International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 05 | May - 2022 Impact Factor: 7.185 ISSN: 2582-3930

NEURAL NETWORK SEGMENTATION IN MRI IMAGES FOR BRAIN TUMOR SEGMENTATION

MS .S. SWETHA , Dr.M.PARIMALA DEVI ,B.E ..,M.E..,Ph.D

[1]Student,Second Year- M.E. (Applied Electronics), [2]Professor, Department of ECE,

Velalar College of Engineering and Technology, Erode, Tamil Nadu, India

ABSTRACT

Individual of the most difficult challenges in medical image processing is detecting brain tumors. The challenge is challenging to complete since the photographs have a lot of variety, as brain tumors exist in a variety of shapes and textures. Tumors can appear in a variety of areas, and the location of a tumor can reveal information about the sort of cells that are creating it, which can help with further diagnosis. The picture intensities of tumor and non-tumor images can overlap, making it challenging for any model to make accurate predictions from raw images.

Magnetic Resonance Imaging (MRI) is a common imaging tool for assessing these tumors, but the vast amount of data produced by MRI makes manual segmentation impossible in a reasonable length of time, limiting the use of exact quantitative values in clinical practice. As a result, approaches for automatic and reliable segmentation are necessary. Because it gives Relevant information for the diagnosis, Monitoring, and therapy of brain tumors, segmentation is individual of the most important processes in interpreting medical pictures. In this paper , we offer a Deep Neural Network-based automatic segmentation and classification approach.

INTRODUCTION:

Tumors are clumps or masses of aberrant cells that can appear in any section of the body. A tumor can lead to cancer, which is the leading cause of mortality worldwide, accounting for over 13% of all deaths. The global prevalence of cancer occurrence is increasing at an alarming rate. As a result, tumor diagnosis in the early stages is crucial. A brain tumor is a mass of abnormal cells that grows in or around the brain . By damaging or penetrating normal brain tissue, it poses threats to the healthy brain. Brain tumors can be either malignant (cancerous) or benign (non-cancerous) (do not contain cancer cells). They can be primary (developed in the brain) or metastatic (cancer cells move from other parts of the body to the brain).

However factors that may increase the risk of brain tumors include exposure to high doses of ionizing radiation and a family history of brain tumors. If a brain tumor develops, doctors may order imaging tests such as MRI, head CT, head PET, etc. However, MRI is the most effective and commonly used technique for detecting brain tumors. Treatment depends on the size and type of tumor, its growth rate, and the general health of the person. Options include radiation therapy, chemotherapy, surgery, targeted biological therapy, or combination of these. Brain tumors are categorized based on the location of the tumor, the type of tissue affected, whether the tumor is benign or malignant, and other factors. Identification of brain tumors by MRI consists of various stages. Segmentation is said to be an important but difficult step for the classification and analysis of medical images. Therefore, it is important to accurately segment the MRI image before asking the processor for an accurate diagnosis.

However manual segmentation is time consuming and can lead to errors between and within evaluators. Therefore, doctors usually use rough criteria for evaluation. For these reasons, accurate semi-automatic or automated procedures are required. However, this is a difficult task due to the great variety of shapes, structures, and locations of these anomalies In addition the effects of the tumor mass change the placement of the surrounding normal tissue. Also, MRI images may have problems such as B. Intensity non-uniformity or different intensity ranges between the same sequence and the acquired scanner.

EXISTING SYSTEM AND RELATED WORK:

Magnetic resonance imaging (MRI) is the most important technique for detecting brain tumors. Brain tumors are the abnormal growth of cells in the brain that affect the way the brain works. If the tumor is detected early, it can stop further tumor growth and the tumor is treated appropriately. The brain is a major organ of the human central nervous system. A new combination technology based on FCM (fuzzy mean) and support vector machine (SVM) for brain tumor classification as been proposed. So here I was trying to find a tumor on an MRI image of the brain. The method used for preprocessing such as gray scale contracts, demising, and threshold. For clustering, we used FCM clustering and a classification SVM classifier.

DISADVANTAGES:

 FCM leads to more iteration costs.

