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BRAIN TUMOR DETECTION FROM MRI IMAGE USING DIGITAL IMAGE PROCESSING

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ABSTRACT:

Tumor detection and removal is one medical issue that still remains challenging in field of biomedicine. Early imaging techniques had the drawback of being invasive and hence the CT and MRI imaging technique help the surgeons in providing a better vision. In this paper, tumor image processing involves three stages namely pre-processing, segmentation and morphological operation. After the acquisition of the source image, it is pre-processed by converting the original image to gray scale in addition high pass filter for noise removal and median filter for quality enhancement is provided which is followed by enhancement stage resulting with histogram equivalent image. Finally segmentation is done by means of watershed algorithm. The above proposed methodology is helpful is generating the reports automatically in less span of time and advancement has resulted in extracting many inferior parameters of the tumor. The present work demonstrates that method can successfully detect the brain tumor and thereby help the doctors for analyzing tumor size and region .The algorithms have been developed by using MATLAB/PYHTON

INTRODUCTION

Machine learning algorithms have the potential to be invested deeply in all fields of medicine, from drug discovery to clinical decision making, significantly altering the way medicine is practiced. The success of machine learning algorithms at computer vision tasks in recent years comes at an opportune time when medical records are increasingly digitalized. The use of electronic health records (EHR) quadrupled from 11.8% to 39.6% amongst office-based physicians in the US from 2007 to 2012 [1]. Medical images are an integral part of a

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patient's EHR and are currently analyzed by human radiologists, who are limited by speed, fatigue, and experience. It takes years and great financial cost to train a qualified radiologist, and some health-care systems outsource radiology reporting to lower-cost countries such as India via tele-radiology. A delayed or erroneous diagnosis causes harm to the patient. Therefore, it is ideal for medical image analysis to be carried out by an automated, accurate and efficient machine learning algorithm. Medical image analysis is an active field of research for machine learning, partly because the data is relatively structured and labelled, and it is likely that this will be the area where patients first interact with functioning, practical artificial in- telligence systems. This is significant for two reasons. Firstly, in terms of actual patient metrics, medical image analysis is a litmus test as to whether artificial intelligence systems will actually improve patient outcomes and survival. Secondly, it provides a testbed for human-AI interaction, of how receptive patients will be towards healthaltering choices being made, or assisted by a non-human actor.

LITERATURE REVIEW

IN "C.-J. HSIAO, E. HING, AND J. ASHMAN, ``TRENDS IN ELECTRONIC HEALTH RECORD SYSTEM USE AMONG OFFICE-BASED PHYSICIANS: UNITED STATES, 2007fl2012,''*NAT. HEALTH STAT. REP.*, VOL. 75, PP. 1fl18, MAY 2014.": This report presents trends in the adoption of electronic health records (EHRs) by office-based physicians during 2007-2012. Rates of adoption are compared by selected physician and practice characteristics.The National Ambulatory Medical Care Survey (NAMCS) is based on a national probability sample of nonfederal office-based physicians who see patients in an office setting. Prior to 2008, data on physician characteristics were collected through in-person interviews with physicians. To increase the sample for analyzing physician adoption of EHR systems, starting in 2008, NAMCS physician interview data were supplemented with data from an EHR mail survey. This report presents estimates from the 2007 in-person interviews, combined 2008-2010 data from both the in-person interviews and the EHR mail surveys, and 2011-2012 data from the

EHR mail surveys. Sample data were weighted to produce national estimates of office-based physician characteristics and their practices

IN "R. SMITH-BINDMAN *ET AL.*, ``USE OF DIAGNOSTIC IMAGING STUDIES AND ASSOCIATED RADIATION EXPOSURE FOR PATIENTS ENROLLED IN LARGE INTEGRATED HEALTH CARE SYSTEMS, 1996fl2010,'' *JAMA*, VOL. 307, NO. 22, PP. 2400fl2409, 2012."

THE USE OF DIAGNOSTIC IMAGING in the Medicare population has increased significantly over the last 2 decades, particularly using expensive new technologies such as computed tomography (CT), magnetic resonance imaging (MRI), and nuclear medicine positron emission tomography (PET).1,2 The development and improvement in these advanced diagnostic imaging technologies is widely credited with leading to earlier and more accurate diagnoses of disease using noninvasive techniques.

IN "G. LITJENS *ET AL.* (JUN. 2017). ``A SURVEY ON DEEP LEARNING IN MEDICAL IMAGE ANALYSIS.'' Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. This paper reviews the major deep learning concepts pertinent to medical image analysis and summarizes over 300 contributions to the field, most of which appeared in the last year. We survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise overviews are provided of studies per application area: neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal, musculoskeletal. We end with a summary of the current state-of-the-art, a critical discussion of open challenges and directions for future research As soon as it was possible to scan and load medical images into a computer, researchers have built systems for automated analysis. Initially, from the 1970s to the 1990s, medical image analysis was done with sequential application of low-level pixel processing (edge and line detector filters, region growing) and mathematical modeling (fitting lines, circles and ellipses) to construct compound rule-based systems that solved particular tasks.

Existing System:

A benign (non-cancerous) brain tumour is a mass of cells that grows slowly in the brain.

It usually stays in one place and does not spread. The symptoms of a benign brain tumour depend on how big it is and where it is in the brain. Some slow-growing tumours may not cause any symptoms at first. Common symptoms include severe, persistent headaches, seizures (fits), persistent nausea, vomiting and drowsiness.

The above proposed methodology is helpful is generating the reports automatically in less span of time and advancement has resulted in extracting many inferior parameters of the tumor. The present work demonstrates that method can successfully detect the brain tumor and thereby help the doctors for analyzing tumor size and region.

