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SALIENCY BASED HOOKWORM AND INFECTION DETECTION FOR WIRELESS CAPSULE ENDOSCOPY DIAGNOSIS

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Abstract - *An ulcer is a discontinuity or breaks in a bodily membrane that impedes the organ of which that membrane is a part of continuing its normal functions. Wireless capsule endoscopy (WCE) is a radical, patient-friendly imaging system that aids non-invasive photographic review of the patient's digestive tract and, especially, small intestine. However, reviewing the endoscopic data is time-consuming and requires the intense labor of highly experienced physicians. In proposed method, a novel multi-level super pixel based image segmentation is used. After that, a particle swarm optimization using color and texture based features are extracted to diagnosis the disease.*

Key Words: WCE (Wireless Capsule Endoscopy), Endoscopic, Super-Pixel, Segmentation, PSO(Particle Swarm Optimization)

1.INTRODUCTION

Peptic ulcer disease (PUD), also identified as a peptic ulcer or stomach ulcer, is a chink in the stomach, first part of the small intestine, or sometimes the lower esophagus. The most common symptoms are waking from sleep with upper abdominal pain that can be reduced by eating. The ache is often explained as a burning or dull ache. Other symptoms include belching, vomiting, weight loss or poor appetite. About a third of older people have no symptoms. Complications may include bleeding, perforation and blockage of the stomach. Bleeding occurs in as many as 15% of people.

Identification and treatment will depend on your symptoms and the sternness of your ulcer. To diagnose a stomach ulcer, the doctor will check the medical history along with the symptoms and any prescription or over-the-counter medications taken. In a breath test, you'll be instructed to drink a clear liquid and breathe into a bag, which is then sealed. Tests and procedure used to diagnose stomach ulcers also include:

- Barium X-Ray
- Endoscopy
- Endoscopy biopsy

1.1 HOOKWORM

Hookworms are parasites that affect your lungs and small intestine. Humans contract hookworms through roundworm eggs and larvae found in dirt contaminated by faeces. The larvae enter your skin, travel through your bloodstream, and enter your lungs. They also travel through your windpipe and are carried to your small intestine when you swallow.

SYMPTOMS:

- Abdominal pain
- Intestinal cramps
- Nausea
- Fever
- Blood in your stool


Fig: Hookworm

2. METHODOLOGY

Endoscopy constitutes the most common approach for diagnosing gastrointestinal (GI) tract related diseases. Traditional endoscopy techniques play an important role to the examination of the upper and lower ends of the GI tract. However, these techniques, apart from being highly inconvenient for the patients, can hardly reach the main part of GI, the small bowel, due to its 7m-length and numerous windings. The solution to this limitation is the recently established WCE. WCE has marked a revolution in the field of GI imaging, beginning an era of non-invasive visualization of the GI tract and, especially, the entire small bowel. One of the most common GI medical findings efficiently detected by WCE is an ulcer. Approximately 10% of the people suffer from ulcerations. The main disadvantage of WCE is the time-consuming task of reviewing the 55.000 images produced.

The analysis of this video data costs 1-2 h of intense labour for an experienced physician. Besides, abnormalities may be easily missed due to oversight since they may appear in only one or two frames. The techniques proposed include texture spectrum along with neural networks and non-negative matrix factorization. Texture and colour features extracted from various colour spaces have contributed to ulcer recognition. At last, the texture analysis output is classified into healthy and ulcerous with the aid of various classification algorithms.

2.1 PRE-PROCESSING

Preprocessing algorithms are the first processing step after capturing the image, as we see in many of the examples. The preprocessing functions discussed here can be divided into two basic groups, reliant on what the resulting brightness value of a pixel in the yield image is derived from:

1. Pixel operations compute the brightness of a pixel in the output image exclusively from the intensity of the matching pixel in the source image. This group also encompasses image arithmetic functions which combine several images. Pixel operations can be further divided into homogeneous and in homogeneous pixel operations. Homogeneous actions use the same transformation function for each pixel, for in homogeneous ones the transformation function depends on the position of the pixel in the image. Pixel operations are discussed in the subsequent sections:
    - Grayscale transformations
    - Image arithmetic
2. Local operations take a certain neighborhood of the present pixel into account when calculating the brightness of the corresponding output image pixel.

