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A Research on Brain Tumor detection using Machine Learning techniques and Deep Learning approach

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ABSTRACT

Abnormal development of cells in the human body leads to the formation of cancer or tumor. The abnormally formed cells during the cell division are called cancer and they have the property to permeate the nearby tissues of the organs and start affecting the blood and lymphatic system, which is termed as metastasis, thereby reducing the lifespan of the patients. Cancer can have its occurrence in any part of the body and it is categorized mainly from the cell where it originates. Cancer arising from the brain and nervous system is called brain cancer. These brain tumors are classified into benign and malignant. Benign tumors are tumors that have inactive tumor cells and the area of these abnormal regions is structured and can be cured by proper medication. Alternatively, malignant tumors are tumors that have active cells and the area of these abnormal cells that are unstructured cannot be cured by medication. Hence, surgery is required for removing these tumors in the brain image. In conventional methods, brain tumors are detected and diagnosed manually by an expert radiologist. It is a time-consuming and error-prone process. Hence, it is not suitable for high population developing countries. Therefore, computer-aided automatic brain tumor detection and diagnosis methods are preferred. The proposed method of screening using the MR imaging technique is quite simple and fast compared to the traditional methods of screening for brain cancer. This method can also be deployed for a large number of cases quite fast and accurately. Hence this proposed research evolves a technique which involves an MR image of the brain region. It presents a digital imaging system which is able to assist physicians to track brain cancer. The goal is to automatically extract the region where the brain cancer starts to occur. MR imaging techniques are one of the tools to diagnose cancer and to detect and identify the malignant and benign tissues in the human body. In this proposed method Computer-Aided Diagnosis (CAD) is used to diagnose brain cancer. The CAD system for the diagnosis of brain cancer iv requires a segmented brain for the analysis. But most of the previous works had concentrated only on the labelling of the brain and only a few attempts were made to segment the brain automatically from the other anatomical structures. This research work is focused on developing a new automatic segmentation algorithm for segmenting brain tumors from MR images. In this work, five different methods for automatic brain segmentation and classification are proposed.

1. INTRODUCTION

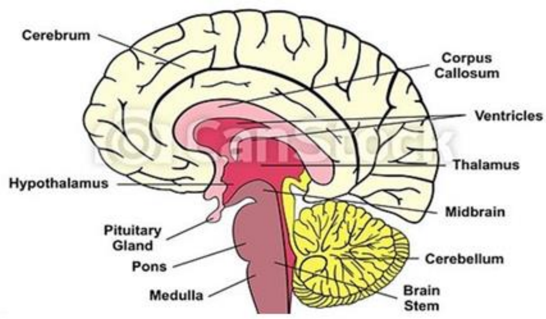
Tumor is a standout amongst the most widely recognized common diseases. The World Health Organization (WHO) estimates that diagnosis and treatment are important for more than four lakh persons suffering from tumors per year in the world [1]. The cells in our body keep growing and multiplicatively increase several times in a single day of our life so that our body can function normally. When there is occasional disturbance during the division of cells in our body, it may lead to the formation of abnormal cells or wrong cells, and this might disturb the cell activities of other parts of the body in an uncontrolled manner, which is termed as cancer. The abnormally formed cells during the cell division are called cancer and they have the property to permeate the nearby tissues of the organs, start affecting the blood and lymphatic system, which is termed to be as metastasis, henceforth reducing the lifespan of the patients. Cancer can have its occurrence in any part of the body and they are categorized mainly from the cell where it originated. Cancer arising from the brain and nervous system is called brain cancer.

