ANALYSIS OF BOWEL IMAGES USING WIRELESS CAPSULE ENDOSCOPY

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ABSTRACT
Bowel tumor is the third common cancer with nearly 2 lakh new cases being diagnosed every year. If gets diagnosed at an premature stage, there is a high likelihood of rehabilitation. Wireless Capsule Endoscopy enables the explicit picturization of gastrointestinal tract with negligible discomfort for the patient, but with considerable time for screening. In order to prune this time, some of the computerized approaches are being incorporated. Initially the WCE images are preprocessed using a median filter for noise removal and then subjected to segmentation using fuzzy active contour method and classification using support vector machines. Eventually these results are analogized with the performance of neural networks and evidenced that SVM provides the better accuracy.

KEY WORDS
Wireless Capsule Endoscopy, Gastro Intestinal tract, Image segmentation, Image Classification, Fuzzy Active Contour, Support Vector Machine.

I. INTRODUCTION

Bowel tumor initially begins as a small benign outgrowth and normally looks like little lumps called polyps, which may augment inside the rectum or colon and become cancerous, as people get older. The progression of bowel tumor substantially takes many years. It starts from the cells that line the intestine. Often very small amounts of blood are leaked from these cancers long before any predominant symptoms and gets passed along with faeces. If left untreated it spreads deeper into the wall of the bowel and to lymph nodes and can even affects liver or lungs[1][2]. So the risk of bowel tumor diminishes to a greater extent when these polyps are detached properly. Certain bowel tumor diagnosing methods include colonoscopy, esophagogastroduodenoscopy, sigmoidoscopy and so on. The vital snag in all these methods is that some segments of the small intestine is left unexamined. So we opt for a special technique called wireless capsule endoscopy[3] in order to examine the subtle abnormalities and noteworthy features of the small intestine in a more reliable and detailed manner.

The WCE system comprises of a sensor array or electrodes, which are attached to the patient's abdomen. A data recorder which is worn by the patient during their study, gets connected with this array. The capsule is 26mm x 11mm in size and consists of an optical dome, a lens, a semiconductor, several light emitting diodes, a transmitter and an antenna as shown in Fig 1. Once swallowed the capsule starts capturing images at the rate of two per second and gets disposed naturally through the bowel movement. Images registered by the capsule camera are transmitted and stowed on the data recorder worn by the patient. After the study, the images are downloaded onto a computer where the images are then observed and interprets by a specially trained gastroenterologist. In the overall scenario of 8 hours, an average of 50,000 images are taken. Scrutinizing all those recorded images is tiring and time consuming. So we opt for computerized approaches such as image segmentation and classification.

Fig 1 Endoscopy Capsule

Some researchers have begun studies concerning the orientation of exploring the automatic scrutinization of WCE images in order to deteriorate physician's burden.

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Using a synergistic methodology that proposes several methods such as local binary pattern, principle component analysis and improved gradient vector flow model into a unique, non conventional practise for automatically and efficiently detecting, extricating and detaching abnormalities in WCE images was formulated [3] [4] [5]. Our method is inspired by the following research: Categorization and Segmentation of Intestinal Content Frames for Wireless Capsule Endoscopy [6].In our paper, a new method incorporating fuzzy active contour segmentation and support vector machine is proposed. The rest of the paper is organized as follows: Section II furnishes information about image preprocessing segmentation and classification, as well as some related works. Section III, IV, V describes the proposed segmentation and classification methods followed by experimental results and conclusion, respectively.

