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Diagnosis of Wilson Disease by Support Vector Machine based on GLCM Features

A. Amsaveni[1]
Associate Professor
Department of Electronics and Communication Engineering
Kumaraguru College of Technology
Coimbatore - India

Angel Lissy George[2]
PG Scholar
Department of Electronics and Communication Engineering
Kumaraguru College of Technology
Coimbatore - India

Abstract: ***Wilson Disease is an Autosomal Recessive genetic disorder which is due to the excess amount of copper accumulation in body tissues. The excess copper accumulation in tissues increases the oxidative processes which results in neurological disorders and liver disease. It can be treated with medication results in the removal of excess amount of copper from the body. The proposed work is based on ocular biometric measurements to detect the origin of neurological disorder and the pathology. The main intend is to provide a non invasive diagnostic technique for improving the accuracy level of present methods being used at present and also it will reduces potential errors. Feature extraction is done by gray level co-occurrence matrix (GLCM). Classification of the image is done by support vector machine for more accuracy.***

Keywords: Neurological disorders; brain; Wilson disease; eye; Biometric measurements; Support vector machine; GLCM.

I. INTRODUCTION

Normally, copper in suitable doses is important for regular growth of our body. Yet high concentration levels of copper in brain may cause neurological problems. A protein called transporter protein has the responsibility to carry the copper inside the cells. It is taken by food in healthy individuals; the mortal balances the copper inside by excretion. Wilson's disease is also called as hepatolenticular degeneration, in which copper accumulates in tissues; there by outcome will be neurological symptoms or liver disease. It can be treated by medication that will help in the reduction of copper content inside the tissues or removes the excess amount of copper from the body, but infrequently a liver transplant is required. The condition is occurs due to the mutation in Wilson disease protein gene (ATP7B).

An increased level of copper in the liver may cause ongoing liver disease. So it affects individuals suffer from chronic liver disease, hepatic and renal failure, hemolytic anemia, and even neuropsychiatric/neurological disorders[1][2]. The first clear signs or symptoms are occurs during the age of 5 to 20 years. Severe symptoms occur mostly in brain and liver. Diagnosis of Wilson disease is based on the liver failure and neuropsychiatric symptoms. A buildup of copper in the brain result in neurologic symptoms including problems like speech or physical coordination, uncontrolled movements, muscle stiffness, behavioral changes[3][5]. Medical science elucidates neurological disorders expand frequently a separate golden brown pigmentation around the cornea of the eye. This trait sign is identified as Kayser-Fleischer ring. Kayser-Fleischer ring result from a increase of copper in the eyes and are the most unique sign of Wilson disease. They emerge in each eye as a rusty-brown ring around the edge of the iris and in the rim of cornea. The iris is the colored part of the eye surrounding the pupil[6][7]. It is the clear sign of copper deposition in Decrement's membrane of corneal tissue. During testing there will be chances for negative results. So to avoid such negative results, automated detection technique has been proposed. The proposed technique is based on the eye image processing by means of segmentation algorithm [8][14]. Biometric measurements provide detailed information on severity level if diseases. Feature extraction is done based on the texture image. The area of interest is the Kayser-Fleisher Ring.

The Segmented part is undergone for feature extraction using gray level co-occurence matrix. Classification of the image is done by Support vector machine. The aim of the present research is to label an alternative and non-invasive screening method to reduce human interpretation errors.