The major life-threatening disease among human beings is a brain tumor. According to the recent statistics taken by various cancer research institutes such as National Cancer Institute (NCI), American Brain Tumor Association, and Advanced Centre for Treatment Research & Education in Cancer (ACTREC), about 20% of cancer death is due to a brain tumor and it's the leading cause of cancer-related death. The accumulation of abnormal cells in the brain forms a mass of tissue which is called a brain tumor. Normally the cells in our body die at a certain period and they are replaced by new cells. When this cycle is disturbed, the old cells don't die and continue to grow. In the meantime, the new cells accompany these old cells and grow along with them and form a mass of tissue known as tumors. Brain cancer is one of the most common cancers worldwide and this kind of cancer has the highest mortality rate. The frequency with which brain tumor occurs increases very fast and it affects the aged people more than the young. All the healthy brain cells are directly destroyed by brain tumors. The detection of cancer is indeed a laborious and repetitive work that needs the abnormal brain images interpreted correctly [2]. As a result, such a course is very expensive and prone to error. Also, the radiologist has to spend a lot of time on it. What we need urgently is the introduction of qualitative and objective analysis. Hence, there is a need for developing a computer-aided diagnostic tool that can diagnose the tumor on its own.

The World Health Organization (WHO) classified brain tumors into four types. Tumors of Class I and Class II are not malignant (benign). Tumors of Class III and IV are cancerous and deadly (malignant). Early detection of malignancies is required for effective treatment planning. A brain tumor can be discovered using a variety of approaches, including symptoms, medical imaging techniques, screening tests, and so on [3]. Using microscopic inspection of the afflicted tissues, a proper diagnosis of a tumor can be made rapidly (biopsy). In modern medicine, treatment options include radiation therapy, chemotherapy, and surgery. The success of treatment is determined by the tumor's size, location, type, and stage.

1.1. OVERVIEW OF BRAIN ANATOMY

The human brain is the most important and complex organ in the human body, controlling and coordinating all physical functions. The brain is a very complex structure made up of billions of nerve cells (neurons), which join together to form the Central Nervous System (CNS). The principal parts of the human brain are the cerebellum, cerebrum, and brain stem. The human brain is divided into three sections: the forebrain, the midbrain, and the hindbrain. The cerebrum, thalamus, and hypothalamus are all part of the limbic system and make up the forebrain [4]. The midbrain is made up of the tectum and the tegmentum. The cerebellum, pons, and medulla make up the hindbrain. The midbrain, pons, and medulla are commonly referred to as the brainstem. The brain integrates various processes of the human body such as vision, memory, learning, and other tasks. A brain is a stable location for various patterns to enter and stabilize other sections. The cerebrum is the largest region of the brain, followed by the cerebellum and the brainstem.



(Source:https://www.canstockphoto.com/human-brain-anatomy-diagram-48996036.html)

Figure 1 Anatomy of human brain

The general structure of the human brain side view is depicted in Figure 1, which consists of two hemispheres, each of which controls the opposite side of the body. That is, the right hemisphere governs the left and vice versa. It is linked to mental functions like thinking, memory, and speaking. There are four lobes in the cerebrum.

They are,

- The first is the frontal lobe which is connected with organizing, solving problems, planning, selective, attention, and emotions.
- The second is the partial lobe which is involved in the movement, orientation, recognition, and understanding of stimuli that control sensation.
- The capital lobe is related to preprocessing visual images.
- The temporal lobe is connected with perception, and recognition of auditory stimulus of factory stimulate and visual and verbal memory.

2. LITERATURE SURVEY

This part is devoted to a review of the literature on brain tumor detection. Medical image analysis is now a large field of study that necessitates breakthroughs. The robustness, efficiency, and accuracy of CAD systems are crucial in clinical diagnostics. For automatic brain MRI processing, software based on a sophisticated algorithm is required for preprocessing, segmentation, feature extraction, and classification. The integration and feasibility of algorithms are critical factors impacting the smooth operation of CAD systems. For each of these stages, several ways of measuring diagnosis performance have been established. Numerous study papers in this literature take varied methods for each operation. One of the most difficulties is to create a CAD system that works in all circumstances, independent of the database's modality, quality, or number. This part provides a comprehensive overview of the various methodologies utilized in CAD systems.

