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Hybrid Model Implementation for Brain Tumor Detection System using Deep Neural Networks

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Abstract: ***A brain tumor arises when there is uncontrolled division of cells forming an abnormal group of cells around or inside the brain. That group of cells can affect the normal functionality of the brain activity and destroy the healthy cells. Brain magnetic resonance imaging (MRI) is one of the best imaging techniques that researchers relied on for detecting the brain tumors and modeling of the tumor progression in both the detection and the treatment phases. MRI images have a big impact in the automatic medical image analysis field for its ability to provide a lot of information about the brain structure and abnormalities within the brain tissues due to the high resolution of the images. There are different techniques like Histogram based, manual, grey shade segmentation which are used to find the edges. Segmentation is used on various structures in a histopathology slide image using methods like thresholding, enhancement, and adaptive thresholding which tends to work only on uniform images. In the proposed work segmentation is used which leads to better separation of objects than the grey-shade-only segmentation. The previous method produces the result without transmission with 97% of accuracy but the proposed work with transmission produced enhanced results with the accuracy of 98%.***
Keywords: MRI, Tumour, Crysts, Deep Neural Network, PSNR, MSE.

I. INTRODUCTION

Brain is one of the most complex organs in the human body that works with billions of cells. A brain tumor arises when there is uncontrolled division of cells forming an abnormal group of cells around or inside the brain. That group of cells can affect the normal functionality of the brain activity and destroy the healthy cells [1].

Brain tumors are classified to benign or low-grade (grade I and II) and malignant tumors or high-grade (grade III and IV). Benign tumors are no progressive (non-cancerous) so considered to be less aggressive. They are originated in the brain and grow slowly; also it cannot spread to anywhere else in the body. However, malignant tumors are cancerous and grow rapidly with undefined boundaries. They can be originated in the brain itself which called primary malignant tumor or to be originated elsewhere in the body and spread to the brain which called secondary malignant tumor [2].

Brain magnetic resonance imaging (MRI) is one of the best imaging techniques that researchers relied on for detecting the brain tumors and modeling of the tumor progression in both the detection and the treatment phases. MRI images have a big impact in the automatic medical image analysis field for its ability to provide a lot of information about the brain structure and abnormalities within the brain tissues due to the high resolution of the images [3].

In fact, Researchers presented different automated approaches for brain tumors detection and type classification using brain MRI images since it became possible to scan and load medical images to the computer. However, Support Vector Machine (SVM) and Neural Networks (NN) are the widely used approaches for their good performance over the last few decades [4].

But recently, deep learning (DL) models set an exciting trend in machine learning as the deep architecture can efficiently represent complex relationships without requiring a huge number of nodes like in the shallow architectures e.g. SVM and K-nearest neighbor (KNN). For that reason, they grew rapidly to become the state of the art in different health informatics areas such as bioinformatics, medical informatics and medical image analysis [5].

The rapid evolution of advanced medical image modalities such as the modern MRI scanners and the large amount of data provided have brought about the need for more automatic processes in computer aided diagnosis. Clinicians need to examine large numbers of complex medical images to detect abnormalities; a difficult and time consuming task. Hence, there is a need for systems that will automatically detect organs and their possible abnormalities and provide useful metrics [6].

This paper is organized in five sections. Section 1, provides the introduction and classification of brain tumors and recent methods of detecting brain tumors. Section 2 describes the brain imaging using MRI and various imaging modalities. Section 3, provides the proposed methodology and flowchart used to obtain brain imaging using MRI. Various results and comparison of existing as well as proposed techniques are provided in section 4. Section 5 provides the different conclusions.

II. BRAIN IMAGING

There exists a variety of different imaging modalities that enable the study of the brain. This section presents a brief overview of the different imaging methods, then focus on Magnetic Resonance Imaging (MRI) which is the most common modality for brain tumor observation.

A. Imaging Modalities

Brain imaging modalities can be grouped in two categories according to the information being captured by them: structural and functional imaging. The structural or anatomical modalities aim at visualizing the different structures and tissues of the brain. Among them, the most popular for Neuro-imaging studies are the Computed Tomography (CT) and MRI. CT imaging relies on X-ray technology that is based on the absorption of X-rays beams as they pass through the different tissues of a patient's body. CT scans are constructed by using a series of X-ray beams that rotate around the patient's head [7-8].