 Prediction efficiency is low.

REVIEW OF LITERATURE:

The purpose of literary studies is to give a brief overview and obtain complete information about reference books. The purpose of literature research are to fully identify the technical details of major projects in a concise and clear manner. Brain tumor segmentation finds several ways to explicitly develop parametric or nonparametric probabilistic models of the underlying data. These models usually contain observations and probability functions that fit the pre-model. As an anomaly, tumors can be segmented as outliers from normal tissue that are constrained in shape and connectivity. Other approaches rely on stochastic atlases. For brain tumors, the shape and location of the neoplasm changes, so the atlas must be estimated during segmentation. The tumor growth model can be used as an estimate of its mass effect and helps improve the atlas. The voxel neighborhood provides useful information for smoother Markova random field (MRF) segmentation. Using Zhao et al. MRF, we used histogram-based likelihood function estimation to segment brain tumors into super voxels after the main over segmentation of the image. As reported by Mense et al. Observed generative models are often generalized with invisible data, but it can be difficult to explicitly transform prior knowledge into a suitable probabilistic model.

Another class of methods learns the distribution directly from the data. The training phase can be a disadvantage, but these methods allow you to learn patterns of brain tumors that do not follow a particular model. With these types of approaches, voxels are generally considered to be independent and similarly distributed, but features can introduce contextual information. Because of this, some isolated voxels or small clusters can be misclassified into the wrong class in places that are physiologically and anatomically unlikely. To overcome this problem some authors incorporate information about the neighborhood by embedding the lassifier's stochastic predictions in a conditional random field. Classifiers such as support vector machines and recent random forests (RF) were well used in segmentation of brain tumors. RF was very high for multi-class issues and its natural ability to generate large feature vectors. Various functions have been proposed in the literature: Code context of the brain symmetry and physical properties of the first ORDER and fractal based texture line.

At the monitored classifier, some authors have developed other ways to apply them. Stetson Et Al We have developed a two-level segmentation ramework based on RF and used the output of the first classifier to improve the second level of segmentation' Geremia et al.

We have proposed a spatially adaptive RF for hierarchical segmentation that moves from a coarser scale to a finer scale. Meier et al. Semi-supervised RF was used to train subject-specific classifiers for postoperative segmentation of brain tumors. Another method, known as deep learning, addresses representational learning by automatically learning a hierarchy of increasingly complex features directly from the data Therefore, the focus is on designing the architecture, rather than developing hand-crafted features that may require expertise.

PROPOSED SYSTEM

This system proposes a new deep neural network-based method for segmenting brain tumors on MRI images. The patient's MRI brain image is taken as input. The image is preprocessed, filtered, segmented, and then the GLCM feature performs feature extraction of the image. The thresholds required for egmentation are set here depending on the segmented area and location. Finally, deep neural network classification produces an image that is compared to the dataset image to show if the tumor is affected and, if so, the stage to which the tumor belongs.

ADVANTAGES

 Data loss does not affect functionality because the input is stored on a dedicated network rather than a database.

 Shortening calculation time and high accuracy

DESIGN OF THE PROPOSED SYSTEM:

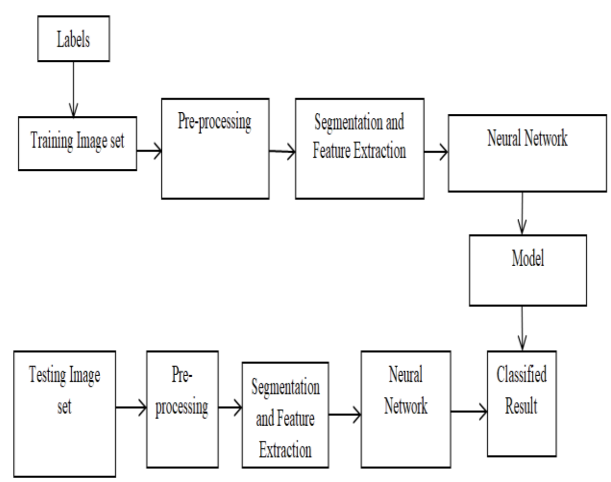

Fig 1. System Design

METHODLOGY:

1. Input Image Search
2. Preprocessing
3. Image Segmentation

4. Feature extraction
5. Classification
6. Display

The image dataset training process is prepared and further process models are developed. First, the input image is selected from the test set. If the input image is a color image, it means converting these color images to gray scale in the preprocessing step and then filtering to reduce noise. Image enhancement is useful for feature extraction, image display, and image analysis

In the segmentation phase, image characteristics such as color, eight, depth, and pixel information are applied before classification. Image segmentation is typically used to find objects and boundaries in an image. In explicit image segmentation, each pixel in the image is assigned a label, so pixels with the same label share certain properties. The result of image segmentation is a set of segments that over the entire image together, or a set of contours extracted from he image Each pixel in the path is the same with respect to properties such as color intensity texture, or calculated properties. The classification phase is used to train the image and build a neural network layer to test the image with the extracted features. Classification compares the segmented image with the dataset image. During the comparison, the segmented tumors are checked for possible similarities in the dataset. After the comparison result, the LCD will show if the input image is affected based on the signal that reaches the Arduino Uno microcontroller from MATLAB over the serial port.

NEURAL NETWORK (NN):

A deep neural cell network (DNN) is an information processing parameter that is inspired by a method of biological nervous system such as a brain. An important factor of this novel structure of an information processing system It consists of a variety of highly interconnected processing lements (neurons) aligned to solve specific issues. NNS learns after an example, like a human being. NN is for a particular application. As pattern recognition or data lassification configured by the learning process' Learning in biological systems involves the coordination of synaptic connections that exist etween neurons.

Neural networks are usually organized in layers. A layer consists of a set of interconnected "nodes" that include an "activate" feature the pattern is presented to the network via the "input layer". The input layer one or more "hidden layers" and the actual processing are done through a weighted "connection" system. The hidden layer is then associated with the "output layer" where the response is output, as shown in the following figure.

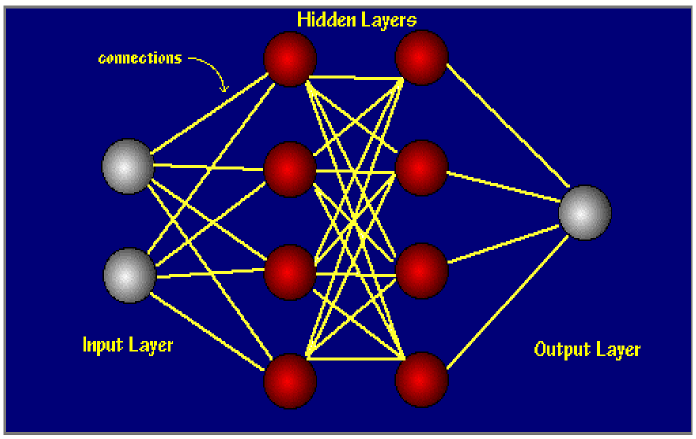

Figure 2. neural network

GUIDE:

GUIDE (Graphical User Interface Design Environment) provides tools for designing user interfaces for ustom apps. The Guide Layout Editor allows you to design the user interface graphically.

GUIDE automatically generates MATLAB code to create the UI. You can change this to program the behavior of your app.

ARDUINO UNO

Arduino is an open source computer hardware nd software ompany, project, and user community that designs single-board microcontrollers and microcontroller kits for building digital and interactive objects that can detect and control objects in the hysical world. And manufacture. arduino is an open source electronics platform ased on easy-to-use hardware and software. The Arduino board can read the sensor's input light, button finger, or Twitter message, convert it to output, activate the motor, turn on the LED, and post something online. Arduino uno is a microcontroller board based on ATmega328 (data sheet). It has 14 digital input / output pins (6 of which can be used as PWM outputs), an analog input, a 16MHz crystal oscillator a USB connector, a power jack, an ICSP header nd a reset button'