[4] used a sigma filter to reduce noise without affecting the edges of the objects in the image. The edges are enhanced by subtracting a blurred image from the original image. [5] used a gabor filter for the reduction of noise in brain MRI. The method was effective in reducing blur that occurred due to noise and necessary structures are maintained.

According to [6], preprocessing is a vital task because the performance of succeeding sections such as segmentation, feature extraction, classification, and so on is dependent on it. Pre-processing begins with the removal of film artifacts using a median filter. The skull region was removed from the image using morphological methods. The fundamental benefit of pre-processing is that it reduces the possibility of over-segmentation issues during image segmentation. By replacing each item with the median of the neighbor pixels, film artifacts were erased. There are various types of windows used to process artifacts, one of which is a simple box window, which is used here to remove artifacts. To remove the skull region, a mathematical morphological procedure such as dilation and erosion is utilized. Both techniques' pre-processing results reveal that image artifacts were satisfactorily removed. The skull is also discovered to have been successfully transported. The successful elimination of an undesired area of the image minimizes the risk of over-segmentation dramatically. Only the preprocessing performance measure is highlighted in this paper.

[7] estimated and removed bias fields using the legendre polynomial. To equalize the intensity levels of all the images included in the experiment, histogram matching was utilized. According to [8]. image processing is critical in biological applications. The tumor is an aberrant tissue formation, and MRI cannot define its precise site. As a result, doctors have been treating it by guesswork until now, and image segmentation is being utilized for analysis to provide complete information on brain tumors. Noise removal (median filter), grayscale and thresholding, histogram equalization, K-means clustering, and morphological processes are all included.

[9] introduced a two-phase clustering-based technique for MR image segmentation utilizing Self Organizing Map. The image goes through a preprocessing method during the first phase. For preprocessing, a weighted average filter for a wide range of nonlinear filtering is used. When compared with other filtering algorithms, the weighted median filter is more robust and capable of maintaining edges.

[10] developed two methods for segmenting brain tumors using MR images: region-based clustering and boundary-based clustering. The deformable contour models were utilized to determine the location of the brain tumor in the MR images. The fuzzy clustering technique was employed in the early stage of the segmentation process based on the observed regions. The deformable contour model then employed the regions identified by the fuzzy clustering approaches to detect contours in the brain images. The GVF and fuzzy approaches were used to finalize the segmentation of the brain tumors. The energy function in the image was reduced using the deformable contour model.

[11] advocated for the separation of a brain tumor in MRI, which is a difficult task due to the various shapes, locations, and image intensities. The authors form their opinions based on the extent of the tumor in a certain area. These are the primary factors considered by the algorithm. Initially, approaches for picture enhancement and noise reduction are used. Following that, a few morphological actions are employed to identify the tumor in the image. These are essentially used on some premises regarding the tumor's size and shape, and the tumor is then mapped onto the original grayscale image to make the tumor appear in the image. This algorithm, having been tested on a numeral of different images from varied angles, has given the correct result.

[12] investigated segmentation, which is significant in medical image processing, and the clustering approach, which is frequently utilized in medical applications, particularly for brain tumor identification in MRI. MRI is also used because it correctly portrays tissue anatomical structure. In addition, a study of many clustering methods utilized for segmentation in MRI is carried out.

[13] explored brain MRI analysis, which is commonly used for measuring and visualizing anatomical structures of the brain, assessing brain variations, designating sick regions, and carrying out surgical planning and image-directed treatments. Following an explanation of many MRI preprocessing techniques such as image registration, bias field correction, and non-brain tissue exclusion, the fundamental ideas of image segmentation are introduced. Following a review of the various brain MRI segmentation methods, the validity issue in brain MRI segmentation is investigated.

[14] separated normal brain tissues from aberrant brain tissues (necrotic core, edema, and active cells) (cerebrospinal fluid, grey matter, and white matter). MRI-based tumor segmentation in brain imaging has gotten more exciting in recent years of research. It is owing to the MRI modality's non-interruptive inspection and enhanced contrast of images corresponding to soft tissues. The segmentation strategies used in this work are both fully automatic and semi-automatic. The overarching purpose of this work is to give a summary of the most important MRI-based segmentation algorithms for brain tumors.