Local operations are discussed in the following sections:

- Linear filters
- Median filter
- Morphological filter
- Other non-linear filters

2.3 FEATURE SELECTION

Feature selection is the process of picking a subset of the original feature spaces according to discrimination capability to improve the quality of data. This paper proposes a suggested image recovery model based on extracting the most applicable features from the whole features according to a feature selection technique. Feature extraction is done using the Gray level co-occurrence matrix(GLCM). It checks the repetition of the abnormal gray levels using a trained database as a reference. It can not only achieve maximum recognition rate but can also simplify the calculation of the image retrieval process. Particle Swarm Optimization (PSO) is used for feature selection technique. PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with certain parameters like;

- Energy
- Contrast
- Correlation
- Homogeneity etc.,

2.4 PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a computational method that heightens a delinquent by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO is a metaheuristic as it makes few or no norms about the tricky being enhanced and can search very great spaces of candidate solutions. PSO can also be used on optimization problems that are partially irregular, noisy, change over time, etc.

2.5 BLOCK DIAGRAM

The proposed block diagram for this project is given as follows:

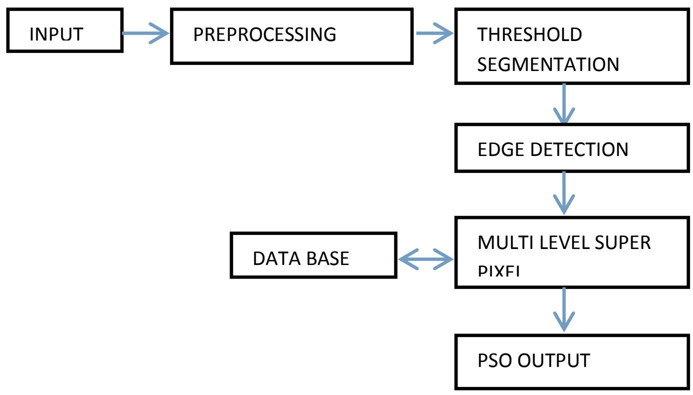


Fig: Block Diagram

2.5.1 INPUT IMAGE

Input images should be in *.jpg; or the *.png format the images used for this project were taken from the related websites.

Fig: Sample WCE images

2.6 ALGORITHM

A basic optional of the PSO algorithm works by having a people (called a swarm) of entrant solutions (called particles). These particles are moved around in the search space according to a few simple formulate. The movements of the particles are guided by their own best-known position in the search space as well as the entire swarm's best-known position. When improved, sites are being discovered these will then come to chaperon the schedules of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

Officially, let f: Rn → R be the charge function which must be minimalized. The function takes a candidate solution as an argument in the form of a vector of real numbers and produces a real number as yield which indicates the objective function value of the given applicant solution. The gradient off is not known. The goal is to find a solution a for which f(a) ≤ f(b) for all b in the search-space, which would mean a is the universal minimum. Maximization can be made by considering the function h = -f instead.

Let S be the number of particles in the swarm, each having a position xi ∈ Rn in the search space and a swiftness vi ∈ Rn. Let pi be the best-known position of particle i and let g be the best-known position of the entire swarm. A basic PSO algorithm is then:

For each particle i = 1, ..., S do:
Initialize the particle's location with a uniformly distributed random vector: xi ~ U(b_{lo}, b_{up}), where b_{lo} and b_{up} are the lower and upper boundaries of the search-space.

Set the particle's best known position to its primary position: pi ← xi
If (f(pi) < f(g)) update the swarm's best known position: g ← pi
Initialize the particle's velocity: vi ~ U(-|b_{up}-b_{lo}|, |b_{up}-b_{lo}|)
Until a expiry criterion is met (e.g. number of iterations performed, or a solution with adequate objective function value is found), repeat:

For each particle i = 1, ..., S do:
For each dimension d = 1, ..., n do:
Élite random numbers: rp, rg ~ U(0,1)
Update the particle's velocity: vi,d ← ω vi,d + φp rp (pi,d-xi,d) + φg rg (gd-xi,d)
Keep posted the particle's position: xi ← xi + vi
If (f(xi) < f(pi)) do:
Apprise the particle's best known position: pi ← xi
If (f(pi) < f(g)) update the swarm's best known position: g ← pi
Now g holds the best-found result.

