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Brain Tumour Detection Using Machine Learning

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ABSTRACT: Brain is the regulatory unit in human body. It controls the functions such as memory, vision, hearing, knowledge, personality, problem solving, etc. The main reason for brain tumour is the abandoned progress of brain cells. Many health organizations have recognized brain tumour as the second foremost dispute that causes a large number of human deaths all around the world. Identification of brain tumour at a premature stage offers a opportunity of effective medical treatment. Use of Magnetic Resonance Imaging images have been recognized as more detailed and more consistent images when compared to Computed Tomography images. There are various techniques to detect brain tumour or neoplasms. The most competent and effective algorithms are discussed in this paper after studying a number of appropriate research papers. Pre-processing brain images, segmenting them, feature extraction; clustering and detection of the tumour are the methodologies in most researches.

Keywords *–Brain Tumour, Magnetic resonance, Machine Learning*

1. INTRODUCTION

Brain tumors pose a formidable challenge in the realm of medical science, demanding effective and efficient diagnostic strategies, particularly during the early stages of tumor growth. The gold standard for brain tumor grading has long been histological grading, which relies on a stereotactic biopsy procedure. However, this invasive method entails significant risks, including bleeding from the tumor and brain, infection, seizures, severe migraines, strokes, comas, and even mortality. Moreover, the inherent limitation of biopsy accuracy raises concerns about potential diagnostic errors and subsequent misguided clinical management. Given the formidable hurdles and risks associated with stereotactic biopsy, there has been a growing reliance on non-invasive imaging techniques, most notably Magnetic Resonance Imaging (MRI), in the diagnosis of brain tumors.The utilization of MRI in brain tumor diagnostics has become increasingly prevalent, underscoring the urgent need to develop systems capable of detecting and predicting tumor grades based on MRI data. However, the initial interpretation of MRI images presents a formidable challenge due to factors such as inadequate illumination, the sheer volume of data generated, and the intricacies and variations exhibited by brain tumors. These complexities manifest as unstructured shapes, variable sizes, and unpredictable locations of tumors within the brain tissue.

In recent years, the emergence of automated defect detection in medical imaging, powered by machine learning, has revolutionized diagnostic applications across the medical field. In particular, its application in the detection of brain tumors within MRI scans has assumed paramount importance. Automated systems harness the potential to unearth crucial information about abnormal tissues, an indispensable aspect of treatment planning. Recent literature has also underscored the potential of automatic computerized detection and diagnosis, grounded in medical image analysis, as a compelling alternative. Not only does it promise to save valuable time for radiologists, but it also holds the prospect of achieving tested levels of diagnostic accuracy. Furthermore, the advent of computer algorithms capable of providing robust and quantitative measurements of tumor depiction has the potential to significantly alleviate the clinical management of brain tumors. These automated measurements can liberate physicians from the laborious burden of manually delineating tumor boundaries and characteristics. The landscape of brain tumor diagnosis and management stands at a critical juncture, where the synergy between cuttingedge technologies, such as MRI and machine learning, offers a glimmer of hope in the battle against this relentless disease. In the following exploration, we delve deeper into the multifaceted challenges associated with brain tumor diagnosis, dissect the merits of non-invasive imaging, and embark on an enlightening journey through the realm of automated defect detection using machine learning. We shall traverse the current state of brain tumor diagnosis, the pivotal role of MRI, and the potential of machine learning-driven automation to usher in a new era of precision and efficiency in the clinical management of this formidable adversary.

2. LITERATURE REVIEW

A survey of MRI-based medical image analysis for brain tumor studies

MRI-based medical image analysis for brain tumor studies is gaining attention in recent times due to an increased need for efficient and objective evaluation of large amounts of data. While the pioneering approaches applying automated methods for the analysis of brain tumor images date back almost two decades, the current methods are becoming more mature and coming closer to routine clinical application. This review aims to provide a comprehensive overview by giving a brief introduction to brain tumors and imaging of brain tumors first. Then, we review the state of the art in segmentation, registration and modeling related to tumor-bearing brain images with a focus on gliomas. The objective in the segmentation is outlining the tumor including its sub-compartments and surrounding tissues, while the main challenge in registration and modeling is the handling of morphological changes caused by the tumor. The qualities of different approaches are discussed with a focus on methods that can be applied on standard clinical imaging protocols. Finally, a critical assessment of the current state is performed and future developments and trends are addressed, giving special attention to recent developments in radiological tumor assessment guidelines.