[15] explored brain tumor segmentation, a popular subject in Information Technology in the biomedical engineering research domain. Brain tumor segmentation is motivated by tumor growth measurement, treatment responses, computer-aided surgery, radiation therapy treatment, and the development of tumor growth models. As a result, a computer-assisted diagnostic system can help to reduce physician workload while offering reliable results in medical treatments.

3. OVERVIEW OF COMPUTER AIDED DIAGNOSIS (CAD) SYSTEM

Computer-Aided Diagnosis (CAD) System gives the radiologist another option for making an expedient judgment. For the detection of cancer in the body, CAD systems employ a precise algorithm. CAD is a large research topic in biomedical imaging science. The University of Chicago created the first CAD system in the mid-1980s. It is ideally suited for usage in CAD systems due to the high image quality and contrast of the supplied image. A skilled radiologist must be able to recognize patterns. A radiologist may employ CAD technologies to provide a second opinion on a diagnosis. CAD systems can classify MRI data into normal and pathological categories. Thus, it is possible to identify the presence of the disease. CAD system's general structure is shown in Figure 2.

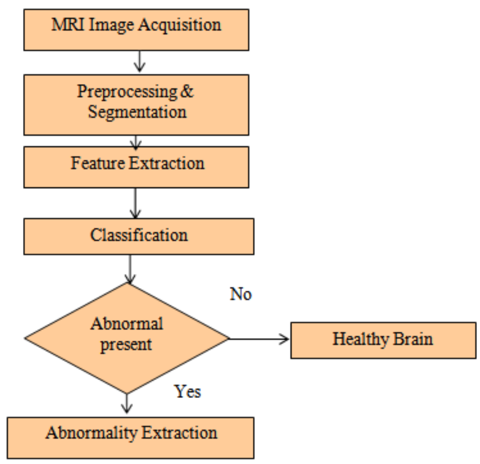


Figure 2 Basic structure of CAD system

The process of acquiring medical images utilizing various modalities such as X-rays, CT scans, Ultrasound scans, MRI, and so on is known as image acquisition. There are noises and other artifacts in these images. Preprocessing, which includes procedures like denoising, filtering, contrast adjustment, and so on, might help to avoid them. Segmentation is used to partition an image into different areas based on pixels or voxels. Disease-affected areas can be identified using these zones. Certain visual features are extracted for additional processing to decrease the image data. This is known as feature extraction. The retrieved features are used to put the given images into various groups, a process known as classification. Finally, the performance of the CAD system is evaluated using various parameters.

4. OVERVIEW OF MEDICAL IMAGE PROCESSING

Medical imaging is an indispensable tool for enhancing the diagnosis, understanding, and treatment of different types of diseases [16]. MRI of the brain has proved to be a very powerful method for diagnosis and is made use of by doctors to find out structural abnormalities in brain disorders pathology. With a growing interest in the medical image processing field, several automatic and semi-automatic tools have been developed to help in medical diagnosis.

3-D Medical Imaging serves promises high effects in the field of medical imaging. 3-D Imaging was the developing field for producing high-quality images. The signal will produce the photographic or else another kind of scripted image. There are three stages in image processing. In the first stage the input is given, then in the second stage processing can be done and in the final stage the clarified output can be obtained. The output can be obtained depending upon the input source given.

4.1. IMAGE ACQUISITION SYSTEM

An image capture system is used to create photographic images, such as a physical scene or the interior structure of an object. Capturing images, processing them, compressing them, storing them, printing them, and presenting them are all part of this process. The BIDC website was used to obtain the MRI brain scans used in this investigation. T1-weighted MRI was performed on MRI brain participants at the prescribed 5 T level. To narrow the MRI brain pixel range, the "head prototype" technique is applied.