Each beam yields a 2D image at a specific angle that is used to construct a 3D volume by tomographic reconstruction. CT scans are well contrasted and high resolution images. The main drawback of this technique is the fact that it uses ionizing radiation. MRI relies on the magnetic property of the hydrogen nuclei present in large quantity in the human body. It is the modality of choice for brain studies due to its high tissue contrast and details and non ionizing property. In the recent years, new techniques have developed such as Diffusion Tensor Imaging (DTI) [9]. This modality enables the reconstruction of the white matter tracts connecting the different parts of the neural networks in the brain by measuring the anisotropic diffusion of water inside the tissues. The presence of a tumor could have a direct impact on the fibre structures by causing disruption, displacement or infiltration of the fibres. Modalities such as MR spectroscopy (measurement of major metabolites in tumor tissue) and Perfusion MRI (measurement of the relative cerebral blood volume using a contrast agent) provide additional information's for the diagnosis and study of brain tumors [10]. The goal of functional imaging is to study the human brain's function based on physiological changes caused by the brain's activity. Electroencephalography (EEG) and Magneto encephalography (MEG) are techniques that offer means of directly measuring the brain activity. EEG detects the electrical impulses in the brain due to the neuronal activity via electrodes placed on the scalp. MEG measures the magnetic flux changes using sensors positioned closed to the scalp [8]. The methods are popular due to their simplicity, the fact that they are non invasive and their very high temporal resolution. Determining precisely the spatial origin of the observed signal is however difficult. Position Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) are nuclear imaging techniques that measure changes in the cerebral blood flow and tissue metabolism and how it is altered by brain disorders. A biological molecule is marked with a radioactive isotope and injected in the bloodstream and accumulated in areas where the molecule has affinity. The advantage of this method is that the radioactive tracer can be designed specifically to target specific organs or processes related to an illness [9]. For instance, a radioactive isotope typically used is the Fluoro deoxy glucose (FDG) that behaves like glucose molecules and therefore is able to trace the brain's metabolic activity. However, the technique is invasive and potentially harmful due to the use of radioactive tracers while at the same time producing the isotopes is costly and difficult. Nowadays, CT and PET technologies are being combined in one device, allowing combining the anatomical information recovered from the CT scans with the metabolic information given by the PET scans [9].

Functional MRI (fMRI) exploits the Blood Oxygen Level Dependent (BOLD) contrast to detect changes in the neuronal activity induced by sensor motor or cognitive tasks. Neuronal activation causes an increase of the blood flow to compensate the oxygen consumption and therefore reduces the amount of deoxygenated haemoglobin molecules. The detection of changes in haemoglobin oxygenation relies on the paramagnetic properties of the deoxygenated haemoglobin which impacts the measured NMR signal [8].

fMRI is often used for tumor surgery planning in order to identify the spatial relationship between the lesion and the functional area and evaluate the corresponding risks. Time constraints in the acquisition of the signal cause the fMRI images to be of lower quality than the structural MRI. Functional imaging is particularly important for brain tumor surgery planning. It enables to establish a relationship between the lesion and the functional area and plan the surgery accordingly (extent of resection, awake craniotomy) [8].

III. METHODOLOGY

The thesis is to implement 3-D detection of brain and their pathology in real time. The whole design & development carried out in three stages: 1) Image Processing involves tumor segmentation 2) Feature Extraction 3) Implementation of classifier. The processing is done on cancer affected MRI images of brain. Image enhancement, tumor separation and then feature extraction using Deep Neural Network. Extracted features are provided to the classifier as an input for classification.

A suitable Auto encoder DNN is developed to recognize the type of tumor in the classifier output. The Graphical User Interface (GUI) is created to make the system user friendly. The block diagram for the proposed system is shown in fig 1.

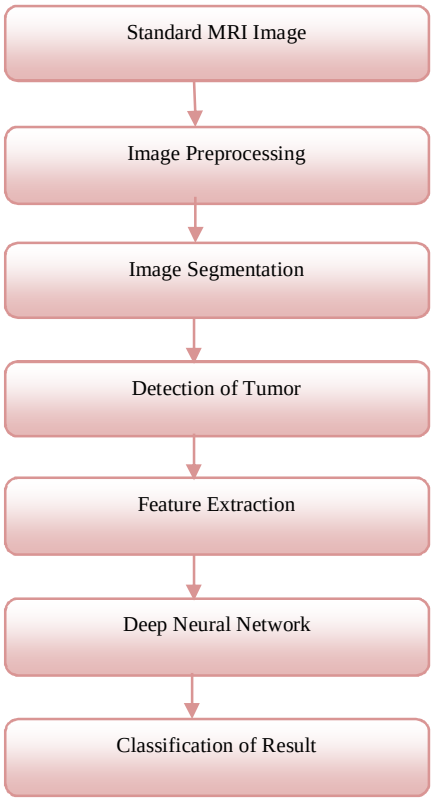

Figure 1: Block Diagram of the System

These aims were achieved by carrying out the steps below:

1) The Region of Interest is defined.

