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IDENTIFICATION OF A PERSONAL ENERGY HOMEOSTASIS FOR DISEASE PREDICTION USING ENERGY MEASUREMENTS

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ABSTRACT

Every organism emits energy around it which comprises UV-radiation, EM-radiation, infrared and thermal radiation. This energy around human body represents health condition of the subject under study. These energy fields are called as aura of the body under consideration. Several types of equipment are there to capture such energy. GDV captures the distribution of energy radiation around each finger of both hands and maps them into energy distribution various organs of our body. In this work classification of human diseases based on GDV image features is done. Few GDV images in each of the 3 different categories of diseased organs of the body are taken and classified based on defected region of the body. The auras are extracted from images using morphological pre-processing, segmentation, shape, and texture features extraction followed by training and classification. Here, we proposed a new, bottom-up conceptual paradigm: Personal Energy Homeostasis Principle for predicting the disease by measuring the energy.

Keywords: Energy Homeostasis Principle, Segmentation, Feature Extraction, Classification, Neural Network (NN).

1. INTRODUCTION

Because human skin provides no barrier to electromagnetic radiation, the bioenergy field can and does radiate outside of the organism to form the Aura [1]. Time measurement of many metrics is difficult for patients. So, by analysing the bio-field, we can discover variances in many parameters and, as a result, we can assess the effectiveness of treatment given to patients. Lifestyle-related illnesses are medical conditions that arise because of changes in one's lifestyle. All lifestyle risk factors have one thing in common: they make breathing difficult and body oxygen levels low. Using infield imaging, we can determine the variance in biological parameters of various disorders. The human body emits low-level light, heat, and acoustic energy, as well as electrical and magnetic energy that physics and chemistry cannot simply define [2]. All these emissions are part of the human energy field, which is also known as the biologic field or bio field.

When any of the information linkages fails, the circuit collapses and de-synchronization ensues, resulting in functional problems at all the most critical levels [3]. All the organs and systems are working in unison under the command of a single commanding system. The ANS and blood provide information control signals to the body's systems and organs in response to commands from the CNS and the surrounding environment. These signals are 'processed' at the physiological level of systems as well as by involving the endocrine and immune systems. This simplified diagram depicts the overall nature of the body's reactions and disease development.

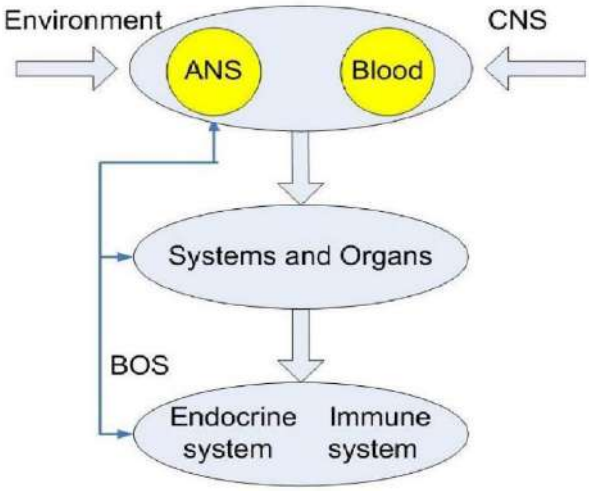

Figure 1: Overall nature of the body's reactions and disease development

Cells use energy to stay alive and at the same time, maintain some reserves to respond and adapt to dynamic situations, maintaining their homeostasis. For neurons, energy availability would be further important, as their energy expenses are high, as compared to other somatic cells. Indeed, the metabolic consumption of the brain, which represents 20% of whole-body oxygen consumption, contrasts with the neural tissue representing only 2% of whole-body weight [4,5]. Interestingly, the total brain energy consumption increases proportionally with the number of neurons among different species, including humans, and the total energy expenditure associated to a neuron during the signaling [6] and resting states is constant in different mammalian species. Thus, neurons seem to present a highly specialized system for managing their energy demands [7]. Every region of the body, however superficial or deep, is crisscrossed with well-studied communication and regulatory systems, including neural pathways, blood-borne hormones, and exosomes (cell-derived vesicles), and immune surveillance [8]. Yet the existence of fluctuating endogenously generated electromagnetic and other fields, which also suffuse all our cells and comprise an additional rich source of biological information and regulation, remains an underappreciated aspect of physiology [9].