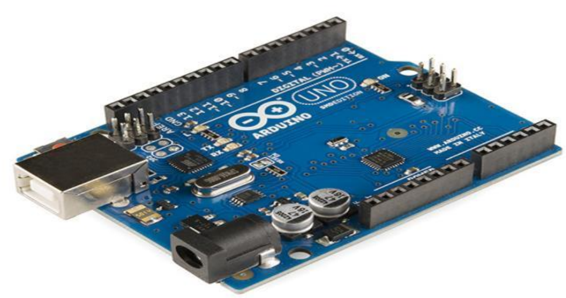

Figure 3.Arduino uno

LCD DISPLAY

LCD (Liquid Crystal Display) are a technology used for displays in notebooks and other small computers. Similar to light emitting diode (LED) and gas plasma technology, LCDs can be used to make displays much thinner than cathode ray tube (CRT) technology. The behavior of LCDs and plasma flat screens is quite different. In a plasma screen each pixel is a small fluorescent light that electronically switches on and off. LCD TVs use LCDs to rotate the polarization to electronically turn pixels on or off.

Figure 4.LCD

CONCLUSIONS

Because brain disorders are dynamic and evolutionary in nature, their perception and treatment also advance based on the dynamic nature of the disorder. Cancer detection and screening techniques need to be reliable, robust, and of high diagnostic value. To this end, work that is effective enough to identify actual indicators of cancer nodules, from image acquisition to cancer detection, is defined. To this end, we propose an NN-based method for classifying segmented MRI images for brain tumor detection. Image processing technology helped solve lighting problems and focus on the tumor. As the size of the training data set is artificially expanded to improve the performance and functionality of the model, we used data expansion to reduce the possibility of over fitting. The results obtained in this paper show that the proposed algorithm is an effective approach for constructing robust image segmentation algorithms and classifications.

REFERENCES

[1] S. Bauer et al ., “A survey of mri -based medical image analysis for brain tumor studies ,” Physics in medicine and biology , vol. 58, no. 13, pp. 97– 129, 2013.

[2] D. N. Louis et al., “The 2007 who classification of tumors of the central nervous system ,” Actaneuropathologica, vol. 114 , no. 2 , pp . 97–109, 2007.

[3] E. G. Van Meir et al., “Exciting new advances in neuro -oncology : The avenue to a cure for malignant glioma ,” CA : a cancer journal for clinicians, vol. 60, no. 3, pp. 166–193, 2010.

[4] G. Tabatabai et al., "Molecular diagnostics of gliomas : the clinical perspective ," Actaneuropathologica, vol. 120 , no. 5 , pp. 585 –592 , 2010.

[5] B. Menze et al., "The multimodal brain tumor image segmentation benchmark (brats)," IEEE Transactions on Medical Imaging, vol . 34 , no. 10 , pp. 1993 –2024 , 2015 .

[6] S. Deelers and S. Auwatanamongkol, "Enhancing K-Means Algorithm with Initial Cluster Centers Derived from Data Partitioning along the Data Axis with the Highest Variance," International Journal of Computer Science, Vol. 2, Number 4

[7] A.M. Fahim, A. M. Salem, F. A. Torkey and M. A. Ramadan, "An Efficient enhanced k-means clustering algorithm," Journal of Zhejiang University, 10(7): 16261633, 2006.

[8] K. A. Abdul Nazeer and M. P. Sebastian, "Improving the accuracy and efficiency of the k-means clustering algorithm," in International Conference on Data Mining and Knowledge Engineering (ICDMKE),Proceedings of the World Congress on Engineering (WCE-2009), Vol 1, July 2009 , London , UK .

[9] F . Yuan , Z. H. Meng, H. X. Zhangz , C. R. Dong, " A New Algorithm to Get the Initial Centroids ," proceedings of the 3rd International Conference on Machine Learning and Cybernetics , pp. 26 -29 , August 2004 .

[10] Koheri Arai and Ali Ridho Barakbah , "Hierarchical K-means : an algorithm for Centroids initialization for k-means ," department of information science and Electrical Engineering Politechnique in Surabaya , Faculty of Science and Engineering , Saga University , ol. 36 , No.1 , 2007 .