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Classification of Parkinson's Disease using MRI Images

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ABSTRACT

A novel method for automatic classification of magnetic resonance image (MRI) under categories of normal and Parkinson's disease (PD) is then classified according to the severity of the medical specialty drawbacks. In recent years, with the advancement in all fields, human suffers from numerous specialty disorders like brain disorder, epilepsy, Alzheimer, Parkinson, etc. Parkinson's involves the malfunction and death of significant nerve cells within the brain, known as neurons. As metal progresses, the quantity of Dopastat made within the brain decreases, defeat someone, and make them unable to manage movements commonly. In the planned system, T2 (spin-spin relaxation time)—weighted MR images are obtained from the potential PD subjects. For categorizing the MRI knowledge, histogram features and Gray Level Co-occurrence Matrix (GLCM) features are extracted. The features obtained are given as input to the two different classifier techniques namely Support Vector Machine (SVM) and Radial Basis Function Neural Network (RBFNN). The classifiers, classifies the categories into normal or abnormal PD. Abnormal PD is classified into three Parkinson's diseases. Two different classifiers are used to classify the three subcategories namely Mild, Moderate and Advanced.

Keywords: *Parkinson's Disease (PD), Region of Interest Cropping (ROI), Gray-level Co-occurrence Matrix (GLCM), Support Vector Machine (SVM), Radial Basis Function Neural Network (RBFNN).*

1. INTRODUCTION

Parkinson's Disease (PD), next to Alzheimer's Disease (AD), is the second most common neurodegenerative diseases affecting, approximately, one percentage of those aged over 65 years. There are four cardinal motor symptoms in the early phases of PD such as Bradykinesia, tremor, rigidity and postural instability [1]. Brain imaging techniques have proved to be useful to increase the knowledge of the specific neurochemical and neuropath logical bases of cognitive impairment in PD [2], [3]. However, prospective cohort studies that aim to identify patients with PD at risk of severe cognitive impairment are lacking. To distinguish between the normal age-related cognitive decline and the early signs of prodromal dementia is a great clinical challenge. In this chapter, substantia nigra region of an MRI image is cropped and feature extraction techniques such as GLCM and histogram are applied on that image. This results in better classification accuracy. Fig. 1.1 shows the procedure of the proposed method for classification of MRI images.

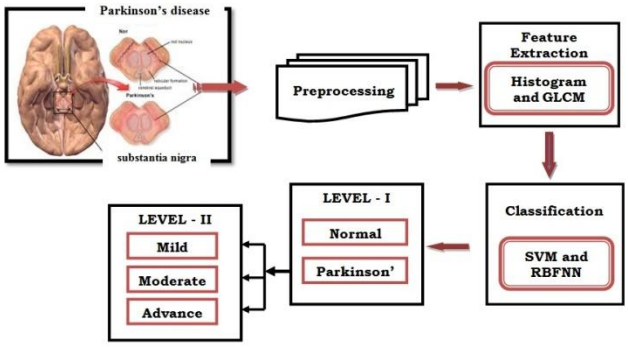

Fig. 1. Proposed method for MRI classification of Parkinson's disease.

2. PREPROCESSING

In the preprocessing stage, the original image is cropped to generate the Region of Interest (ROI), where the symptoms of Neuro problem are highly visible. Next, the cropped image is enhanced to extract high valued features, which increases the classification accuracy of MRI image.

2.1 Region of Interest Cropping

For volumetric examinations, automatic freehand ROI technique, presented in the system of MRI is used. To quantitatively analyze the substantia nigra, an image that contains the superior colliculus and the largest low-

intensity area of the red nucleus is selected. On this image, the pars reticular area of the substantia nigra visualized as an obvious low-intensity area, which is anteriorly merged into the cerebral peduncle with reduced signal intensities. T2-weighted axial midbrain image of a patient after ROI cropping is shown in Fig. 1.2.

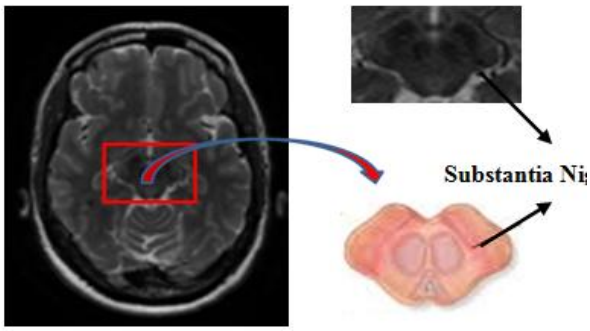

Fig. 2. MRI image before and after ROI.