Image descriptors can help images convey more information. These intricate auras are used to extract features. These images are suitably classed based on them. Neural network technique are used to study training and classification. In this research, preliminary work on GDV images for the body's illness detection is carried out. The remainder of this essay is structured as follows. The methodology for the proposed work is presented in Section II, the findings of the system are described in Section III, and the conclusions and future work of the research are presented in Section IV.

2. METHODOLOGY

The suggested procedure comprised processes including pre-processing, segmentation, and feature extraction. Figure 2 displays the proposed structure's general block diagram. Pre-processing is necessary for feature extraction to deal with the images' noise reduction and contrast adjustments. Then segmentation process is done with the preprocessed image. Finally, the features are extracted from the preprocessed images. The preprocessed image is split into a training dataset and a test dataset before segmentation. The model is created using a training set, and it is validated using a test set. The models are then balanced and tested using the training data.

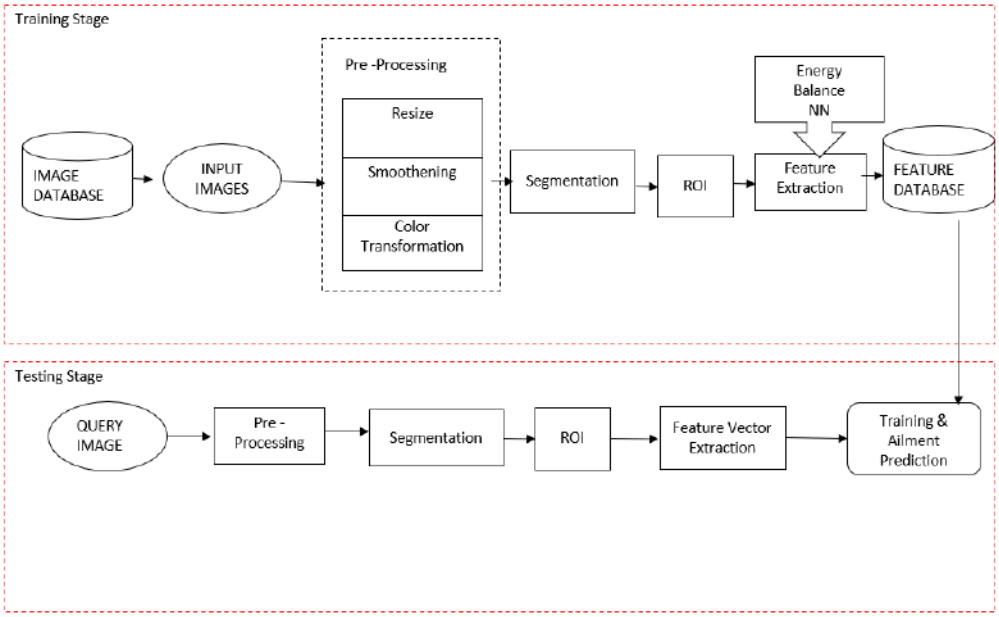

Figure 2: Detailed block diagram of the proposed methodology

i. Preprocessing

Pre-processing refers to acts performed on images at the most fundamental level. Intensity images are utilized as input and output. These recognized images are identical as the original sensor data, with an intensity image frequently represented by a matrix of brightness values for image functions. The purpose of pre-processing is to increase certain image characteristics necessary for smoothing and to improve the image data by suppressing unintentional distortions. As a preprocessing technique for the examination of huge databases, resizing methods are used. The primary pre-processing approach in the suggested work is colour transformation. The goal of colour transformation is to identify the best colour space to utilise for the backdrop of the human image and the foreground of AURA separately. 16,777, `216 colours (256 * 256 * 256) are possible with plane colours at 24 bits per pixel (8 for each RGB value). A hue of 0 to 360 corresponds to blue, 120 to green, and 240 to red. Higher values signify purer colors, and the saturation scale goes from 0 to 208. Higher numbers indicate brighter colours, and the value spans from around 0 to 512. The image's luminance or brightness values fall between [0, 100], where 0 denotes black and 100 denotes white. Colors get brighter as L rises 'A' denotes how much of the image's tones are red or green. Red/magenta is represented by a strong positive value for 'A'. Green is represented by a significant negative 'A' value. Although 'A' does not have a specific range, values frequently fall between [-100, 100] and [-128, 127]. the image's proportion of yellow or blue tones. Yellow appears when the 'B' value is extremely positive. Blue is represented by a significant negative 'B' value. Although 'B' does not have a single range, values frequently fall between [-100, 100] and [-128, 127] [10]. Additionally, the chrominance information is stored as two color-difference components (Cb and Cr), while the luminance information is stored as a single component (Y).

