Brain Tumor Feature Extraction from Image Analytics Using Intelligent Techniques

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Abstract— Image analytics is the specification of relationship between variables, features and time stamped values. It needs the extraction of large amount of feature from images and it is a kind of special task in machine learning algorithm with appropriate preprocessing to dataset.For example, Medical Image analytics is one of the most important challenging tasks nowadays. The content based medical image retrieval (CBMIR) system is used to analyze the large volume of images. This existing method is used to classify the semantic interface between low level (Cerebrum) and high level (Cerebellum) feature extraction for brain tumor in Magnetic Resonance Image (MRI) by imaging device or normal human. However, most of the existing classifications techniques are extracting and detecting the brain tumor in medical image analytics, but the performance of existing methods are very less accurate and it was more tedious and time consuming task. To overcome the above problem, using Hybrid Intelligent technique (HIT) is proposed for feature extraction and brain tumor classification in medical image analytics. The proposed technique will evaluate and validate for performance of MRI brain images and also improve overall processing speed.

Indexed Terms-- Feature, Brain tumor, Classification, Magnetic Resonance Image, Machine Learning, Image analytics

I. INTRODUCTION

One of the most important techniques in medical image analytics is automated and classification approaches. These approaches are used for MRI brain images operation. This MRI images have been classified either normal or abnormal by using hybrid optimization technique. The implementations of these techniques have been combined with a various artificial neural network classifier and also improve classification accuracy using various optimal parameters [1].

The machine learning algorithm has help to radiologists in brain tumor diagnostics without insidious measures. This algorithm has achieved substantial results in image segmentation and classification using convolutional neural network (CNN). The CNN architecture for brain tumor classification of three different pre –trained tumor models such as (VGG16, AlexNet, and GoogleNet) to classify the brain tumors into pituitary, glioma, and meningioma [2].

Brain tumor is one the most dangerous and deadly cancer in adults and children. The treatment process of the brain tumor diagnosis is very important at earlier stage for the normal human being. The specialists are used to detect the brain tumor using computer aided systems and also perform the tumor detection very easily. This is aimed to diagnose the brain tumor using MRI images. CNN models and deep learning networks have used for various diagnosis process. The past 5 layers of the Resnet50 model have been removed and added 8 new layers. This model is obtained results with 97.2% accuracy value. These results are obtained with Alexnet, Resnet50, Densenet201, InceptionV3 and Googlenet models. These models has classified the brain tumor images with high performance. [3]

Magnetic resonance imaging (MRI) images have been used to diagnose brain tumors. Many of the system are attempting to define such a tumors are based on tissue analysis methods. Even though, the various factors such as the quality of an MRI device, noisy images and low image resolution may decrease the quality of MRI images. The proposed method benefits from single image super resolution (SISR) and maximum fuzzy entropy segmentation (MFES) for brain tumor segmentation on an MRI image. The pre-trained ResNet architecture is a convolutional neural network (CNN) architecture and support vector machine (SVM) are used to perform feature extraction and classification. This has observed in experimental studies that SISR displayed a higher performance in terms of brain tumor segmentation. The similar way, it is displayed a higher performance in terms of classifying brain tumor regions as well as benign and malignant brain tumors. As a result, the present study indicated that SISR yielded an accuracy rate of 95% in the diagnosis of segmented brain tumors, which exceeds brain tumor segmentation using MFES without SISR by 7.5% [4].

In current years, improved deep learning techniques have been applied to biomedical image processing for the classification and segmentation of different tumors based on magnetic resonance imaging (MRI) and histopathological imaging (H&E) clinical information. Deep Convolutional Neural Networks (DCNNs) architectures include tens to hundreds of processing layers that can extract multiple levels of features in image-based data, which can be very difficult and time-consuming to be recognized and extracted by experts for classification of tumors into different tumor types, as well as segmentation of tumor images. The latest studies of deep learning techniques applied to three different kinds of brain cancer medical images (histology, magnetic resonance, and computed tomography) and highlights current challenges in the field for the broader applicability of DCNN in personalized brain cancer care by focusing on two main applications of DCNNs: classification and segmentation of brain cancer tumors images.[5]