2) The parameters used to accurately find the organ and its boundaries are defined: Width (for smoothing the histogram and get the correct boundaries of the organ), ascending and descending (for identifying local minimums), threshold (for removing the noise from the use of erosion—dilation morphological filters) and area (for initial identification of the organ ignoring tiny areas).

3) The parameters to find the correct seeds for the pathology detection to feed to the region growing algorithm are also defined: Grayscale and a tolerance value for the range of values to represent a dysfunction, as well as a threshold value for the erosion filter used to change the sensitivity governing the discard of seeds that are not strong enough.

A. Algorithm Used

1) *Step 1:* Start image reading using imread command.

2) *Step 2:* To select the Training database location

a) Traindatabase = uigetdir();

b) if image is color image then convert into grayscale image using rgb2gray (original_Image); else go to step 3.

3) *Step 3:* Apply histogram equalization using imhist (original_Image).

4) *Step 4:* Fill the image using color with command Imfill (binary_Image, 'holes');

5) *Step 5:* Apply region processing using region props (labelled_Image, original_Image, 'all').

6) *Step 6:* Detect black and white boundary of image.

a) detect_boundary (labelled_Image, 'clockwise');

7) *Step 7:* Detect different parameters like Segment, Mean, Intensity, Area, Perimeter, Centroid, and Diameter.

8) *Step 8:* Detect boundary of effect part of MRI image.

9) *Step 9:* Apply Hybrid technique Deep Neural Network and FFT.

10) *Step 10:* Classify the result and calculate PSNR and MSE. [T train_number CT] = Conn_classify (train_database, LD);

11) *Step 11:* Stop

IV. RESULTS

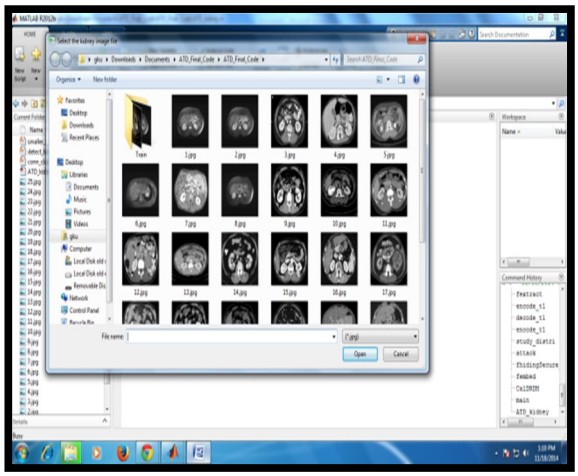

Figure 2: Browsing the input image

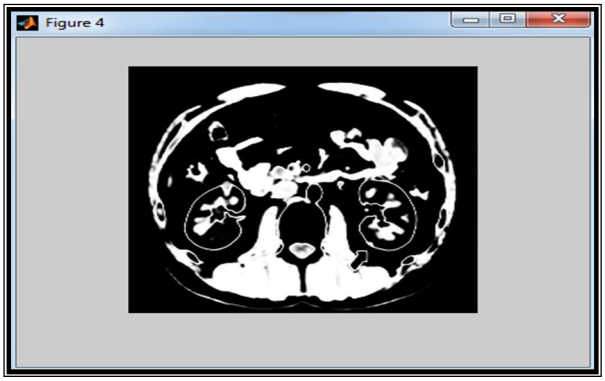

Figure 3: Outlining of Affected portion

In figure 2 the input image is browsed to detect any abnormality in the image. In figure 3 the affected (abnormal) portion is outlined to conduct the testing using MRI. Figure 4 provides the various results obtained using MRI testing. Figure 5 identifies the abnormality in image and detect any tumour in brain.