II. IMAGE PREPROCESSING, SEGMENTATION AND CLASSIFICATION

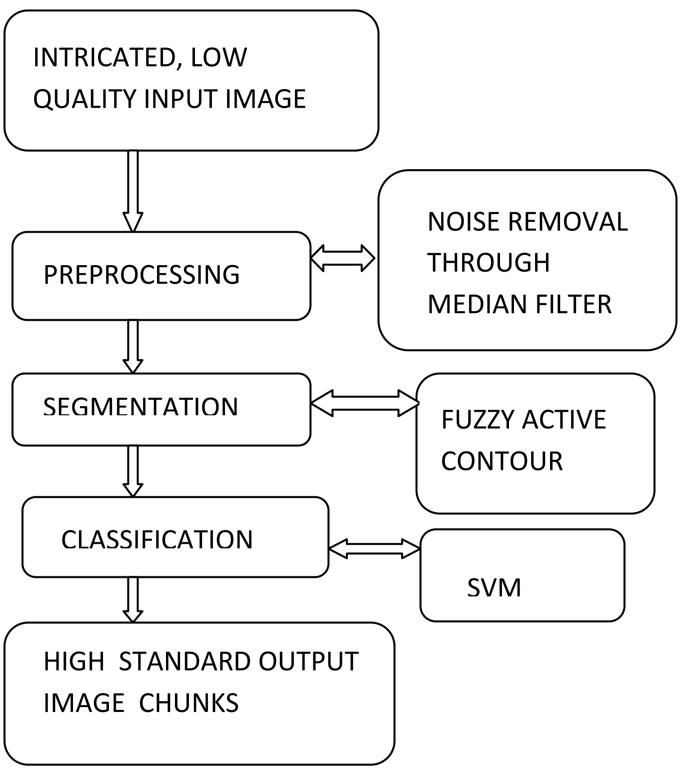

Fig 2 System Configuration

Medical imaging is very robust on its unique way, but not always intuitive. There is no universal algorithm for segmentation of every medical image. All imaging system has their own specific limitations. The techniques obtainable for processing the medical images are specific to application, imaging modality and type of body part to be analyzed. Image preprocessing, also called image restoration, involves the correction of distortion, degradation and noise introduced during the imaging process. This process produces a corrected image that is as close as possible, both geometrically and radiometrically, to the radiant energy characteristics of the original scene. The intents of preprocessing includes, enhancement of the visual appearance of images , improvement of the manipulation of datasets and formulation of the images more suitable for further processing in CAD systems .

If not correctly used, the enhancement techniques can emphasize image artefacts, or even lead to a loss of information. Some of the pre-processing methods include, image resampling, grey scale contrast enhancement , noise removal and mathematical operations. In our system, median filter is used in which the 3x3 sub-region is scanned over the entire image and at each position the centre pixel is replaced by the median value. The precise tumor segmentation is possible only if image is pre-processed as per image size and quality.

Segmentation involves the partitioning of an image or volume into distinct (usually) non-overlapping regions in a meaningful way. It can also be thought of as a labeling operation: a label corresponding to tissue type or anatomical label corresponding to tissue type or an anatomical structure is assigned to each pixel or voxel in the image. The exigency of segmentation includes, improving the analysis of an image when there is no direct correspondence between the image pixel properties and the type of tissue, labeling the pixels of an image according to semantic content and facilitating the manipulation and visualization of the data with a computer. Segmentation aids in identifying separate objects within an image, discovering regions of connected pixels with similar properties, spotting boundaries between regions and in removing unwanted regions[7]. However, it is well accepted that there is no general method for solving all segmentation problems. Instead, the algorithms have to be highly revamped to the application in order to procure a valid performance. In this paper, fuzzy active controur segmentation methodology is proposed.

Image classification analyzes the numerical properties of various image features and assigns a tissue class to a each point in the image, where the classes are agreed in advance and organizes data into categories[8]. Classification algorithms typically employ two phases of processing namely training and testing. In the former case, characteristic properties of typical image features are segregated and, based on these, a unique description of each classification category, i.e. training class, is generated. In the later case, these feature-space partitions are used to classify image features. In classification process, the elucidation of training classes is the salient component. Classification can be classified as supervised and unsupervised. In supervised classification , training classes are nominated based on the mastery of the user. Unsupervised classification depends on clustering algorithms to automatically segment the training data into prototype classes. Here, supervised SVM classifier is described.

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III FUZZY ACTIVE CONTOUR SEGMENTATION

An active contour is an energy shrinking spline that discerns specified features within an image. It is a flexible curve which can adapt itself to required edges or objects in the image . It consists of a cluster of control points connected by straight lines as shown in Fig 3. The active contour is expounded by the amount of control points it possess as well as sequence of each other. Fitting active contours to shapes in images is an interactive process. The user must propose an initial contour, as which is quite in proximity to the intended shape as visualized in Fig 4.The contour will then be allured to features in the image extracted by the internal energy generating an attractor image. Fuzzy active contours uses a fast marching method to proliferate the initial seed outwards followed by a level set method to fine tune the result[9][10].

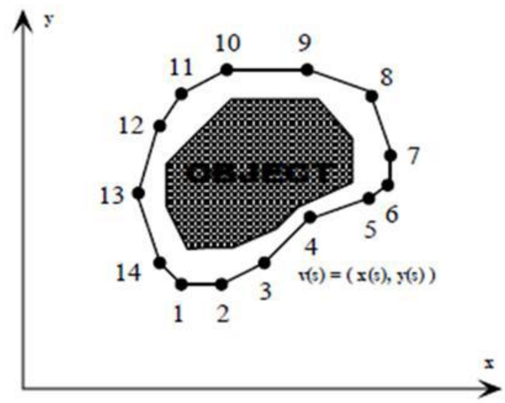

Fig 3 Basic Form Of Active Contour

The basic idea is to progress the curve outwards with the rate that relies upon the image itself:

- When the curve sweeps over places where the image gradient is little, it let the curve expand rapidly.
- When the curve sweeps over places where the image gradient is more, it suspect the contours are near the boundary and slows down the curve. Here image gradient refers to the change in the value from one pixel to the next.