3. HISTOGRAM EQUALIZATION

A popular general-purpose method of image enhancement is histogram equalization [16]. In this method, a monotonically increasing transformation function, T(r) is used to map the original gray values, r_i of the input image, into new gray values, si of the output image, such that

$$S_i = T(r_i) = \sum_{j=0}^{i} p_r(r_i) = \sum_{j=0}^{i} \frac{n_j}{n} \; for \; i = 0,1,..,L-1 \; (1)$$

(1)

Where $p_r(r_i)$ is the probability-based histogram of the input image that is transformed into the output image with the histogram $p_s(s_i)$. Transformation or mapping of each pixel of input image into corresponding pixel of processed output image is called Histogram Equalization. The transformation function $T(r_i)$ in equation (1) stretches the histogram of the input image such that the gray values occur in the output image with equal probability of occurrence. It should be noted that the uniform distribution of the histogram of the output image is limited by discrete computation of the gray-level transformation. The histogram equalization method forces image intensity levels to be redistributed with an equal probability of occurrence [4]. The histogram equalization method may cause saturation in some regions of the image resulting in loss of details and high-frequency information that may be necessary for interpretation [5].

4. FEATURE EXTRACTION

ROI is identified from the image data manually. From the ROI, features are extracted using Histogram and GLCM. Histogram is an image enhancement technique which normalizes gray level in the image. 8 histogram features and 22 GLCM features are extracted from the image data which are combined to form a 30 dimensional feature vector. The training set includes 25% normal, and 75% AD affected (25% of very mild, mild and moderate each samples).

4.1 Histogram Features

In an image processing context, the histogram of an image normally refers to a histogram of the pixel intensity values. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit grayscale image, which is used in this work, there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values. 256 features could be reduced by dividing the feature set into bins. The image is scanned in a single pass and a running count of the number of pixels found at each intensity value is kept. This is then used to construct a suitable histogram. If a bin is specified, the first n (n = 256/bin) values are summed together to represent the first bin. Next n values count will be used in specifying the 2nd bin and it go on. The intensity histogram has many uses. In this work, the intensity histogram is used to determine the intensity values range in deciding the level of severity of
Alzheimer's disease in the subject to be studied.

4.2 Gray Level Co-occurrence Matrix Features

Gray Level Co-occurrence Matrix exploits the higher-order distribution of gray values of pixel that are defined with a specific distance or neighbourhood criterion. In [6] the simplest form, the GLCM P(i,j) is the distribution of the number of occurrence of a pair of gray values i and j separated by a distance vector d = [dx;dy].
The GLCM normalizes each value in the matrix by dividing the total number of occurrence, providing the probability of occurrence of a pair of gray values separated by a distance vector. Statistical texture features are computed from the normalized GLCM as the second-order histogram H(yq,yr,d) representing the probability of occurrence of a pair of gray values yq and yr separated by a distance vector d. Texture features can also be described by a difference histogram, Hd(ys,d), where ys = |yq −yr|. Hd(ys,d) indicates the probability that a difference in gray levels exists between two distinct pixels [7]. We used 22 textural features in our

study. The following equations define these features. Let s(a, b) be the (a, bj)th entry in a normalized GLCM [8], [9]. we define also

$$s_x(a) = \sum_{b=1}^{N} s(a,b) \quad (2)$$

$$s_y(i) = \sum_{a=1}^{N} s(a,b) \quad (3)$$

Table 1: Haralick texture features (characteristics 1 to characteristics 22)

