. Finding these boundaries—a process known as feature segmentation—may be aided by texture analysis. Two instances of texture analysis techniques utilized for brain tumor classification are grey level co-occurrence matrices (GLCM) [21] and gabor texture [24]. Harlick features, also known as statistical texture features, are frequently extracted using the GLCM technique.

III. CONCLUSION

The application of computer science to the study of disease is becoming increasingly significant in the process of making medical decisions. Magnetic resonance imaging, or MRI, is used extensively in many different kinds of study. Consequently, the MRI brain image is used to create the system. Using morphological surgery, the tumor's exact location is identified. It requires little time and is simple to apply. This investigation's evaluation of brain scans is now complete. Regarding brain imaging, this technique yields trustworthy results. Further processing methods will be required if a brain picture shows evidence of a tumor location. Accurate segmentation of brain images requires pre-processing. The brain scan has been smoothed out and the noise removed, making it ready for analysis. A threshold-based scam has targeted this system. This technique might successfully extract the image of the brain from the skull. The watersheds were divided using a marker-based technique as the final step. As a result, we may categorize tumor locations based on their intensity differently from normal brain tissues. The final segmentation map is produced by partitioning the image into normal brain tissue and tumor. Using a morphological approach, the resulting segmentation map is then employed to pinpoint the location of the tumor. This study distinguished between malignant and normal brain tissue using pictures from brain magnetic resonance imaging (MRI). Two of the primary objectives of pre-processing are the removal of photo noise and smoothing. The signal-to-noise ratio is improved as a result.

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