The parameters ω, φp, and φg are selected by the expert and control the behavior and efficacy of the PSO method.

2.7 MEDIAN FILTER

A median filter is used to preserve edges while eliminating random clatters present in the image. For a two-dimensional image, the pictures are of 3-by-3 neighborhood value. The median filter swaps each entry with the median of the neighboring entries.

2.8 SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple segments

- *THRESHOLDING*

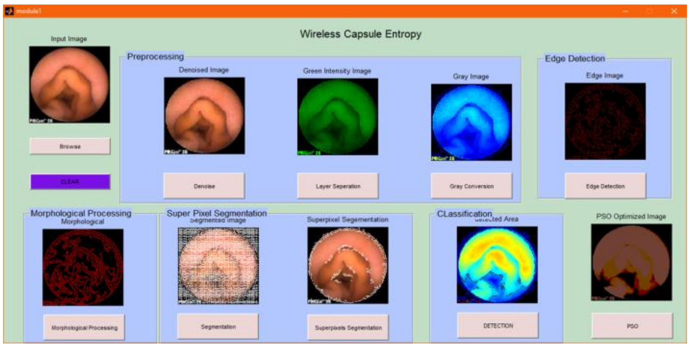
The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity is fewer than some static constant T or a white pixel if the image intensity is greater than that constant. Here, instead of using a local threshold value we use a formulated global threshold value.

- *EDGE SEGMENTATION*

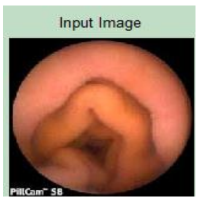
Image processing is any form of information processing for which the input is an image, such as frames of video; the output is not necessarily an image but can be a set of features giving information about the image. Since images contain lots of redundant data, scholars have discovered that the most important information lies in its edges. Edges typically correspond to points in the image where the gray value changes significantly from one pixel to the next.

3 RESULT

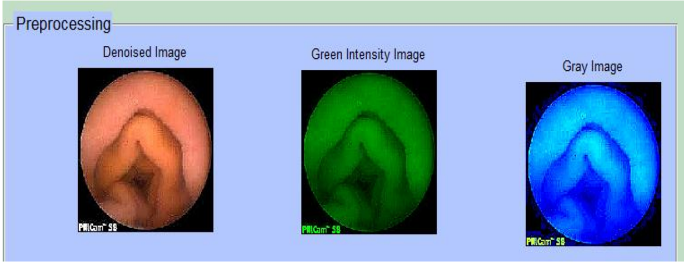
3.1Analysis of a Normal or Healthy abdomen image:



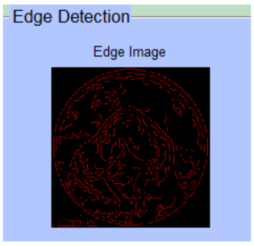
(a) Input *Image*

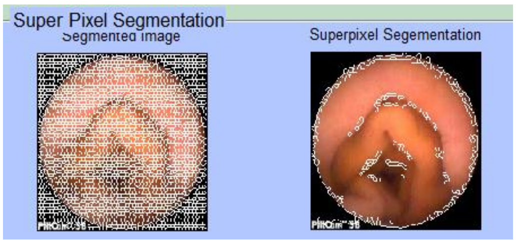


(b) Pre-processed image

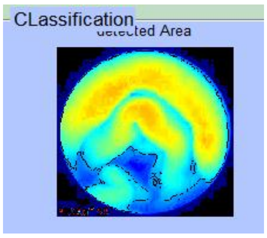


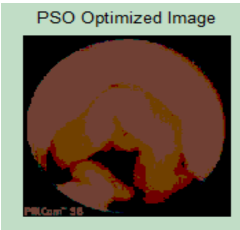
(c) Segmented image



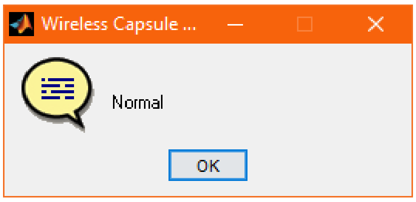


(d) Classification (e) Optimized Image

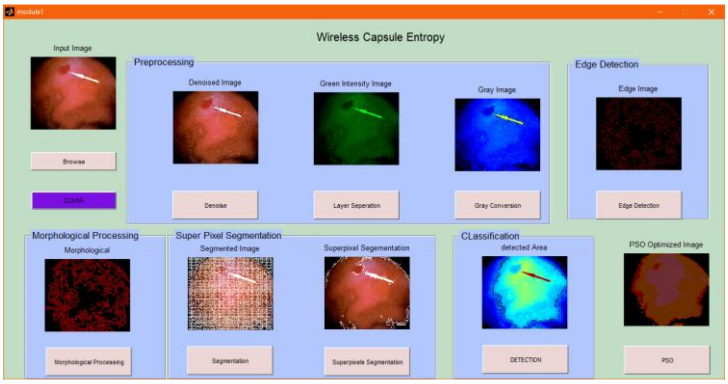




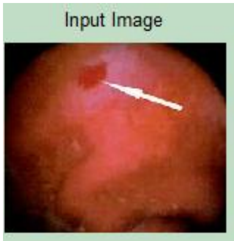
(f) Output



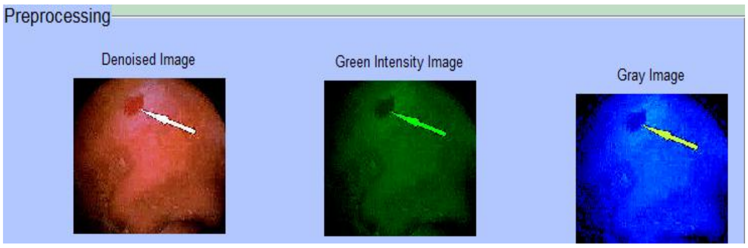
3.2 Analysis of abnormal or infected abdomen image:



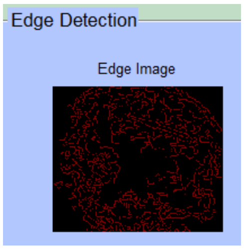
(a) Input Image

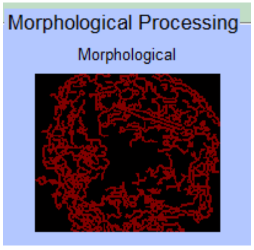


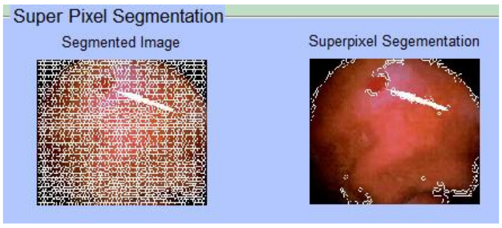
(b) Pre-processed image



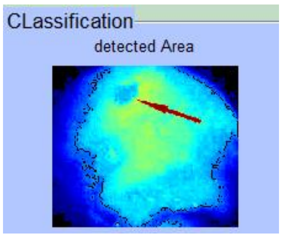
(a) Segmented image



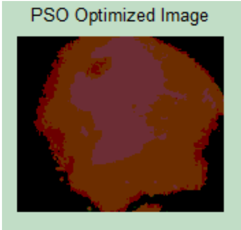




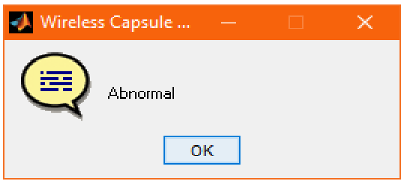
(d) Classification



(e) Optimized Image



(f) Output



4.CONCLUSION

In this paper, we have detected the abnormalities in the abdomen using the wireless capsule endoscopy (WCE) images. The microscopic images of ulcer are examined by changes based on texture, geometry, colour, statically analysis used as the input. We have trained and classified the microscopic images. This system is reliable and cost-effective.

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