Additionally it includes a curvature term to the speed, in order to annex a little surface tension to the expanding contour.

A main advantage of active contour methodology is that they partition an image into sub-regions with uninterrupted, continual boundaries as shown later in Fig 6.As we consider image segmentation, it gets classified into two types namely: edge- and region- based. Edge-based segmentation method partitions an image based on discontinuities among sub-regions, in contrast, region-based segmentation concentrates on the uniformity of a desired property within a sub-region.

a)Edge-based Active Contours

Edge based active contour models holds two parts namely the regularity part, which focuses on the determination of the shape of contours, and the edge detection part, which concentrates on attracting the contour towards the edges.

b)Region-based Active Contours

Likewise region-based active contour models also incorporates two divisions namely the regularity part, which aims at determining the smooth shape of contours, and the energy minimization part, which hunts for uniformity of a desired attribute within a subset.

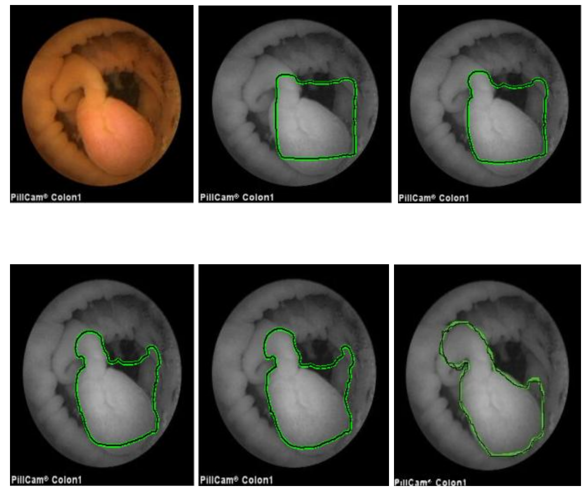

Fig 4 Initial Boundary Shape Of Tumor In A WCE Image And Its Corresponding Contour Evolution By Expand And Shrink Operations.

IV. SUPPORT VECTOR MACHINE

Support Vector Machines mainly relies on the conception of decision planes that elucidates decision boundaries. According to learning algorithms, a decision plane is one that distincts set of objects having disparate class memberships. In terms of machine learning, SVMs are supervised learning models with analogous learning algorithms that scrutinize data and identify patterns, used for classification and regression analysis[12][13]. A SVM model is a delineation of the examples as points in space, plotted so that the examples of the separate categories are divided by a clear wide gap. New examples are then plotted into that same space and foreseen to belong to a category based on which side of the gap they descend on as shown in Fig 5.

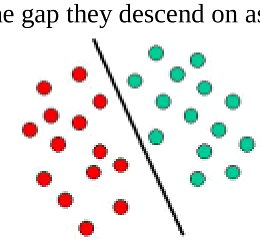

Fig 5 Hyper Plane For A Svm Trained With Samples Separating Two Classes

The main goal is to set a decision boundary between two classes that is extremely far from any point in the training data. Support vector machines use a linear separating

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hyperplane to generate a classifier with a maximal margin. When a given class cannot be linearly separated in the original input space, the SV machine first (non-linearly) transforms the original input space into a higher dimensional feature space and proceeds with it.

The two major types of SVM includes,
SVM-RFE (Recursive Feature Extraction)is an iterative algorithm that starts executing backward from an initial set of features. At each iteration it,

- fits a simple linear SVM,
- ranks the features depends on their weights in the SVM solution, and
- eradicates the feature with the least weight.

SVM- SFFS (Sequential Forward Floating Search) executes in three steps namely,
• Step 1: Inclusion. It uses the basic SFS method to choose the most significant feature with respect to X and include it in X. terminate if d features have been chosen, orelse go to step 2.
• Step 2: Conditional exclusion. Determine the least significant feature k in X. If it is the feature just included, then retain it and get back to step 1. Orelse, exclude the feature k. Note that X is now superior than it was before step 1. Continue to step 3.
• Step 3: Continuation of conditional exclusion. Once more determine the least significant feature in X. If its exclusion will (a) leave X with at least 2 features, and (b) the value of J(X) is substantial than the criterion value of the best feature subset of that size found so far, then exclude it and repeat step 3. When these two conditions cease to be contented, return to step 1.