S.No	Characteristics	S.No	Characteristics(cont..)
1	Contrast	12	Maximum probability
2	Correlation	13	Sum of squares
3	Energy/angular second moment	14	Sum of average
4	Homogeneity	15	Sum of variance
5	Autocorrelation	16	Sum of entropy
6	Maximal correlation coefficient	17	Difference variance
7	Cluster prominence	18	Difference entropy
8	Cluster shade	19	Information measure of correlation 1
9	Dissimilarity	20	Information measure of correlation 2
10	Entropy	21	Inverse difference normalized
11	Homogeneity	22	Inverse difference moment normalized

$$S_{x+y}(k) = \sum_{a=1}^{N}\sum_{b=1}^{N} s(a,b), \quad k = 1,2,\ldots,2N$$
$$a + b = k$$

$$S_{x-y}(k) = \sum_{a=1}^{N}\sum_{b=1}^{N} s(a,b), \quad k = 0,1,\ldots,N-1$$
$$|a - b| = k$$

and μ_x, μ_y, σ_x, and σ_y as the means and standard deviations of S_x and S_y, respectively. We used the [10] and [11] Haralick texture features with their equations (1–22) in Table 1.

5. CLASSIFICATION USING SVM AND RBFNN

5.1 Support Vector Machine

SVM is used to construct the optimal separating hyperplane for MRI image features. The SVM constructs linear model based upon support vectors in order to estimate decision function. If the training data are linearly separable, then SVM finds the optimal separating hyper plane that separates the data without error. The patterns lying on the margins which are maximized are the support vectors [12].

The SVM is trained to classify based on the features that belong to a class. For testing, the features are extracted from each class and given as input to the SVM model [13]. The class is correctly classified, if the distance between the feature vectors and the SVM hyperplane is greater than a threshold value.

5.2 Radial Basis Function Neural Network

Radial Basis Function Neural Network is feedforward architecture with an input layer, a hidden layer and an output layer [14]. One of the key differences between the RBN and MLP is the neuron transfer function inside the hidden and output layer. The RBN generally uses a Gaussian function as shown in (4). The RBN consists of only two layers with a single neuron in the output layer essentially and it is merely a weighted linear combination of the hidden layer neuron outputs.

$$gi(x_j) = exp\left(\frac{-||x_j - \mu_i||^2}{2_i^2}\right) \quad (4)$$

where μ_i and σ^2_i are the mean and standard deviation of i^{th} cluster. A clustering algorithm such as k-means clustering is used to cluster the training vectors into N_h clusters, where N_h is the number of units in the hidden layer.

Here, however, for the comparison conducted, it focused on the specific data considered, in terms of signal frequency. There are two design aspects to RBF network, (1) Determination of the parameters of the RBF neurons, which can also translate into Gaussian function widths; (2) Calculation of the connection weights between the hidden and output layers [15].

6. EXPERIMENTAL RESULTS

6.1 Dataset

The experiments are conducted using the dataset of the Parkinsons Progression Markers Initiative (PPMI) database. In this prospectively designed study, 60 patients with PD (26 women, 34 men) and 26 healthy subjects (11 men, 15 women) are taken as control group.

The 30 abnormal data consist of 10 mild, 10 moderate and advanced level. The mean age of the patient group is 66.7 ± 8.5 and of the control group is 57.19 ± 9.46. The PD patients had a mean disease duration of 6.25 ± 3.31 years. **Imaging Protocol**: The structural T2-weighted magnetization ready fast gradi-ent echo images are non-heritable on a 1.5-T Vision scanner during a imaging period. From the original image knowledge, the region of interest is fixed at a size of 95 × 95. The ROI is fixed such that it provides enough information for feature selection. Image parameters include: TR=9.7 msec, TE=4.0 millisecond, Flip angle=10, TI=20 mil-lisecond, TD=200 unit of time, one twenty eight mesial 1.25 millimeter slices without gaps and pixels resolution of 256 × 256.

6.2 Feature Extraction

ROI is identified from the image data manually. From the ROI, the features are extracted using histogram and GLCM. Histogram is an image enhancement technique which normalizes gray level in the image. The 8 histogram features and 22 GLCM features are extracted from the MRI image (substantia nigra) data which are combined to form a 30 dimensional feature vector.

6.3 Evaluation using SVM and RBFNN

Initially the histogram features with 8 bins and GLCM features with 22 features that are extracted from the MRI image are used to train the SVM. In SVM the model is generated in the training phase and validated in the testing phase. Two levels of classification are performed on the extracted features. In Level - I, the extracted features are supplied to SVM which create models numbered 0 and 1, 0 belonging to Normal and 1 belonging to PD. In Level - II, the extracted features are supplied to SVM which create models numbered 0 to 2, 0 belonging to Mild, 1 belonging to Moderate and 2 belonging to Advanced.