The multimodal brain tumor image segmentation benchmark (BRATS)

In this paper we report the set-up and results of the Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) organized in conjunction with the MICCAI 2012 and 2013 conferences. Twenty state-of-the-art tumor segmentation algorithms were applied to a set of 65 multi-contrast MR scans of low- and high-grade glioma patients - manually annotated by up to four raters - and to 65 comparable scans generated using tumor image simulation software. Quantitative evaluations revealed considerable disagreement between the human raters in segmenting various tumor sub-regions (Dice scores in the range 74%-85%), illustrating the difficulty of this task. We found that different algorithms worked best for different sub-regions (reaching performance comparable to human inter-rater variability), but that no single algorithm ranked in the top for all sub-regions simultaneously. Fusing several good algorithms using a hierarchical majority vote yielded segmentations that consistently ranked above all individual algorithms, indicating remaining opportunities for further methodological improvements. The BRATS image data and manual annotations continue to be publicly available through an online evaluation system as an ongoing benchmarking resource.

Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

Among brain tumors, gliomas are the most common and aggressive, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of oncological patients. Magnetic resonance imaging (MRI) is a widely used imaging technique to assess these tumors, but the large amount of data produced by MRI prevents manual segmentation in a reasonable time, limiting the use of precise quantitative measurements in the clinical practice. So, automatic and reliable segmentation methods are required; however, the large spatial and structural variability among brain tumors make automatic segmentation a challenging problem. In this paper, we propose an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3 ×3 kernels. The use of small kernels allows designing a deeper architecture, besides having a positive effect against overfitting, given the fewer number of weights in the network. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Our proposal was validated in the Brain Tumor Segmentation Challenge 2013 database (BRATS 2013), obtaining simultaneously the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric (0.88, 0.83, 0.77) for the Challenge data set. Also, it obtained the overall first position by the online evaluation platform. We also participated in the on-site BRATS 2015 Challenge using the same model, obtaining the second place, with Dice Similarity Coefficient metric of 0.78, 0.65, and 0.75 for the complete, core, and enhancing regions, respectively.

Brain tumor detection based on watershed transformation

In this paper, a watershed transformation technique is used with gradient magnitude with morphological open image and two important features is used as foreground and background to identify the tumor. First the Magnetic Resonance imaging (MRI) Scan of tumor is given as an input and it undergoes into watershed technique which is a topological boundary dividing into two adjacent brain cells. With the gradient magnitude for segmentation technique the rate of inclination or declination of a tumor will be identified. To identify the foreground of the tumor, open the image morphological, thus it acquires clear idea about how the particular tumor will be closer to normal cells. With the background marker, the invisible tumor will be identified using threshold value. In the segmentation output finally, the intensity, size, shape of the tumor in the brain is displayed and can be analysis.

An adaptive filtering technique filtering technique for brain tumor analysis and detection

Brain tumor detection in an early stage is a difficult task, as the imaging is quite unclear. The necessity of automated brain tumor segmentation and detection is high. To obtain an accurate MRI image of the brain tumor is challenging. An MRI image has high contrast images indicating regular and irregular tissues that help in differentiating the overlap margins. But in case of an early brain tumor, the edges of the image are not sharp which causes the segmentation results to be inaccurate. Hence, this paper puts forth a method for detection and segmentation of the tumor. The method proposed here is a segmentation process of 2D MRI image using various filtering techniques. MATLAB has been used for the implementation.

3. METHODOLOGY

MRI provides valuable tissue contrasts for brain tumor diagnosis. Manual segmentation is time-consuming, requiring neuroradiologists. Automated tumor segmentation can improve diagnosis, treatment, and aid in timely neuro disorder management.

Disadvantages:

- It manual detection is a time taking process to detect brain tumor from MRI scan

Automated brain tumor detection in MRI scans is vital due to impractical human inspection. Machine learning methods offer accuracy and efficiency, addressing the complexity of tumor detection in this project.

Advantages:

- It is considered as the best ml technique for image classification due to high accuracy.
- It can automatically learn to perform any task just by going through the training data i.e. there no need for prior knowledge.

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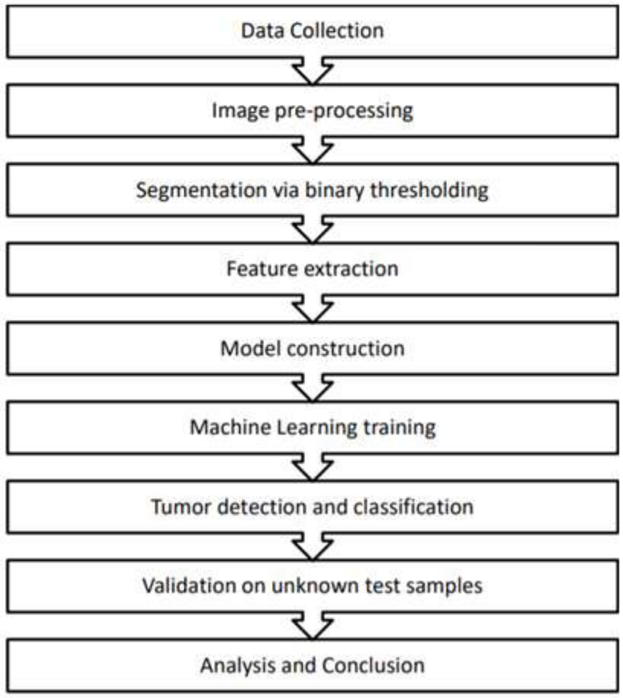

Fig.1: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Upload image Dataset-we will upload sample images from dataset
- Preprocess Dataset-using the module we will read data for processing
- Splitting Data-using this module data will be divided into train and test
- Model Generation-build model Random Forest, accuracy calculated.
- Run Random Forest Algorithm
- Run KNN Algorithm
- Upload Test Image Data-using this module we will give input for prediction
- Accuracy Graph-final prediction displayed.