Brain tumor classification is an important role in clinical diagnosis and effective treatment. The propose a method for brain tumor classification using an ensemble of deep features and machine learning classifiers. The frameworks have adopted for the concept of transfer learning and use several pre-trained deep convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features have evaluated by several machine learning classifiers. The first three deep features are performing very well on several machine learning classifiers. This is used to evaluate the different kinds of pre-trained models such as deep feature extractor, machine learning classifiers, and the effectiveness of an ensemble of deep feature for brain tumor classification. We can use these three different brain magnetic resonance imaging (MRI) datasets. These datasets are openly accessible from the web. The Experimental results can demonstrate that an ensemble of deep features can help improving performance significantly and then the support vector machine (SVM) with radial basis function (RBF) kernel outperforms other machine learning classifiers, especially for large datasets.[6]

II. BACK GROUND OF RESEARCH

Brain tumors are a major challenge in the clinicians that leads to sudden death of normal human being in this world. These tumors have been classified either benign or cancerous. This may be critical when people are not properly diagnosing and treating their issues. They must diagnosis of their brain tumor problems at begin stages for betterment of them health. The patients can be easily getting recovery and also got proper results in their brain. Medical image analytics plays an important role for diagnosing brain tumors. The more information is used to extract from medical image images with help of laboratory analysis, clinicians and surgeons and also they have been done recoding by using different systems such as MRI-Magnetic resonance imaging, X-Ray and Computed tomography (CT).

The semantic gap between the low-level visual information captured by the MRI system and the high-level information perceived by the human evaluator and this method was produced the less accuracy results in brain tumor classification. Required for more processing time to extract the features and also categorize the brain tumors in image analytics by using transfer learning and fine-tuning methods.

Brain tumors are complicated to classify by using classifier, because they are not enhanced with contrast medium usage. This was produced less feature extraction in brain tumor classification.

The MRI brain image features have been extracted based on various feature extraction techniques and also produced less accuracy for final results. This proposed method will improve the classification accuracy and also categorize the abnormalities more accurately. This technique is very useful for radiologist and pathologist to increase the productivity with quality image.

The primary challenge in the extraction of low level and high level image feature will be attained using this intelligent technique. This automatic technique will be used to connect patients with the resources for self management and provide accurate information about patients for decision making.

III. RESEARCH METHODOLOGY

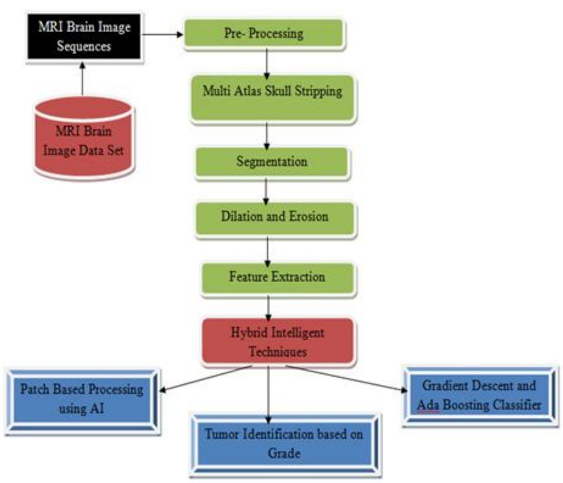

Fig: 1The Proposed Hybrid Intelligent Techniques Architecture

In this research, the hybrid intelligent techniques are using for MRI brain tumor classification and feature extraction are described in the above architecture. MRI is an important diagnostic tool for normal human being for various researches and testers. In this architecture have several stages such as preprocessing, multi-atlas skull stripping, segmentation, dilation and erosion , feature extraction and hybrid intelligent techniques(Patch based processing using AI, Gradient descent and ada boosting classifier, and Tumor identification based on grade).

i) Pre-Processing:
This preprocessing method is one of standard analysis MRI brain images in prior stages. These are used to analysis the quality of the MRI images and also have to start the processing through normal human being or machine.

ii) Multi Atlas skull stripping:
Multi-Atlas skull stripping is one of the most important roles to play in medical image analytics and also this is one of the software package tools for brain extraction accurately using unix command. This is suitable for challenging in various medical brain data sets. Skull tripping is used to extract various brain issues in MRI images. Here, we can apply the many of skull stripping techniques like dilation, erosion and

$$M= \sum fx/\sum f \quad (4)$$

segmentation analysis. These techniques are easily able to find the tissues in low level (Cerebrum) and high level (Cerebellum) feature extraction in MRI medical image analytics.

iii) Segmentation, Dilation and Erosion:
The morphological consists of two operations such as dilation and erosion. The dilation operation used to add the pixels in MRI images. This insertion is fully depends upon the boundaries of objects. But the erosion operation is used to remove the pixels in boundaries of objects in brain images. The

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2} \quad (5)$$

pixels insertion and deletion is carried out the shape and size of the structuring elements in MRI images. We can dilate an image using imdilate function. These operations is having two important arguments such as the input of the brain images have to be processed and defining the neighborhood of a

$$(W\psi f)(a,b) = \int_{-\infty}^{+\infty} f(x)\psi a, b\,(x)dx \quad (1)$$

structuring element in a binary matrix for various objects.