ii. Segmentation

Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler. Segmentation in easy words is assigning labels to pixels. All picture elements or pixels belonging to the same category have a common label assigned to them. In the proposed methodology the preprocessed image is clustered using K-means and then the output it segmented using Region based segmentation. The figure shows the general block diagram for segmentation part. Aura is connected with edges of the samples. They presented an algorithm to remove aura accurately by an image segmentation process. They extracted the aura by using Sobel

gradient masks. Gradient masks are used to find the areas of constant intensity value approximately. Areas of high gradients are considered as an aura and left unchanged. After the aura is extracted, mask is subtracted from the analysed image and then image is applied to segmentation process [11].

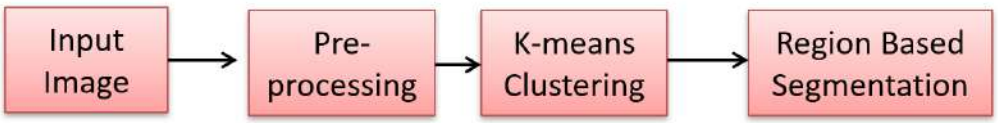

Figure 3: General block diagram for segmentation process

YIQ colour transformed images is an input of clustering algorithm. Here K defines the number of pre-defined clusters that need to be created in the process, as if K=2, there will be two clusters. It allows us to cluster the data into different groups and a convenient way to discover the categories of groups in the unlabeled dataset on its own without the need for any training. It is a centroid-based algorithm, where each cluster is associated with a centroid. The main aim of this algorithm is to minimize the sum of distances between the data point and their corresponding clusters [12]. The k-means clustering algorithm mainly performs two tasks where it determines the best value for K center points or centroids by an iterative process. Assigns each data point to its closest k-center. Those data points which are near to the k-center, create a cluster. Figure shows the image after and before performing K-means algorithm.

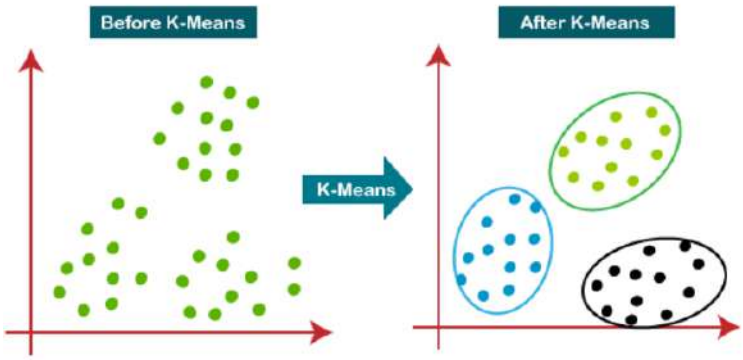

Figure 4: K-means Clustering Algorithm [13]

Algorithm for K-Means clustering

- Step-1: Select the number K to decide the number of clusters.
- Step-2: Select random K points or centroids. (It can be other from the input dataset).
- Step-3: Assign each data point to their closest centroid, which will form the predefined K clusters.
- Step-4: Calculate the variance and place a new centroid of each cluster.
- Step-5: Repeat the third steps, which means reassign each data point to the new closest centroid of each cluster.
- Step-6: If any reassignment occurs, then go to step-4 else go to FINISH.
- Step-7: The model is ready.