3. IMPLEMENTATION

Machine Learning:

Before we take a look at the details of various machine learning methods, let's start by looking at what machine learning is, and what it isn't. Machine learning is often categorized as a subfield of artificial intelligence, but I find that categorization can often be misleading at first brush. The study of machine learning certainly arose from research in this context, but in the data science application of machine learning methods, it's more helpful to think of machine learning as a means of building models of data.

Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models tunable parameters that can be adapted to observed data; in this way the program can be considered to be "learning" from the data. Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain. Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches we'll discuss here.

Challenges in Machines Learning:-

While Machine Learning is rapidly evolving, making significant strides with cyber security and autonomous cars, this segment of AI as whole still has a long way to go. The reason behind is that ML has not been able to overcome number of challenges. The challenges that ML is facing currently are −

Quality of data − Having good-quality data for ML algorithms is one of the biggest challenges. Use of low-quality data leads to the problems related to data preprocessing and feature extraction.

Time-Consuming task − Another challenge faced by ML models is the consumption of time especially for data acquisition, feature extraction and retrieval.

Lack of specialist persons − As ML technology is still in its infancy stage, availability of expert resources is a tough job.

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No clear objective for formulating business problems − Having no clear objective and well-defined goal for business problems is another key challenge for ML because this technology is not that mature yet.

Issue of over fitting & under fitting − If the model is over fitting or under fitting, it cannot be represented well for the problem.

Curse of dimensionality − another challenge ML model faces is too many features of data points. This can be a real hindrance.

Difficulty in deployment − Complexity of the ML model makes it quite difficult to be deployed in real life.

Algorithm:

Random Forest: Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of over fitting.

The below diagram explains the working of the Random Forest algorithm:

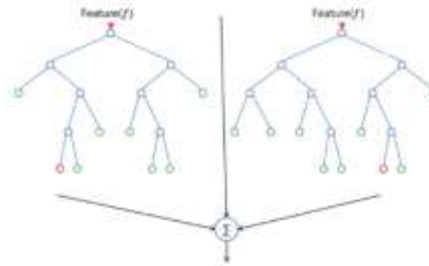

Fig.2 : Random Forest Architecture

5. EXPERIMENTAL RESULTS

Fig.3: Output

Fig.4: Output

Fig.5: Output

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Fig.6: Output

Fig.7: Output

Fig.8: Output

Fig.9: Output

Fig.10: Output

6. CONCLUSION

The proposed system represents a significant advancement in the field of brain tumor detection, utilizing a combination of machine learning techniques, specifically the Random Forest Algorithm and the K-Nearest Neighbors (KNN) Algorithm. This innovative approach offers a mechanical means of detecting brain tumors with impressive efficiency and accuracy. The process begins with the extraction of pertinent features from medical images, a critical step in identifying potential abnormalities within the brain. These features are then subjected to the KNN Algorithm, which clusters the data points, aiding in the identification of patterns and anomalies. By employing KNN, the system can effectively group similar image regions, streamlining the subsequent analysis.

The core of the system's intelligence lies in the application of the Random Forest Algorithm, another powerful machine learning technique. Random Forest leverages an ensemble of decision trees to make robust and precise predictions. In this context, it plays a pivotal role in distinguishing abnormal brain regions, enabling the early detection of tumors. One of the standout advantages of this system is its efficiency in terms of training data requirements. It demands fewer samples for training, a critical factor in medical applications where acquiring a vast dataset can be challenging. Moreover, the system's speed in processing medical images is noteworthy, resulting in faster tumor detection. Ultimately, this hybrid approach represents a promising step forward in the medical field. By combining the strengths of KNN and Random Forest, it enhances the accuracy and efficiency of brain tumor detection, offering the potential to save lives through early diagnosis and intervention.

7. FUTURE WORK

The future scope of this brain tumor detection system is promising and can be further enhanced in several ways. Firstly, integrating deep learning models like Convolutional Neural Networks (CNNs) can improve the accuracy of feature extraction from medical images. Additionally, expanding the dataset with diverse cases and including advanced image processing techniques can make the system more robust and adaptable to various scenarios. Furthermore, incorporating real-time monitoring and cloud-based solutions can enable remote diagnosis and collaboration among medical professionals. Finally, exploring the potential for early detection and prediction of tumor growth using longitudinal data and AI-driven analytics could revolutionize brain tumor diagnosis and treatment.

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