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k2^j}{2^j}\right) \quad (3)$$

In this research, continuous wavelet transformation can be used to calculating efficiency of segmentation in brain Magnetic Resonance image.
The (Wψf)(a,b) is produce the efficiency of the brain objects with different time intervals.

Where the primary object of the brain image is used to represent the mother wavelet transform equation (2).

Where a,b is a real integer variables, a,b € R and ψ €L^2 , ψ is a wavelet function and ψa,b are called wavelets.

This discrete wavelets can be used as a calculating the coefficient of a set of sub wavelets of the above discrete mother function ψ(t).These mother wavelets is moving and scaling by powers of two. Where j and k is integer variables such as j is called the scale parameter and k is called the shift parameter.

iv) Feature Extraction:
The feature extraction is one of the techniques for reducing the number of features or pixels in a MRI data set and also it has been creating new features from their existing features. The current features have reduced and also able to classify most of the relevant as well as important information. This feature consists of original data set of MRI images features. It is a type of high dimensionality reduction, where a large number of pixel of a MRI brain images are more efficiently represented in which images are captured an effectively.

a) Mean:
The mean is the average or most common image in a collection of real time data sets. This is used to display the average number image features to their corresponding users.
Where M is Mean operation and f is set of features (f).

b) Standard deviation:
This mathematical formula is used to determine the central region of the brain image contrast and also increase the resolution of images. This measures the absolute variability of a distribution. It may be either higher dispersion or lower dispersion based on the variability of brain image distribution.

Where N is the number of MRI brain image features and x indicates individual feature vector values.

c) Entropy:
This entropy operation is used to measure and classifying the texture of images. This is calculating the

$$E(S) = \sum - (Pi*\log 2Pi) \quad (6)$$

homogeneity of different samples.

Where E(S) is an Entropy samples and p is represented probability values.

d) Skewness:
The skewness is used to analysis the shapes of different MRI brain images collected from the given data set. Suppose the data set is not a symmetrical distribution, this may be distributed skewness results either positive or negative manner. (7).

$$E = \frac{M-M1}{SD} \quad (7)$$

$$K = \frac{\sum_{i=1}^{N} Xi - X}{N} / S^4 \quad (8)$$

$$T(N) = 2N + T(\frac{N}{2}) \quad (9)$$

Where M is mean, M1 is mode and SD is standard deviation.

e) Kurtosis:
This Kurtosis is stated the shapes of a random variable in probability distribution. The Kurtosis(K) is used to referred the random variables with N samples and S is standard deviation.

f) Hybrid Intelligent Techniques:
In this research, we can identify the most important characteristics of MRI brain tumors like location,

type and size with help of feature extraction techniques and also they can easily diagnosis the tumor in brain.

The Patch-based image processing hybrid intelligent technique using AI, the most of the brain images are divided into two important groups such either small or large.

The some images are processing in small groups with appropriate processing speed to detect the tumors and then send to them for larger groups further processes. This proposed Hybrid intelligent based Gradient descent and Ada boosting classifier is one the famous classifier technique in machine learning algorithm. The threshold weights are re –assigned to each instance of class1 to class N.

The smaller weights of brain tumor objects are classified into one class and higher weights objects are classified into another class. Similarly, this operation has been performed by until reach to end of the operation like N.

