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Brain Tumour Classification using Artificial Neural Networks: A Survey

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Abstract— Artificial Intelligence (AI) is making its presence felt in diverse areas. One such area which has been invaded by artificial intelligence is brain tumour classification using Artificial Neural Networks because of the complexity in human intervention based approaches. Automated classification reduces the possibility of human errors and reinforces classification at hindsight. The entire process of classification using Artificial Neural Networks (ANN) can be broadly bifurcated into two steps viz. Feature Extraction and Classification. Here, in the proposed paper, a survey on the various mathematical tools required for the feature extraction and classification of brain tumour cases using MRI images is put forth and analyzed. Also previous work and their salient features have been cited.

Keywords— Artificial Intelligence (AI), Artificial Neural Network (ANN), Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), adaptive thresholding, binarization.

I. INTRODUCTION

Classification that is automated and tumours detection in various medical images draws motivation from the arising need of high levels of accuracy when handling with a human life. Adding to that, the computer assistance is required in medical institutions attributing to the fact that it could help to enhance the estimates or accuracy of classification pertaining to brain diagnostic disease classification. Conventional methods of diagnosis coupled with monitoring the diseases rely on detection of the presence of specific features by a human observer. Due to the magnanimity of patient count suffering from brain tumors and fatality of such conditions, a plethora of techniques for automated diagnostic systems have been created in the contemporary times as a cure for the ailment. The sequential steps involved are loading data, data pre-processing, feature extraction, smoothening feature values using DWT and finally finding regular trends in the feature values using principal component analysis. The paper illustrates all the steps in automated classification of brain tumors. The paper is designed in the following sections. Section I puts forth the introduction regarding the need of automated brain tumor classification. Section II presets the basics of digital image processing. Section III summarizes for the sake of brevity the contemporary work done by authors in the same field of research. Section IV describes in fair detail the basic techniques needed in the automated classification specifically aimed at the data type of brain MRI images. Finally, section V culminates with the conclusive remarks about the entire process. The references are enlisted hence forth.

II. DIGITAL IMAGE PROCESSING

An image may be referred to as a two dimensional function, I= f(x, y) where x and y are co-ordinates that are spatial form i.e. co-ordinates corresponding to location. The characteristic I basically consists of two samples of information contained in it. One is called the intensity attribute or the gray scale value which is a metric demarcating the brightness of the pixel spot. The other is the colour component metric or the R-G-B value in conformance with the frequency or colour information of the pixel spot. If it happens in order that the values of (x, y), and the gray scale value of [f(x, y)] possess discrete sample values of the corresponding continuous values, then such an image is referred to as a digital photo. If we manner the digital photographs using a virtual pc, then this manner is known as digital photo processing. Before the onset of the feature extraction stage, proper pre processing stage in very crucial for the correct extraction of features. The features are then fed to a system designed for classification. The feeding of the feature values trains the designed system to learn about the relations among various class values of the dataset. The system is then tested for accuracy with datasets whose classification results are prior known. This helps in estimating the classification accuracy of the designed system.

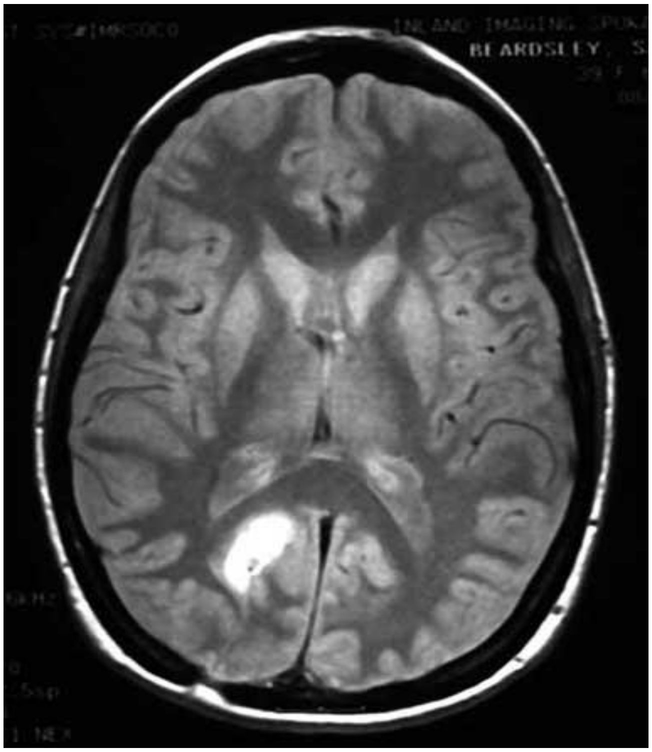

Fig. 1 Typical MRI Image of Brain

A typical MRI brain image is shown in figure 1 so as to get hold of the fact that it becomes incomprehensible to detect the differences in the tumors which have the possibility of causing cancer versus the ones which don't.