Proposed System:

Threshold is used to convert an intensity image. On applying morphological operation erode the image to get tumor portion image. To test the effectiveness of the proposed scheme, we have tested the density based morphological brain MR image segmentation method, proposed algorithm is applied on the image.

The proposed system is developed for the diagnosing of tumour from magnetic resonance imaging pictures of the brain. This method makes the diagnosing in many phases. In the preprocessing stage filtering is performed on brain MR images. In image segmentation stage K-mean clustering method used to segment an MR image.

Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous or non-cancerous. When cancerous or non-cancerous tumors grow, they can cause the pressure inside or skull to increase. This can cause brain damage, and it can be life threatening.

Advantage:

Certain atomic nuclei can absorb and emit radio frequency energy when placed in an external magnetic field. In clinical and research MRI, hydrogen atoms are most-often used to generate a detectable radio-frequency signal that is received by antennas in close proximity to the anatomy being examined. Hydrogen atoms exist naturally in people and other biological organisms in abundance, particularly in water and fat.

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful

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information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies

This operation is the collection of nonlinear operation related to the shape or morphology of features in an image. Morphological operation on a binary image creates a new binary image in which the pixel has non-zero value only if the test is successful at that location in the input image.

Disadvantage:

Image processing basically includes the following three steps:

(i) Importing the image via image acquisition tools;

(ii) Analyzing and manipulating the image;

(iii) Output in which result can be altered image or report that is based on image analysis.

REQUIREMENT ANALYSIS

The project involved analyzing the design of few applications so as to make the application more users friendly. To do so, it was really important to keep the navigations from one screen to the other well ordered and at the same time reducing the amount of typing the user needs to do. In order to make the application more accessible, the browser version had to be chosen so that it is compatible with most of the Browsers.

REQUIREMENT SPECIFICATION

Functional Requirements

- Graphical User interface with the User.

Software Requirements

For developing the application the following are the Software Requirements:

1. Python
2. Django

Operating Systems supported

1. Windows 10 64 bit OS

Technologies and Languages used to Develop

1. Python

Debugger and Emulator

- Any Browser (Particularly Chrome)

Hardware Requirements

For developing the application the following are the Hardware Requirements:

- Processor: Intel i3
- RAM: 4 GB
- Space on Hard Disk: minimum 1 TB

INPUT AND OUTPUT DESIGN

INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy. Input Design considered the following things:

- What data should be given as input?
- How the data should be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occur.

OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.

2.Select methods for presenting information.

3.Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the
- Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

CONCLUSION:

Arecurring theme in machine learning is the limit imposed by the lack of labelled datasets, which hampers training and task performance. Conversely, it is acknowledged that more data improves performance, as Sun et al. [85] shows using an internal Google dataset of 300 million images. In general computer vision tasks, attempts have been made to circumvent limited data by using smaller lters on deeper layers [47], with novel CNN architecture combinations [86], or hyperparameter optimization [87]. In medical image analysis, the lack of data is two-fold and more acute: there is general lack of publicly available data, and high quality labelled data is even more scarce. Most of the datasets presented in this review involve fewer than 100 patients. Yet the situation may not be as dire as it seems, as despite the small training datasets, the papers in this review report relatively satisfactory performance in the various tasks. The question of how many images are necessary for training in medical image analysis was partially answered by Cho et al. [88]. He ascertained the accuracy of a CNN with GoogLeNet architecture in classifying individual axial CT images into one of 6 body regions: brain, neck, shoulder, chest, abdomen, pelvis. With 200 training images, accuracies of 88-98% were achieved on a test set of 6000 images. While categorization into various body regions is not a realistic medical image analysis task, his report does suggest that the problem may be surmountable. Being able to accomplish classication with a small dataset is possibly due to the general intrinsic image homogeneity across different patients, as opposed to the near-innite variety of natural images, such as a dog in various breeds, colors and poses. VAEs and GANS, being generative models, may sidestep the data paucity problem, by creating synthetic medical data. This was done by Guibas and Virdi, who used a 2 stage GAN to segment and then generate retinal fundus images successfully [89]. Their work was built on the research of Costa et al. [90], which rst described using GANs to generate retinal fundus images. Aside from synthetic data generation, GANs have been used in brain MRI segmentation as well by Moeskops et al. [91], Kamnitsas et al. [92] and Alex et al. [93]. Data or class imbalance in the training set is also a signi cant issue in medical image analysis [94]. This refers to the number of images in the training data being skewed towards normal and non-pathological images. Rare diseases are an extreme example of this and can be missed without adequate training examples. This data imbalance effect can be ameliorated by using data augmentation to generate more training images of rare or abnormal data, though there is risk of overtting. Aside from data-level strategies, algorithmic modication strategies and cost sensitive learning have also been studied [95], [96]. An important, non-technical challenge is the public reception towards their health results being studied by a nonhuman actor. This situation is not helped by the apocalyptic articial intelligence scenarios painted by some. Machine learning algorithms have surpassed human performance in image recognition tasks, and it is likely that they will perform better than humans in medical image analysis as well. Indeed some of the papers in this review report that dermatologists and radiologists have already been bested by machine learning. Yet the question regarding legal and moral culpability arises when a patient is misdiagnosed, or suffers morbidity as a result of AI or AI-assisted medical management. This is accentuated by our inability to fully explain how the blackbox of machine algorithmswork. However, it is likely that our relationship will continue evolve and recalibrate as AI-based technologies mature and inexorably permeate different facets of our lives

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