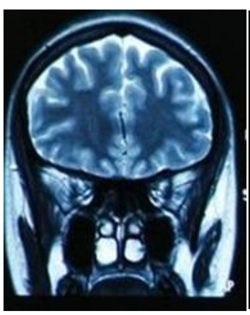

Fig 2: MRI Brain Image Before Feature Extraction Tumor Detection

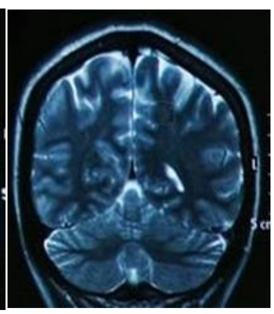

Fig 3: MRI Brain Image After Feature Extraction Tumor Detection

Algorithm: Hybrid Intelligent based Gradient descent & Ada Boosting Classifier
Input: MRI Brain Dataset
Output: Feature extraction & Brain tumor classification
for i to N Max Images

Classifier Performance		Continuous wavelet statistical features	Discrete wavelet statistical features
Proposed: Hybrid Intelligent Techniques	Accuracy	95.67	96.45
	Sensitivity	94.35	95.32
	Specificity	93.53	94.42
Existing : Content Based Systems	Accuracy	93.85	94.25
	Sensitivity	92.56	93.23
	Specificity	89.34	90.45

a) Classifier to training dataset using weights

b) Compute mean and Standard deviation (Equation 1 to 2)

c) Calculate Entropy and Skewness for specify texture & Shape(Equation 3 to 4)

for m to M threshold

$$fM(x) = \sum_{m=1}^{M} T(x, \psi m)$$

Where T is Time and N is number of time the process is executed .The above recurrence relation is used to calculate the time complexity for the above classifier algorithm an accurately. This proposes, Intelligent based gradient descent and ada boosting classifier algorithm is produce the better results than existing method.

IV. EXPERIMENTAL RESULTS AND EXECUTION

Table 1: BRATS'20 Data set (Overall Classifier Performance)

Classifier Performance		Continuous wavelet statistical features	Discrete wavelet statistical features
Proposed: Hybrid Intelligent Techniques	Gradient descent and Ada Boosting Classifier	93.4	94.33
	Patch based processing using AI	92.78	93.96

	Grading Approach	92.43	93.12
Existing : Content Based Systems	Content Based Medical image retrieval Technique	90.89	91.65

Table 2: BRATS'20 Data set (Performance based on individual parameters)

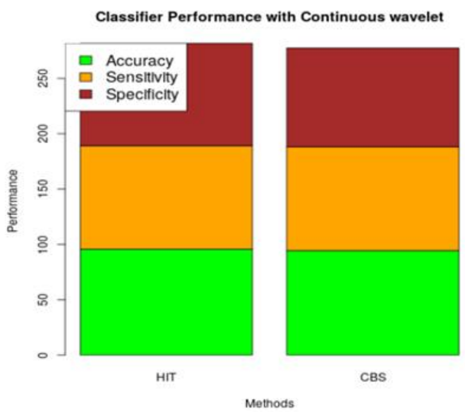

Fig 4: Proposed Method for Classifier Performance with Continuous Wavelet

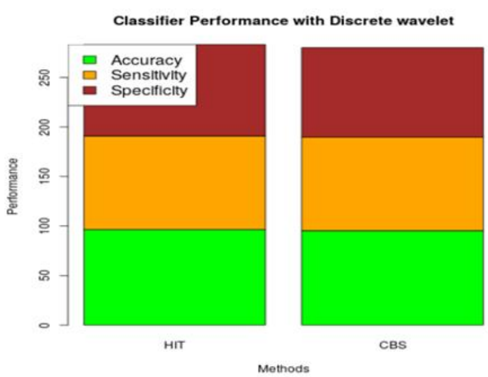

Fig 5: Proposed Method for Classifier Performance with Discrete Wavelet

The MRI brain tumor features are used to extracting and also depends on a method of intelligent based classifier and also produced less accuracy for final results in existing content-based image retrieval method at 94.25%. This proposed hybrid Intelligent Technique (HIT) is executed an effectively and also improve the classification accuracy is 96.45 %, and also categorize the abnormalities more accurately. This technique is very useful for radiologist and pathologist to increase the productivity with quality image. The primary challenge in the extraction of low level and high-level image feature will be attained using this intelligent technique. This intelligent technique will be used to connect patients with the resources for self-management and provide accurate information about patients for decision making.

V. CONCLUSION

In this research proposes Hybrid intelligent techniques for brain tumor detection, feature extraction and classification using gradient descent and ada boosting classifier. These proposed techniques are used to identify the region of tumor in intrinsic MRI structure and also classify the features of information. In this research, the proposed algorithm can achieve an efficient brain tumor detection, feature extraction and classification. Our experimental results shown that proposed method is used to classify the brain tumor in MRI medical images and also detecting the tumors in various region of brain in an exactly. In future, the same dataset will support and produce the good research results for various intelligent based techniques.

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