II. Neurological Disorders and Wilson Disease

Copper accumulation in the brain causes neurological problems. Several neuropathies and disorder will affect the brain and its cognitive capacity [1][7]. Copper obtained from the food is not properly excreted from urine and feaces is because of defected gene. For a healthy individual intake and excretion of copper should be well balanced. A standard copper intake is about 2mg/day. Nearly 25% of copper is excreted through faeces. About 25% will reaches liver and bonds with protein. It will be excreted through bile, a small amount of copper circulates freely in blood. About 50% of copper losses through feces and urine bonding with protein called metallothionein[1][2]. Persons affected with Wilson disease having less amount of copper excretion taken place in body. About 25% amount will reaches the liver, but doesn't bind with protein. Also excretion in the faces is decreased. Depends on the copper accumulation in the organism symptoms can be identified, like liver disease, when acute liver disease occurs the individual must have to undergone for liver transplant. About 35% of patient is affected from neurological disorders. They include speech abnormalities, dystonia, ataxia, depression. In these patients are observed with Kayser-Fleicher ring. This is the frequent sign of Wilson disease. The deposition of copper in the cornea is the cause of Oxidation of tissues. So a golden brown region appears in peripheral iris, as shown in fig.1. It has a ring shape and it is almost always bilateral. It appears in a step by step process at the first as a superior crescent then it develops inferiorly becoming circular. Depends on the severity of pathology the thickness and density of ring can be identified. We can view through our naked eye by increasing the disease at the extreme level. Since it a asymptotic, it can be recognized by routine eye exam. In fact it is found in 95% of individuals. So detection can be able to make decision quickly for diagnosis.

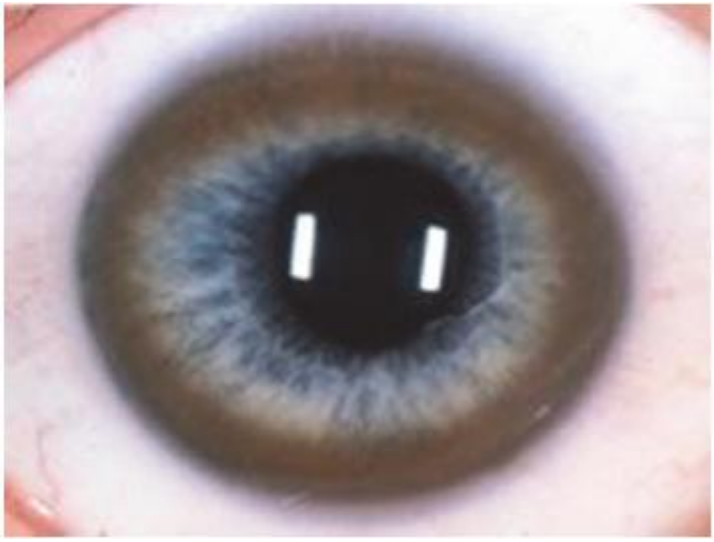

Fig. 1 kayser-fleischer ring

III. Overview

Segmentation process can able to simplify the interpretation of available information. The physicians points out only the anatomical region of image. While considering about Kayser-Fleischer ring, it is a visible symptom for patients having Wilson disease. There will be chances for human errors due to the inexperience of operator or some wrong interpretation. So the main aim of this paper is to enhance an automated process to avoid the errors due to interpretation. A segmentation algorithm partitions the image into several subsets of pixels. Each subset is a non overlapping segment in which each pixel has their own specific common visual feature[8][15]. So the segmentation is essential part of recognition process for the image have typically the same levels of texture or colour. Segmentation algorithm can be classified into three categories: region based segmentation, data clustering and edge-based segmentation[8][20].

The first stage is done based on expanding each region pixel by pixel according to the pixel value. The second phase of algorithms we have to consider the whole image, the main criteria is the pixels distance for segmentation. The third phase is done based on edge detection algorithms. Later the image is being transformed into a set of connected curves which represents the boundaries and surfaces. Additional segmentation techniques have been proposed[22]. In this paper, a colour discrimination algorithm with respect to the eye image is considered. It is a complex task to identify both the boundaries and homogeneous regions between them. So that, the detection of the Kayser-Fleischer ring needs a segmentation process based on spatial and colour features[18][19]. A detection algorithm is done based on JSEG segmentation [20][21] has been urbanized. The algorithm is based on the characterization of regions with homogeneous colour-texture values. The segmentation process is divided in two stages, colour quantization and spatial segmentation. The first step performs a quantization of the image colors into a fixed number of classes except the spatial distribution of the pixels. Similarly, the image is primarily divided into a set of disjointed regions. A label equivalent to the quantization class is assigned into each pixel. As a result of the quantization process, a class-map is obtained in the colour space. The second step performs the final segmentation. Consequently, anatomical structures or regions can be detected in the image. At the last stage feature extraction can be done using gray level co-occurrence matrix . With the features the image is classified using the Support vector machine. The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. co-occurrence distribution is defined over an image to be the distribution of co-occurring values at a given offset. In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. A support vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. A good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class. In general the larger the margin the lower the generalization error of the classifier.