iii. Region Based Segmentation

In this segmentation, we grow regions by recursively including the neighboring pixels that are similar and connected to the seed pixel. We use similarity measures such as differences in each plane levels for regions with

homogeneous each plane levels. We use connectivity to prevent connecting different parts of the image. For top-down approach, we need to define the predefined seed pixel. Either we can define all pixels as seed pixels or randomly chosen pixels. Grow regions until all pixels in the image belongs to the region. During the process, the acquired images will be divided into two groups, inner aura and outer aura. The human aura is linked with several organs. Therefore, to interpret the diseases, practically, it is observed by many researchers, that the part which is affected will generally consider higher concentration of energy field and therefore these images are used diagnosis of diseases. Higher accumulation of energy field in the aura indicates the possibility of defect in that region or corresponding organ [14].

iv. ROI Detection

The binarized result of k-means segmentation considered as Initial Mask for ROI detection [15]. This bounding box is shown as a green rectangle in Figure. The four edges of *body Bounds r*espectively specify the leftmost, rightmost, topmost, and bottommost coordinates of the points of body contour as shown in figure. *Get 3 body parts Upper body, Abdominal body, Lower body.* Algorithm integrated with bio-well software removes unwanted pixel from the ROI by area parameter. Use of ASF filter on original image before segmentation process by morphology resulted in poor smoothing effect and does not restore the significant details in the image [16].

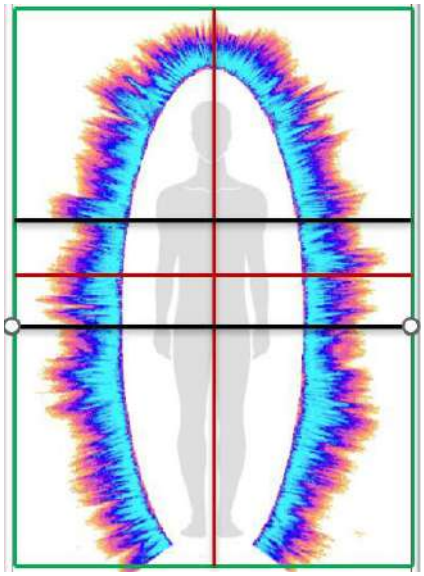

Figure 5: Four edges of body bounds [16]

v. Feature Extraction

Feature extraction is the process of extracting an image's global or local features. Features are succinct, direct explanations of the data included in the images. Three main mathematical operations make up the Colour Co-occurance Marix (CCM) procedure: (1) The image is converted from RGB to other colour representations such as grey [18], HSL and HSV [19], L*a*b* and XYZ [24], LCH and Luv [20] and CMY and CMYK [21], (2) Spatial Gray-Level Dependence Matrices (SGDMs) are calculated, producing one colour space model (CCM) for each colour space, and feature vector extraction Neural Network feature and NN is used as classifier for more accurate.

$$FV_I = \{I_{energy}, I_{Balance}, I_{NN}\} \quad [1]$$

3. RESULTS AND DISCUSSION

In this section, we first present the experimental preprocessed output and then the segmented result of different clusters like edge based and threshold which is shown in Figure 6. Moreover, the region based segmented image is shown in figure 7. To evaluate the performance of the proposed approach, we then done the ROI which is

depicted in Figure 7. The selected ROI is depicted in Figure 8 and the proposed three regions like, Up, abdominal, and lower part is shown in Figure 9.

