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Image Classification with Application to MRI Brain using 2^{nd} Order Moment Based Algorithm

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ABSTRACT
Presented work is a feature extraction and classification study for tumour disease and normal brain subjects. The proposed technique consists of two stages, namely feature extraction and classification. In the feature extraction stage features are extracted using 2^{nd} order moment wave algorithm. An non parametric statistic technique based (k-NN) algorithm is used for classification. The classifier has been used to classify subjects as normal or abnormal MRI human images. A classification with a success of 98.6% has been obtained by the proposed classifier k-NN.

Keyword –classification, k-NN, MRI, moment wave algorithm, tumour disease.

I.INTRODUCTION

Human have extraordinarily large and complex brains. The anatomy of the brain is complex due its complicate structure and function. The brain is the part of the central nervous system. It is the centre to control the mental processes and physical action of a human being. Brain abnormality is a symptom where motor impairment and neuropsychological problems affect the central nervous system. It is an abnormal growth of cells within the brain, which can be cancerous or non-cancerous. To date, numerous researches of brain abnormality detection had been conducted due to its important roles in identifying anatomical areas of interest for diagnosis, treatment, or surgery planning paradigm. Magnetic Resonance Imaging (MRI) is a primary medical imaging modality that commonly uses to visualize the structure and the function of human body . It provides rich information for excellent soft tissue contrast which is especially useful in neurological studies. In previous years, MRI is observed to play an important role in brain abnormalities research in determining size and location of affected tissues Magnetic resonance imaging (MRI) is an imaging technique that produces high quality images of the anatomical structures of the human body, especially in the brain, and provides clinical information for clinical diagnosis and biomedical research .MRI is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to classify brain tissue. MRI is widely used in tumour studies as it can non-invasively quantify gray and white matter integrity with high reproducibility [3]. In 2000, approximately 24 million people over the age of 60 were diagnosed with dementia worldwide, and this number is expected to reach over 81 million by 2040.

The most important advantage of MRI is that it is non-invasive technique. The use of computer technology in medical secession support is now widespread and pervasive across a wide range of medical area such as cancer research, brain tumours, and gastroenterology. The diagnostic values of MRI are greatly magnified by the automated and accurate classification of the MR images. In recent years, researchers have proposed two categories of approaches to obtain this goal. The first category is supervised classification, such as support vector machine (SVM) and *k*-nearest neighbours (*k*-NN).The other category is Recent work has shown that classification of human brain in magnetic resonance (MR) images is possible via supervised techniques such as artificial neural networks and support vector machine (SVM), and unsupervised classification techniques unsupervised such as self organization map (SOM) and fuzzy c-means combined with feature extraction techniques. Other supervised classification techniques, such as k-nearest neighbours (k-NN) also group pixels based on their similarities in each feature image can be used to classify the normal/pathological T2-wieghted MRI images. K-Nearest Neighbour (k-NN) classification technique is the simplest technique conceptually and computationally that provides good classification accuracy. The k-NN algorithm is based on a distance function and a voting function in k-Nearest Neighbours, the metric employed is the Euclidean distance. The k-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but has a slow running time. Yet, the issues of poor run time performance is not such a problem these days with the computational power that is available. We used supervised machine learning algorithms k-NN to obtain the classification of images under two categories, either normal or abnormal. Unsupervised classification, such as self-organization feature map (SOFM) and fuzzy *c*-means. While both of these methods achieved satisfactory results, supervised classification performs better than unsupervised classification in terms of classification accuracy (successful classification rate) [1].

The contribution of this paper is the integration of an efficient feature extraction tool and a robust classifier to perform a more robust and accurate automated MRI normal/abnormal brain images classification..This paper is organized as follows: A short description on the input dataset of images and methodology is presented in Sections 2 and methods for feature extraction as well for classification are presented in Sections 3. Section 4 contains results and discussion, conclusions and future work.

II. INPUT DATA SET

In this section, the proposed hybrid techniques have been implemented on a real human brain MRI dataset. All the input dataset (total images is 70: 60 images are abnormal and 10 normal) used for classification consists of axial, T2-weighted, 256 -256 pixel MR brain images, 60. [3] These images were collected from the Harvard Medical School website (http:// med.harvard.edu/AANLIB/). Fig 2 shows some samples from the used data for normal and pathological brain: a- normal, b- benign tumour ,c- malignant tumour.