IV. PROPOSED ALGORITHM

A. Detection Algorithm

Consecutively to diagnose Wilson disease in patients suffering from neurological disorders. In the first step acquires the eye image *I*. A primary colour quantization is performed. During this process the image quality is not significantly corrupted. A standard palette of 256 colors has been considered. The main aim is to extract a set of colors in order to single out neighboring regions of the image. According to the *RGB* colour system, each image pixel has a set of three values (Red, Green, and Blue). The starting colors palette has been discredited into 256 classes with respect to the quantized colors set. The image is pre-processed to make simpler the segmentation process and the detection of homogeneous portions having the same colour and texture.

Consequently, the algorithm assigns a label to each pixel with respect to the quantized colors. Pixels with the same label represent an image class. Then, the image is partitioned in a class-map.

Let as consider a 2-D plane *xy*, the class-map can be modeled as spatial data points located in the plane. So the bidimensional function *L(x,y)* provides the label of them pixel with position *(x,y)*. The second step of the algorithm performs a spatial segmentation starting from the class-map. Let *CM be* the new class-map image. Assume *m* to be the spatial mean of all data points *z=(x, y)* in *CM*:

$$m = \frac{1}{N\_dp} \sum_{z \in CM} Z$$

Where *N_dp* is the number of data points or pixels belonging to *CM*.Assume Vt *to* be the total variance of all data points in *CM*:

$$V_{t=} \sum_{z \in CM} |Z - m|$$

Whereas *vT, CM* is the total variance of pixels in *CM:*

$$v_{T,CM} = \sum_{i=1}^{N\_c} \sum_{z \in CM} \|z - m\|^2$$

The degree of the distribution of the colour classes *J* can be obtained by the following expression:

$$J = \frac{v_T - v_{T.CM}}{v_{T,CM}}$$

The degree of distribution will provides useful information about the distribution of classes in class-map. Itis used to optimize the segmentation process. In another way, if several homogeneous colour regions are present and the classes are clustered in specific regions of the image, the degree of distribution J is higher. In order to complete the spatial segmentation, the average *Jm* and local *Jk* distribution values have to be estimated. The average *Jm* distribution value will provides the information about performance of segmentation. If the class-map is divided in *k* regions, the average *Jm* value is obtained as sum, on the whole all the regions of the local *Jk* values estimated in the *k-th* region:

$$J = \frac{1}{N_{dp}} \sum_{k} N_{k.} J_k$$

where *Nk* is the number of pixels in the *k-th* region. Low *Jm* values indicate good segmentation results. A *J-image* is generated as a gray-scale image, whose pixel values are the *Jk* values calculated over the local windows centered on each pixel.

A region-growing method is used to complete the segmentation process. The spatial segmentation starts to segment the regions with an initial large scale until the fixed minimum scale. The region-growing algorithm is applied recursively and the process is repeated until on the newly segmented regions at the next lower scale. The new regions of the segmented image area are obtained by means of the region growing algorithm. Fig. 2 shows the flowchart of the procedure. It summarizes the main steps of the segmentation process previously described. After that feature extraction and classification is done. Feature extraction is done based on the Gray Level Coocurrence Matrix and classification is being done by Support vector machine. A Flow chart is shown in Fig. 2.