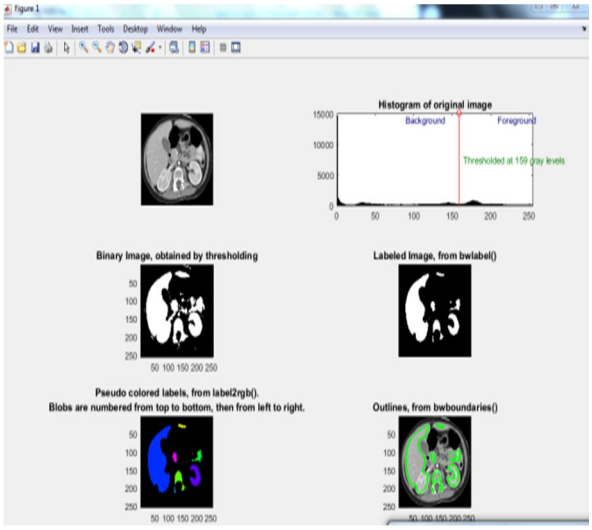

Figure 4: Result of the MRI after testing

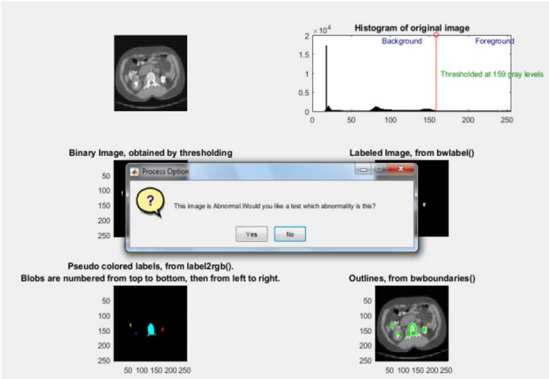

Figure 5: Identifying the abnormality in image

Table 1: Existing and Proposed work Comparison

Images	Existing		Proposed	
	PSNR	MSE	PSNR	MSE
1.jpg	14.011	6.121	15.5488	6.1373
2.jpg	13.82	3.116	14.2965	3.1255
3.jpg	14.12	8.068	15.1218	7.1073
4.jpg	13.86	4.77	14.6575	3.885
5.jpg	13.79	5.84	14.8564	4.85
6.jpg	13.82	7.79	14.5823	6.1373
7.jpg	13.99	6.92	14.6575	6.02
8.jpg	14.004	7.35	15.5486	6.1337
9.jpg	14.066	6.215	15.54	6.132
10.jpg	14.03	6.172	15.457	6.012

Table 1 compares the results of ten selected images using existing and proposed techniques in terms of peak signal to noise ratio (PSNR) and mean square error (MSE). Analyses of these results provide that proposed method results are better for all the images. The result comparison is also provided in figure 6.

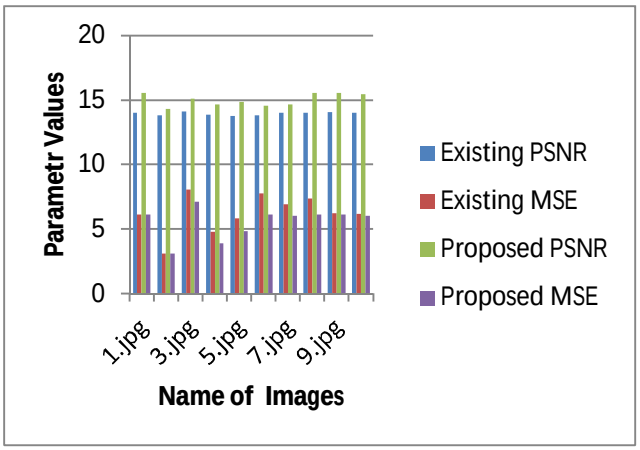

Figure 6: Comparison of existing and proposed work

The figure 6 is the comparison of existing and proposed work. In this figure existing and proposed work PSNR and MSE is plotted. In this figures are plotted on x-axis and parameters are plotted on y-axis.

V. CONCLUSIONS

The originality of this work lies in the full automation of the methods due to original translation of anatomical knowledge into topological and geometrical constraints. Our multifunctional platform focusing on the clinical diagnosis of kidneys and their pathology (tumors, stones and cysts), using a "templates"-based technique. Apart from being accurate, the automatic mode is notably faster compared with any existing method to date for the automatic recognition of the kidneys, while it is also the first platform that simultaneously identifies abnormalities in the organ's area such as tumors, stones, and cysts. It also aids in the intra-operative localization of structures (tumors, anatomical segments). In image processing, images convey the information where input image is processed to get output also an image. In today's world, the images used are in digital format. In recent times, the introduction of information technology and e-healthcare system in medical field helps clinical experts to provide better health care for patients. This study reveals the problem segmentation of abnormal and normal tissues from MRI images using gray-level co-occurrence matrix (GLCM) feature extraction and deep neural network classifier. In this work maximum PSNR is 15.5488 and MSE is 3.1255 but existing work PSNR is 14.066 and MSE is 8.068.