III. Previous Work

Several new techniques for brain tumour classification are coming up, some of the most substantial ones are enlisted here.

In [1], the authors have presented twenty different state of the art techniques for image segmentation for glioma patients—which has been manually annotated using four raters. It was found that different segmentation techniques yielded different results and also resulted in different feature data dimensionality thereby increasing the complexity of the system. The authors propounded a technique for sub region based analysis with sparse representation for sub-regions segmenting out the tumor affected part. The amalgamation of a multitude of such techniques can at hindsight render effectiveness to individual algorithms, indicating towards chances of further up gradation possibilities. The BRATS based annotations of the MRI image data lay publicly available through a web assessment device as an ongoing benchmarking resource.

In [2], the authors showed that it was possible to achieve high classification accuracy of brain tumors using MRI image database. However, the authors clearly showed that the pixel values correspondence did not exist for brain tumor cases that are clearly distinguishable or could not be demarcated. This means that the images of malignant and benign tumors did not show significant pixel level differences so as to be differentiated by manual or automated inspection. However, using parameters which are critical in defining images (often called feature values) could be used for the purpose of classification.

In [3], the authors have used the technique of probabilistic classification in training of Artificial Neural Networks. The approach is often termed as Probabilistic Neural Network (PNN). The technique involved in the computation of parameters used for the classification of different sets of the images and is accomplished using the concept of conditional probability. Feature parameter computation was a critical step prior to training the designed PNN with the obtained feature value of the training data set. The simulations were run on MATLAB 2014. The performance evaluating parameter was the classification accuracy.

In [4], the authors devised that identification comprising of various pre-processing and feature extraction stages was significantly non-trivial in nature. Designing of neural network structures working on probabilistic models was an effective way out though in case the neural structure was fed well structured data. The MRI is a good and effective visualization tool for the structural visualization of the human brain's internal structure. MRI method incorporates several salient imaging parameters needed for the apt representation of the human brain's internal structure. The authors have focused on noise removal paradigms, extraction of features from gray-level co-prevalence matrix (GLCM) capabilities, DWT-based denoising to enhance the performance. The approach focusing on the dimensional reduction after pre-processing was achieved by allowing lesser sample of the continuous wavelet transform (CWT) boiling down to the discrete wavelet transform (DWT) to be used prior to final classification. The neural network design used the probabilistic Baye's rule to classify the different cases that came up. The backbone of the classification process remained computing the probability of the classes in which a certain data sample was to be kept in. The highest probability class would be finally adjudged as the category of the data sample. This approach was however not very effective in reducing the actual data dimensionality that the neural network was to be handle due to the increase in DWT co-efficient values. This was the con that the approach had even being highly accurate in classifying.

IV. Common Techniques Used in Automated Classification of Brain Tumors

Based upon the previous discussions, the most common techniques used for brain tumor classification are presented here to provide a clear idea pertaining to the commonly used techniques or tools.

a) Discrete Wavelet Transform (DWT)

The Wavelet Transform is rather a recent methodology for the analysis of randomly fluctuating non-smooth signals.[2]
While conventional Fourier methods like the Fourier Transform can analyze smoothly changing data, it is not capable enough to analyze abruptly changing data like ECG, images etc[14]. The reason for this is the fact that the Fourier Transform has base signals as sine and cosine which are smooth in nature. Whereas the Wavelet Transform has abruptly changing base signals. A comparative analysis ensues:

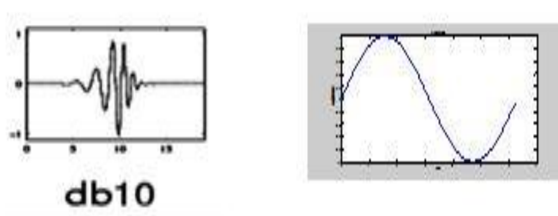

Fig.3 Base Functions of Fourier Transform and Wavelet Transform

The mathematical description of the wavelet transform can be given by:

$$C(S, P) = \int_{-\infty}^{\infty} f(\mathrm{t})\ ((S, P, t))\ dt$$

Here S stands for scaling
P stands for position
t stands for time shifts.
C is the Continuous Wavelet Transform (CWT)
The main disadvantage of the CWT is the fact that it contains an enormous amount of data. The sampled version of the CWT is the Discrete Wavelet Transform (DWT). The DWT is a version of the CWT that is down sampled and its characteristic nature is to smoothen out abrupt fluctuations which are possible due to both abruptly changing base functions and down sampling.
The scaling function can be defined as:

$$W\Phi\ (\mathrm{Jo}, \mathrm{k}) = \frac{1}{\sqrt{M}} \sum_n S(n).\Phi(n)_{jo,k}$$

The Wavelet function can be defined as:

$$W\psi\ (\mathrm{j}, \mathrm{k}) = \frac{1}{\sqrt{M}} \sum_n S(n).\psi(n)_{j,k}$$

Where $\frac{1}{\sqrt{M}}$ is Normalizing term

The DWT coefficients can be plotted to see the smoothening effect of the tool. Now, wavelets have different families depending upon the base function of the wavelet. A few common families are shown.