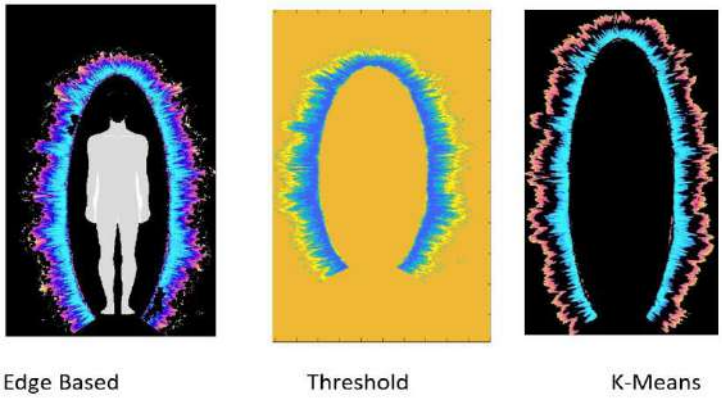

Figure 6: Output of segmentation using edge based, threshold and k-means clustering

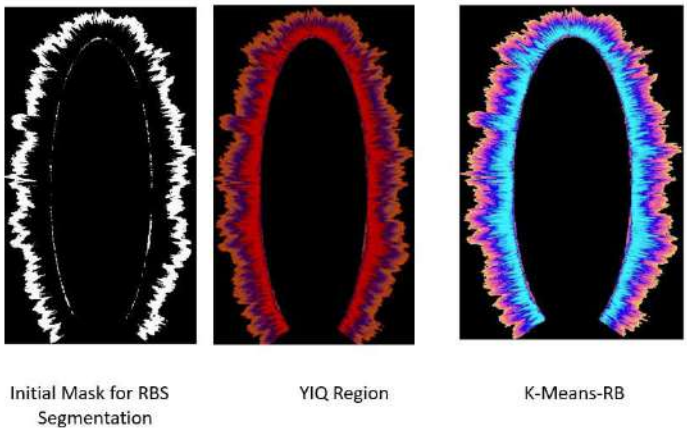

Figure 7: Output of Region based segmentation performed in initial mask, YIQ region and K-means

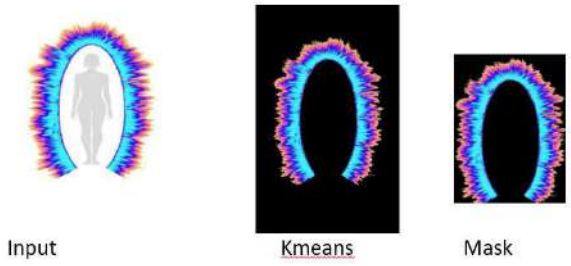

Figure 8: Selected region of interest

Figure 9: output images of ROI (up, abdominal and lower)

From the feature extraction, the energy and balance is extracted and using the neural network features, the balance were partitioned into very low balance, low balance, high level, low level, optimal level and typical balance. Similarly, the Energy features were classified as low level, optimal level, and high level. For both feature level, the output condition is depicted in table 1. For instance, if the energy is low level and the balance is very low balance then the condition of the patient is considered as "immediate". Also Table 2 shows the threshold indication of energy and balance.

Table 1: Disease prediction using energy and balance features

Energy	Balance	Output
LL	VLB	Immediate
LL	LB	Immediate
LL	TB	Moderate
OL	VLB	Immediate
OL	LB	Moderate
OL	TB	Healthy
HL	VLB	Immediate
HL	LB	Immediate
HL	TB	Moderate

Table 2: Various level of energy and balance

LL	Low Level
OL	Optimal Level
HL	High Level
VLB	Very Low Balance
LB	Low Balance
TB	Typical Balance

Energy	
<20 %	LL
20-60 %	OL
>60 %	HL

Balance	
0-50%	VLB
50-85 %	LB
85-100 %	TB

4. CONCLUSION

The detection of diseases is the focus of the biometrics subfield known as medical biometrics. AURA pictures from the GDV will be used to identify the variances. The present needs of medical biometrics to recognise a disease at an early stage of development, which will manifest as a rise in entropy and divergence from the normal functional state, may be satisfied by GDV. For colour information in this work, colour spaces like HSV, L*a*b, YCbCr, etc. can be utilised. For disease prediction the preprocessed images were segmented, and the ROI were selected. The upper, lower and abdominal portions were selected for ROI. Additionally, several segmentation techniques may be used with ROI detection to determine which organ or region is most likely to be affected. Additionally, databases on various demographics need to be extended so that we can compute the energy and balance. Finally, to improve the performance of the learning models, more pertinent feature selection techniques are applied using NN.

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