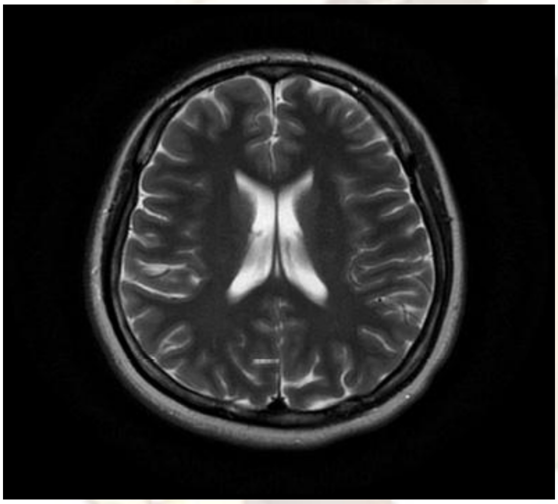

Fig 2 a: A normal brain

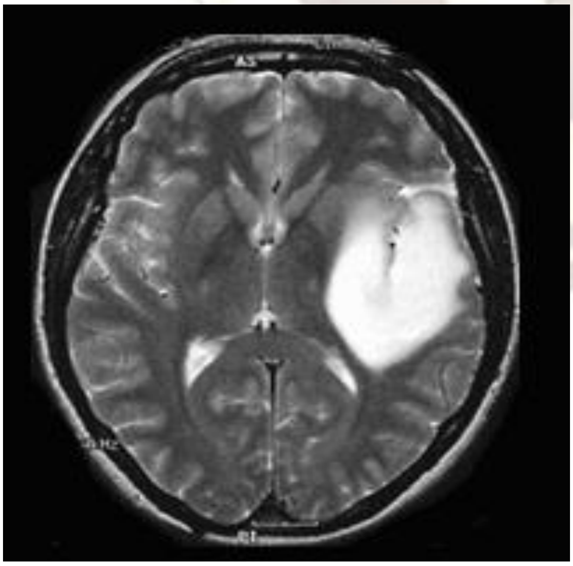

Fig 2 b: benign tumour

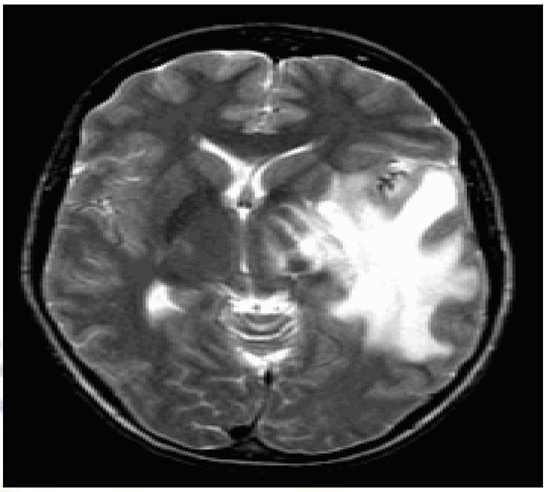

Fig 2 c: malignant tumour

The determination of normal and abnormal brain image is referred at the symmetry. [4] Asymmetry in an axial MR brain image strongly indicates abnormality. Hence symmetry in axial MR images is an important feature that needs to be considered in deciding whether the MR image at hand is of a normal or an abnormal brain.

III. FEATURE EXTRACTION AND CLASSIFICATION

3.1Feature Discrimination Using moment Algorithm

When a set of values has a sufficiently strong central tendency, that is, a tendency to cluster around some particular value, then it may be useful to characterize the set by a few numbers that are related to its *moments*,[9] the sums of integer powers of the values. second order moments

((p,q)=(2,0) or (0,2) or (1,0)))

$$m_{2,0} = \iint dxdyx^2 f(x,y)$$
$$m_{0,2} = \iint dxdyy^2 f(x,y)$$
$$m_{1,1} = \iint dxdyxy\, f(x,y)$$