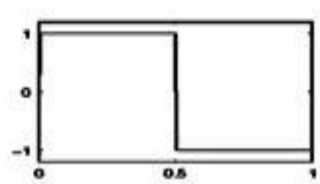

Fig.4 The Haar Wavelet

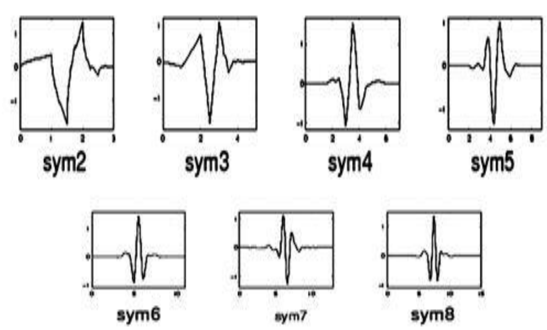

Fig.5 The Symlet

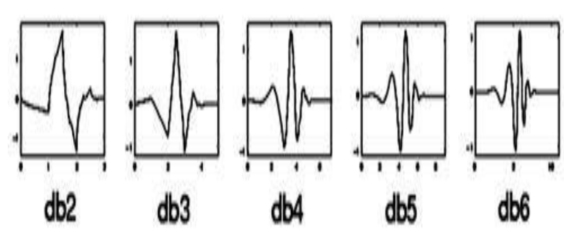

Fig.6 The DB Wavelet

One common attribute of the different wavelet families is the fact that all of them exhibit sudden or abrupt changes. This is the main reason because of which wavelets can be used for the analysis of abruptly changing signals like the Electrocardiogram (ECG) which do not follow the Dirichlet's conditions necessary for analysis using the Fourier Transform.

b) Principal Component Analysis (PCA)

Principal Component Analysis is a technique that helps to find the attributes which contribute the most to the final classification of the data set.[16] Principle component evaluation (PCA) is a mathematical technique that converts a hard and fast of correlated variables into a hard and fast of values of uncorrelated variables referred to as fundamental additives. The quantity of unique variables is usually extra than or same to the main components generated by means of PCA. This transformation may be described because the first predominant additives holds the greatest contribution to the final characteristics of the facts sample and each succeeding issue is high next and it is in no way related to the preceding aspect. This linear transformation has been widely used in sample class statistics evaluation and compression.

c) Segmentation:

The process of separating the tumour region of the image from the entire image is called segmentation.[3] Segmentation can be carried out in several ways, some of the typical categories of which are:

- **Threshold Based Segmentation:** In this method of thresholding, according to the values in which a pixel resides, pixels are allotted to the different categories.
- **Edge Based Segmentation:** In edge-based segmentation, there is application of edge filter to the image. The filter outputs the image into segments with sharp demarcating edges corresponding to disjoint groups.
- **Region Based Segmentation:** In this method, the operation of segmentation algorithms are in segmented fashion that group together pixels which are adjacent to each other with similar values and splitting groups of pixels which are dissimilar in value.

The type to be chosen depends upon the application.

d) Feature Extraction

Since Artificial Neural Networks do not understand any other data format apart from numbers. Hence its mandatory to extract numerical values form images which bear maximum significance corresponding to images. Typical feature values that have the most significance pertaining to images are:

Energy, Entropy, Mean, Standard Deviation, Brightness, Contrast, Skewness etc. It should be noted though that the more the number of features computes, better would be the training of the ANN.[2]

V. Conclusion

This paper presents a survey on the various tools and techniques that have been proven to be effective in automated brain tumor classification. The underlying idea is shown to be feature extraction followed by training a neural network using the same extracted feature data. A summary of contemporary techniques has also been put forth for ready reference. It has be shown that the system's performance can be evaluated based on the accuracy of classification. This in turn can be increased by effective data pre-processing, exhaustive set of feature selection and finally designing an optimal neural network that would render the final classification. It is expected that the proposed technique will prove to be instrumental in designing future approaches with higher accuracy. The subsequent section puts forth some areas which can be explored to attain better results compared to existing methodologies.

VI. Future Scope

Futures research may be driven in the direction of evolving data pre-processing techniques such as the maximum overlap discrete wavelet transform (MODWT) which does not down sample the number of data sample and may prove to be more promising. Moreover hybrid AI based classifiers can be also investigated pertaining to the present work.

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