4.2. PREPROCESSING

The initial stage of image processing is utilized to improve the detection of suspicious areas. Smaller image details are increased, and noise in the image is removed. Clinical MRI is contaminated by noise, decreasing image accuracy. This noise reduction is performed by employing several filters.

4.3. SEGMENTATION

The technique of segmentation is used to isolate the target object from the testing image. It deconstructs the image into its essential related pieces. The problem at hand determines the level at which the subdivision is carried out. Based on the amount of feature extraction required after segmentation, we can divide the technique into pixel-oriented, edge-oriented, and texture-oriented techniques. Hybrid approaches, which combine many treatments, can also be used.

4.4. FEATURE EXTRACTION

The segmentation result, which is usually a specifically selected region of the image separated from the rest of the image, is then followed by representation and description. It is critical to transform data into a format suitable for computer processing. The purpose of feature extraction is to emphasize visual information at a specified level where the methods listed below can function. As a result, other layers' information must be suppressed. Approaches to feature extraction were used at numerous levels, including the data level, the pixel level, the edge level, the texture level, and the regional level. The description is also known as feature selection. It is focused on getting the characteristics that result in quantitative information useful for differentiating one sort of thing from another.

4.5. CLASSIFICATION

Classification, also known as detection, is the process of assigning certain classes of objects to all connected regions produced by segmentation. Region-based characteristics that suitably abstract the attributes of the objects are commonly utilized to aid the classification process.

4.5.1. OVERVIEW OF MACHINE LEARNING

Machine learning is the only data analysis technology that automates the development of analytical models by identifying patterns and drawing conclusions with minimal human interaction [17]. Machine learning works as an integral component of intelligent computer vision systems when such adaptability is necessary. Recent advancements in the science of 'Machine Learning' have opened up a new avenue for the creation of intelligent computer-controlled machinery and software [18]. A large community of researchers, engineers, and academics is continually developing new machine learning algorithms to be used in the development of automated systems for applications ranging from object detection to medical diagnosis. Machine Learning is a subset of 'Artificial Intelligence' that uses data to learn. It examines existing patterns in data to respond to a circumstance for which they were not specifically programmed.

4.5.2. MACHINE LEARNING TECHNIQUES

There are various types of machine learning algorithms but broadly classified into four categories based on their purpose.

- Supervised Learning: A function is inferred from labeled training data in this learning that maps a new input to an output based on the function that it has learned from a collection of training instances [19]
- Unsupervised Learning: Prior training is not given in this type of learning because of the unlabelled dataset [20]
- Semi-Supervised Learning: This learning falls in between supervised and unsupervised learning because the input data is partially-labeled in semi-supervised learning [21]
- Reinforcement Learning: A machine is educated using the trial-and- error method in this learning [22]

4.5.3. DEEP LEARNING APPROACH

Deep Learning is a novel subset of machine learning that was developed in the traditional method to overcome the limitations of the existing machine learning approaches. Because of the performance of most classical classification algorithms is dependent on the feature extraction step. Extraction of significant features from data is sometimes difficult and time-consuming. Furthermore, substantial prior domain understanding is required for the design of a feature extractor to efficiently obtain information from data. Deep networks, as opposed to hand-crafted feature engineering, extract sophisticated hierarchies from raw data and generate a hierarchical data representation. A learning model with many levels of representations is presented to develop higher levels of abstraction. Each level of representation in the model is used to extract particular features of the data, where higher-level features are determined from lower-level features to make some sense to data [23].

A typical example of deep learning is demonstrated in Figure 8 which shows how deep networks suppress irrelevant information for the tasks of face recognition and amplify the significant features of the input image which are essential for discrimination. The first layer of deep networks is representing the edges at a particular location with a specific orientation. The second layer detects the recurrent elements by spotting a peculiar arrangement of edges without considering the variations in the edges' position and direction. The third layer tries to put the detected recurrent elements together that resemble a portion of the familiar faces. In this manner, the deep networks assist the face recognition model to determine the face similarity. Similarly, subsequent higher representation layers in the network would detect faces by combining these parts. In deep networks, hand-crafted engineering is not required to construct a layer of features. The technique requires very small engineering by hand and is capable of handling massive data.