In image processing, computer vision and related fields, an image moment is a certain particular weighted average of the pixel's intensities, or a function of such moments usually chosen to have some attractive property or interpretation Method of moment invariants is derived from algebraic invariants applied to the moment generating function under a rotation transformation. The set of absolute moment invariants consists of a set of nonlinear combinations of central moments Theremin invariant under rotation sometimes it is convenient to convert moments about the origin to moments about the mean. The general equation for converting the n^{th}-order moment about the origin to the moment about the mean is [10]

$$\mu_n = \sum_{j=0}^{n} \binom{n}{j} (-1)^{n-j} \mu'_j \mu^{n-j},$$

The 2nd moment about the mean of a real-valued random variable X is the quantity $\mu_k := E[(X - E[X])^k]$ where E is the exception operator. For a continuous univariate pdf with function f(x,y) the moment about the mean μ is

$$\mu_{m,n} = \iint (x-c_x)^m (y-c_y)^n f(x,y)\,dy\,dx$$

3.2 k-NN CLASSIFIER ALGORITHM

Significant difference between tissue types, observed in variety of textural measurements in MR image, is used for this classification. The various measurements based on statistical and co occurrence matrix textural features from the MR images are given as input to the classifiers for training. If the features of new slices are given as input, the trained classifier can able to classify it.

k-Nearest Neighbours based Classifier. One of the simplest classification techniques is the k- Nearest Neighbour classifier. Classification of an input feature vector X is done by determining the k closest training vectors according to a suitable distance metric. The vector X is then assigned to that class to which the majority of that k nearest neighbours belong to. The k-NN algorithm is based on a distance function and a voting function in k nearest neighbours, the metric employed is the Euclidean distance. The k-nearest neighbour classifier is a conventional nonparametric supervised classifier that is said to yield good performance for optimal values of k. Like most guided learning algorithms, k-NN algorithm consists of a training phase and a testing phase. In the training phase, data points are given in a n-dimensional space. These training data points have labels associated with them that designate their class. In the testing phase, unlabeled data are given and the algorithm generates the list of the k nearest (already classified) data points to the unlabeled point. The algorithm then returns the class of the majority of that list. Required: distance function on instances. Model will be as labelled training data (a1; c1); (aN; cN).Classify a new instance as follows:- Let (aj1 ; cj1); : : : ; (ajK; cjK) be the K training instances whose attributes are closest to a. Label a with the class label that occurs most frequently among cj1...... cjK., Can give higher weight to close neighbours weighted vote for label [10]

$$v(c) = \sum_{x=1, cji=c}^{k} \frac{1}{d(a_{ji}, a)}$$

Now weighted voting is calculated with the c that has highest v(c) value. [1]

Algorithm 2 k-NN algorithm

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1 Determine a suitable distance metric.

2 In the training phase: Stores all the training data set P in pairs(according to the selected features) P = (yi, ci), i=1. where yi is a training pattern in the training data set, ci is its corresponding class and n is the amount of training patterns.

3 During the test phase: Computes the Distances between the new feature vector and all the stored features (training data).

4 The k nearest neighbours are chosen and asked to vote for the class of the new example. The correct classification given in the test phase is used to assess the correctness of the algorithm. If this is not satisfactory, the k value can be tuned until a reasonable level of correctness is achieved.

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5. CONCLUSION AND FUTURE WORKS

In this section we experimented with k-NN, and compared its performance to other classifiers (Kernel based and parametric based).k-NN classifier is extremely simple and requires no learning/training, its performance ranks among the top leading learning-based image classifiers. The main advantage of k-NN algorithm is it provides accurate about distance, weighted average about pixels and it can be used for large number of training sets.

For more accurate results, several algorithms use weighting schemes that alter the distance measurements and voting influence of each instance. A survey of weighting schemes is given by (Wettschereck et al.1997).The power of kNN has been demonstrated in a number of real domains, but there are some reservations about the usefulness of kNN, such as: i) they have large storage requirements, ii) they are sensitive to the choice of the similarity function that is used to compare instances, iii) they lack a principled way to choose *k*, except through cross-validation or similar, computationally-expensive technique (Guo et al. 2003).

The disadvantage of this algorithm is the choice of *k* affects the performance of the k-NN algorithm. The following reasons propose k nearest neighbour classifier might incorrectly classify a query instance: When noise is present in the locality of the query instance, the noisy instance(s) win the majority vote, resulting in the incorrect class being predicted. A larger *k* could solve this problem. When the region defining the class, or fragment of the class, is so small that instances belonging to the class that surrounds the fragment win the majority vote. A smaller *k* could solve this problem.

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