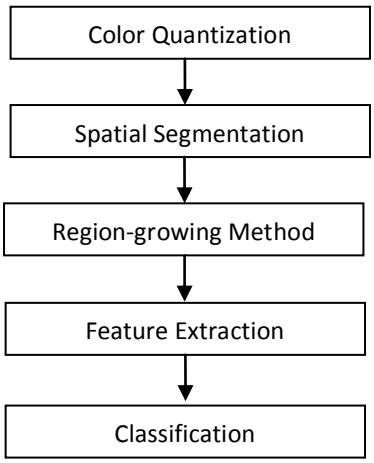

Fig.2: Flow Chart

B. Biometric Measurement

In order to estimate the severity of the pathology, a biometric parameter has been specified, the algorithm measures the extent of the Kayser-Fleischer ring by counting the number of pixels in the eye image affected..Let $N_{K\_F,r}$ be the number of pixels associate with the Kayser-Fleischer ring. In order to estimate the percentage of the oxidized eye area, the region of the iris is considered. Let N_e be the number of pixels of iris region. In this way, it is possible to estimate the extent of the Kayser-Fleischer ring by the equation:

$$\%p = \frac{N_{K\_F,r}}{N_e}$$

V. RESULTS AND CONCLUSION

Wilson disease affected image will have all the procedures to be done and the results are furnished below. From the segmented image the features are reduced using the gabor filter and is classified using the Neural networks. In the classification the final result would be the presence or absence of the Kayser-Fleischer ring, the presence of which indicates the Wilson disease. This method proves efficient when compared with other methods.

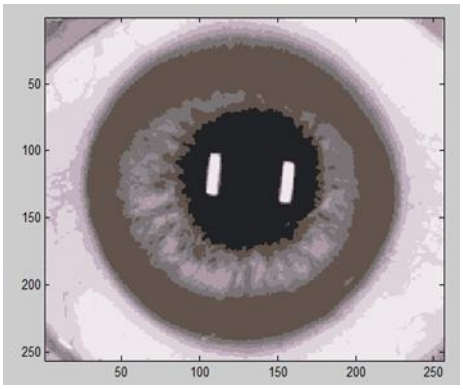

Fig.3 Color Quantization

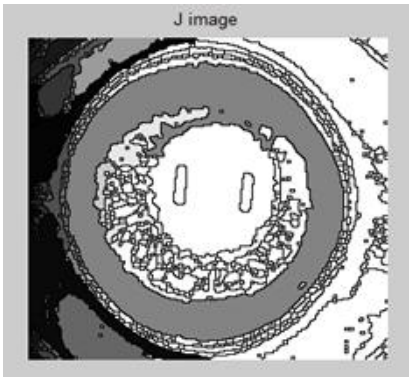

Fig.4 Spatial segmentation

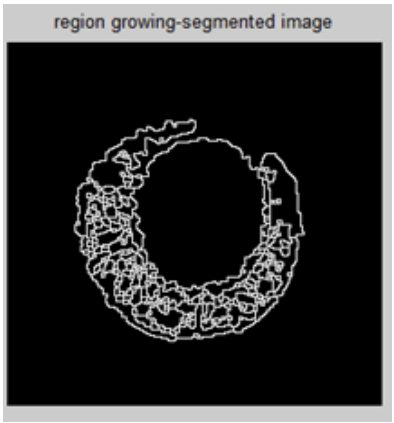

Fig.5 Region of Kayse-Fleischer ring

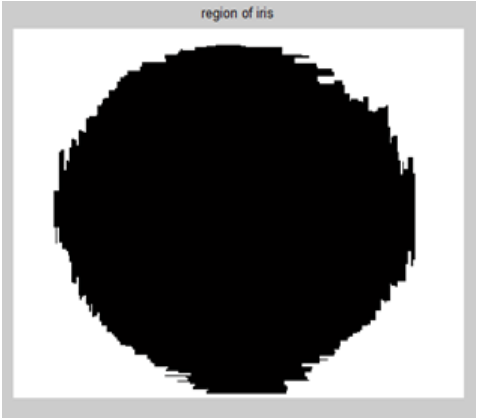

Fig.6 Region of iris

The Biometric parameter %p estimates the algorithm. In table 1 experimental result for the case study is shown. The accuracy of the proposed algorithm depends on the resolution of initial image.

TABLE I
Biometric Measurements

Parameter	**Value[#pixel]**
N_{K-Fr}	15316
N_c	26066
%p	58.7585

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