This research work can extend on liver and the real time dataset of coloured images of the different patients to detect the stone and cysts with the help of different algorithms.

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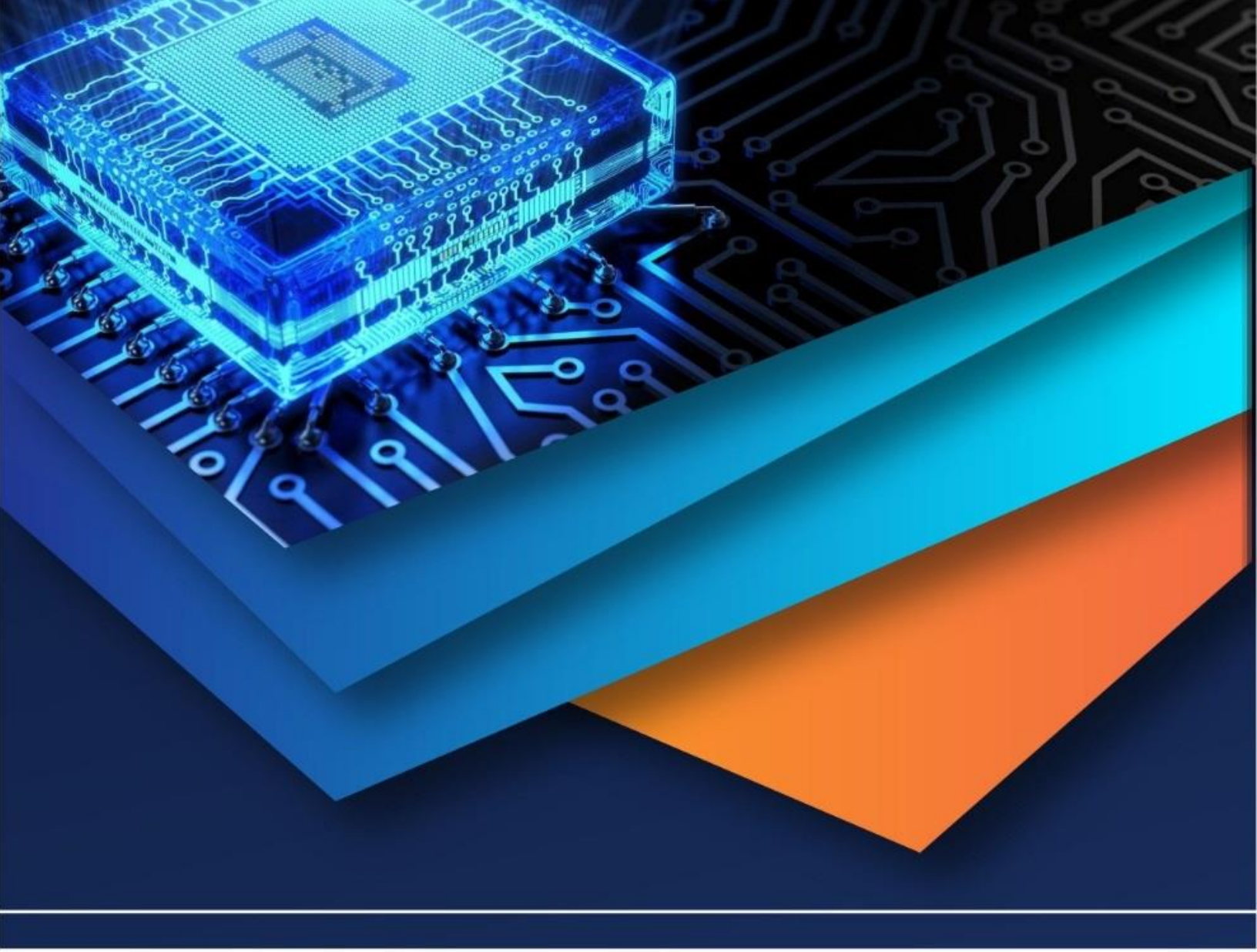

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