V. RESULTS AND DISCUSSION.

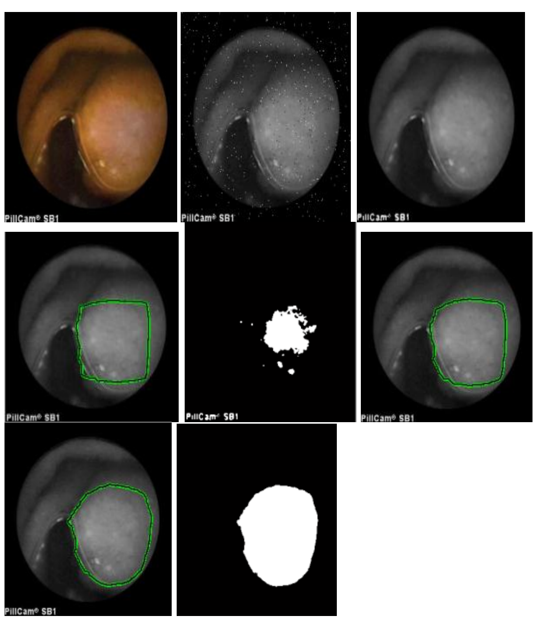

Fig 6 Segmentation Of WCE Image Using Fuzzy Active Contour Method.

In our research, the efficiency of svm is compared with neural network and cascade feed forward neural networks. The development of ANNs involves extensive experimentation preceding theory. Conversely , the evolution of SVMs initially involved sound theory, then proceeds with the implementation and experiments. Neural networks are generally elucidated as, "a computing system comprises of a number of simple processing elements which are immensely interconnected to process information by their dynamic state response to external inputs".
Neural networks are organized in layers which are made up of numerous interconnected nodes which hold an activation function. Patterns are fed to the network via the input layer, which interfaces to one or more hidden layers to execute the actual processing via a system of weighted connections. Then the hidden layers are linked to an output layer where the output is obtained. Cascade-forward networks are similar to neural networks, but they include a connection from the input and each possible preceding layer to following layers[14].

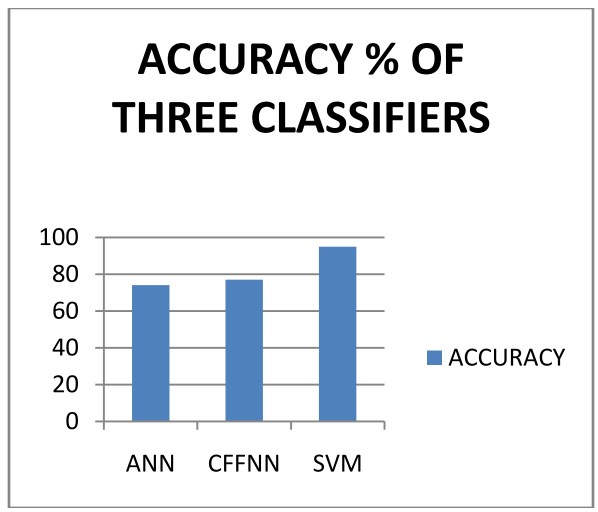

Fig 7 Graph Demonstrating The Accuracy Of Three Classifiers

The reasons for the superiority of SVM over neural networks include,

- SVM provides a global and unique solution, while ANNs can suffer from multiple local minima,
- SVMs delivers a sparse solution and have a simple geometric interpretation.
- Unlike ANNs, the SVMs computational complexity does not lie on the the input space's dimensionality.
- SVMs use structural risk minimization, where as ANNs use empirical risk minimization,
- The significant advantage of SVM approach is that it does not attempt to control model

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complexity by keeping the number of features small.

- Neural networks mainly suffers from their theoretical inadequacy, e.g. back-propagation generally converges only to locally optimal solutions. Here SVMs can provide a considerable improvement.
- The main reason that SVMs very often outperform ANNs is that SVMs are rarely vulnerable to over fitting.
- In our system, initially 9 WCE images were taken. These images were trained and tested with each of the three classifiers namely artificial neural network(ANN), cascade feed forward neural network(CFFNN) and support vector machines(SVM). As described earlier, classification algorithms involves two phases such as training and testing. In the training phase, salient attributes from this 9 images are isolated and a unique description of each classification category, i.e. training class, is generated. In the testing phase, these feature-space segregations are employed to classify image features. Finally the accuracy of all three classifiers are compared and inferred that SVMs remains the best with almost 98% efficiency, in classifying bowel abormalities in WCE images as shown in Fig 7.

VI. CONCLUSION

Since the integration of computerized approaches becomes an eminent factor in the medical field, with the tremendous growth of patient data every second. In this paper, WCE images are subjected to preprocessing, segmentation and classification and abnormalities within the bowel structures are successfully detected. And also the results of SVM classifier is compared with neural network classifiers and proven that SVM achieves a superior accuracy in classifying images.

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