In the testing period, the total 30 features are given as input to SVM model and the distance between each of the feature vectors and the SVM hyperplane is obtained. The average distance is calculated for each model for classification. The same process is repeated for all the abnormal sub categories of the diseases, and the performance of MRI image classification for Polynomial, Gaussian and Sig-moidal kernels are studied. From the analysis, Gaussian kernel function in SVM using combined features provides better performance for the two levels of classification.

For RBFNN training, 30 dimensional histogram and GLCM features are extracted from the MRI image frames for each category. These features are given as input to the RBFNN model. The RBF centers are located using k-means algorithm. The weights are determined using least squares algorithm. The value of k varies from 1 to 10 in the study for each subject. Two levels of classification are performed on the extracted features [163], [164].

In Level - I, the features are classified into Normal and PD. In Level - II, the features are classified into Mild, Moderate and Advanced. The value of k = 2, 4, 5 and 6 means has been used in the study for each category. In both the levels, the system gives better performance for k = 6 means as shown in Fig. 6.4.

6.4 Normal and PD Classification (Level-I)

This level mainly focused on classifying the normal and Parkinson's category of MRI images. From the experimental analysis it is observed that combined features with RBFNN shows good results than the other techniques. The performance of different kernel functions of SVM for normal and Parkinson's classification is shown in Fig. 6.3.

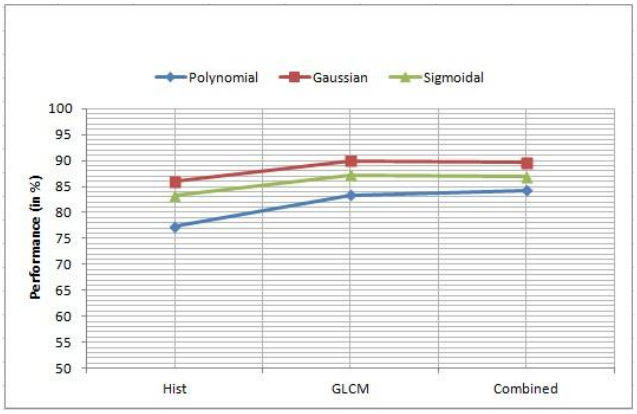

Fig. 3. Performance of SVM kernel functions for normal and Parkinson's classification.

6.5 PD Subcategory Classification (Level -II)

Level - II focuses on classification of three categories of Parkinson's diseases. The performance of three subcategories, namely Mild, Moderate and Advance using two different classifier techniques, namely SVM and RBFNN are discussed in this section.

From the analysis, it is observed that RBFNN provides better performance com-pared to other classifiers. Experiments are conducted for analyzing the performance using features, namely histogram, GLCM and combined features. F or combined features, 8 dimensional histogram features and 22 dimensional GLCM features are fused to form a 30 dimensional feature vector for each image. The performance of the system for combined features using different means of RBFNN for three subcategories of Parkinson's disease is shown in Fig. 6.4.

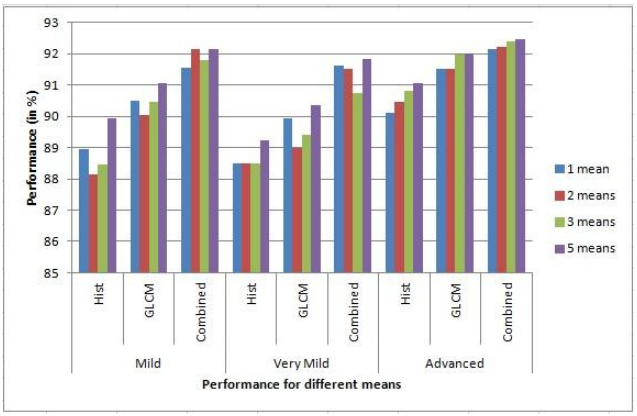

Fig. 4. Performance of RBFNN for Parkinson's subcategory classification.

6. CONCLUSIONS

In this work, 8 dimensional histogram features, 22 dimensional GLCM features and 30 dimensional combined features are used for classification of normal and three categories of Parkinson's diseases. The performance is studied for all the three diseases. From the results, it is observed that combined features with RBFNN gives better performance when compared to the other techniques.

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