In short, this method is expected to be extremely effective in addressing the artificial intelligence dilemma. Autoencoders, Restricted Boltzmann machines, and Convolution Neural Networks (CNN) are the three most fundamental forms of deep neural networks for processing data such as pictures, videos, and audio signals [24]. CNN, on the other hand, is proven to be incredibly effective in a wide range of practical applications such as object recognition, natural language processing, semantic analysis, face recognition, anomaly detection, and signal processing.

The final output of the each module has been displayed in the figure 3. figure 2 shows the model of the CNN algorithm.

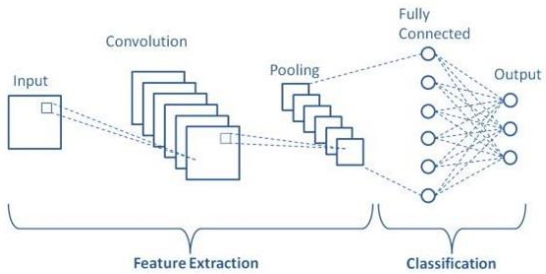


Fig.2 : Convolutional neural network architecture

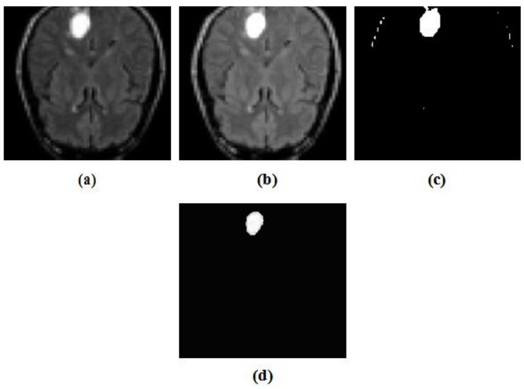


Fig 3: Segmented image of benign case sample (a) Input image, (b) Pre-processed image, (c) Segmented image and (d) Tumor ROI extracted image

5. RESULT AND DISCUSSION

The results of image enhancement, image segmentation, abnormal detection, and feature extraction are similar to the Improved SVM classifier. This section describes the classification stage's results. For classification purposes, Improved CNN is adopted. The Faster Region CNN algorithm is used to classify MR brain tumor images as benign or malignant. MRI brain tumor images from the BRATS dataset are taken to run the classification process. In a 3x3 confusion matrix, SVM with CNN output is presented. We can determine the image's accuracy by looking at the results of the classifier.

The confusion matrix obtained from the SVM with CNN is shown in Figure 3. The first two diagonal cells in this figure represent the number and percentage of correct classifications made by the trained network. For instance, 280 MR images of brain tumors are appropriately labeled as benign. This represents 46.7 percent of the 699 MR images of brain tumors. In the same way, 365 cases are accurately labeled as malignant. This represents 45.75 percent of all MR images of brain tumors. 20 benign images are wrongly identified as malignant, accounting for 3.3 percent of the data's 699 brain tumor MR images. Consequently, 34 of the brain tumor MR images are labeled wrongly as malignant, accounting for 4.25 percent of the data. In total, 92.29 percent of predictions are correct, while 7.71 percent are incorrect.

5. CONCLUSION

In this part, the block diagram of Improved SVM with CNN classifier proposed system is discussed. This research work investigates the preprocessing techniques to remove the noise and improve the contrast of the image by using Anisotropic Diffusion with Median Filter. Segmentation technique Improved Hierarchical Macqueen's Firefly K-Means Clustering is used to identify the abnormality. Finally, CNN classifier is used to classify the MR image into either benign or malignant cases. Each step result is briefly discussed in this chapter. A total of 699 brain tumor MR images are taken for classification purposes from the BRATS dataset, here the false positive rate is 20% and the classification accuracy is 92.29%.

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