# Detection of Diseases in Intestinal Lumen by using SVM-Classifier Algorithm

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*Abstract*— The wireless capsule endoscopy is an emerging technology which is used to detect the abnormalities in Gastrointestinal (GI) tract (i.e. small intestine and large intestine). A endoscopic video consists of more than 57000 images and it is very difficult for physicians to examine the intestinal diseases like ulcer, cancer, bleeding, tumor out of thousand endoscopic images makes the task very difficult and expensive. Our goal is to develop a detection method by using support vector machine classifier. SVM is a non-linear classification which performs efficiently using kernel trick and mapping their inputs into high-dimensional feature spaces, which showed good results in the medical diagnostics and other fields. First, frames presenting intestinal images are detected by an SVM classifier using textural and color information. Secondly, intestinal images are segmented into regions. We show a detailed validation using a large dataset and there may not be large differences in accuracy, there is difference between them in complexity by using SVM algorithm. This paper shows that SVM can be very efficient and yield high accuracy rate of 98.6% and precision of 95.5%.

***Key words:*** Wireless Capsule Endoscopy, Lumen segmentation Classification, Support Vector Machine (SVM)

## I. INTRODUCTION

The intestinal tract in the human gut is the host of trillions and trillions of microorganisms in both commensal and pathogenic forms. In fact, the microbial community in the human gastrointestinal (GI) tract is one of the most crowded population on earth. The relationship of these microorganisms with the human GI tract is responsible for human health and several diseases. It is essential to comprehend their roles to human ailments related to the GI tract.In modern machine wireless endoscopy[3],[5] plays a vital role as it allows physicians to detect severe diseases in early development stages. Especially the gastrointestinal tract is examined routinely in order to detect ulcer, bleeding, tumor, cancer. The term lumen refers to the image region which inturn refers to the farthest image region of tissue, relative to the camera, when the capsule is even coarsely aligned with the GI tract. As a consequence, the mortality rate for many diseases, especially different types of cancers, has been lowered drastically. This support method targeting the gastrointestinal tract as those potentially help to save time, lower the cost and lower the risk for the patients.

In Capsule Endoscopy, a patient is allowed to swallow a capsule which consists of high resolution color camera, a wireless transmitter, a battery and LEDs. Once it is activated, this camera will take 57,000 color images through its 8-hour of journey in the GI tract. The images are transmitted continuously to data recorder. The recorded images are collected and are analyzed by physicians. He will examine the images to identify the diseases, e.g. bleeding, tumor and this process usually takes few hours for physicians to complete the process with accuracy.

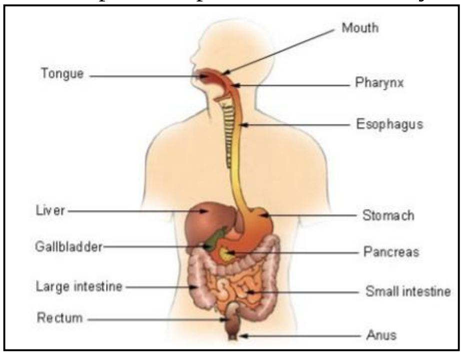


Fig. 1: Gastrointestinal Tract

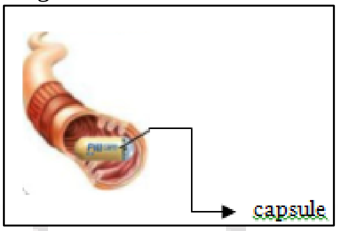


Fig. 2: Micro-robot Capsule

Wireless capsule endoscopy helps to evaluate different types of features, classifiers throughout the work in order to obtain the robust system for classification of endoscopic images. Wireless capsule endoscopy is an imaging capsule which helps to view the intestine. The entire intestine is examined through this technique without pain, sedation and air insuflation. It is a tool for detection of abnormalities in the small intestine. This wireless endoscopy takes digital images from the gastrointestinal tract. To reduce the computational complexity grouping of pixels is done.

Classification of the images can be done in few minutes by using the computer aided diagnosis system. Among most of the classification algorithm, SVM – a binary classifier is used. The main aim of SVM is to separate two classes with decision surface that has maximum margin. SVM is a classifier algorithm used in medical diagnosis for the detection of tumor, cancer, ulcer, bleeding in endoscopy color images. SVM has been applied to many problems including classification of diseases, texture detection, bioinformatics and medical diagnosis particularly for tumor, cancer detection in color images.

## II. RELATED WORK

Several previous works have been considered for the detection of intestinal diseases in Capsule Endoscopy images. Lumen detection is to focus interest on the dark image region considering that it corresponds to the lumen and finding the shape of this region [9]. For better estimation of lumen boundary adaptive thresholding, region segmentation were employed in[10],[13]. Color image enhancement is done in region extraction method [14]. The task in [2] detects the abrupt changes in the lumen. Capsule endoscopy equipped with movement mechanism which was more comfortable and non invasive to patients. Designed in accordance with the hardware related to FPGA in that energy was consumed [3]. Chipset is designed and implemented for micro ball endoscopy system [5]. The video is segmented to find the contraction in intestine which was the effective algorithm to segment the image [7]. Digital IC is designed inside the capsule which eliminates complication associated with endoscopic procedures [8] to develop new wireless robotic capsule endoscope with external guidance system. Threshold is selected to minimize the separability of the resultant classes in gray levels [16].

Adaptive threshold method fails to acquire a proper threshold to extract the lumen in the presence of turbid liquid in Intestinal lumen detection method. In Real-time polyp detection, the detection rate is lowered. In endoscopic micro ball design, spots are omitted by camera due to its limited field of view. In video Capsule Endoscopy, due to intestinal contractions the camera cannot be adaptable to the human intestine as it has twists and turns around. In a threshold selection method from Gray level Histogram the process is tedious and sometimes unstable calculation.

## III. METHODS

### A. *Input Image*

Wireless Capsule Endoscopy method involves swallowing a capsule that takes multiple digital photos of the intestine. If the lumen is invisible or partially imaged the capsule is rotated and the entire lumen appears centered in it. It transfers the captured image wirelessly to an external receiver worn by the patient around waist. The collected images are then transferred to the computer for diagnosis, review and display. From the collected images, a single static image is used to detect the disease in the Lumen. The image is then processed, segmented, extracted and then classified.

### B. *Image Pre-processing*

The real time biomedical images contain very large amount of noise as well as it is not clear to recognize accurate structure of components. The input image obtained is pre-processed to enhance image feature by removing noise and to increase brightness, etc. Some image features are very important for further processing. Image pre-processing is done to increase the reliability, to suppress the noise present in the image and to enhance the image. Contrast enhancement, Pixel adjustment, Cropping, Resizing followed by Filtering are done in image processing.

#### 1) *Contrast Enhancement*

Contrast Enhancement is done in image processing in order to increase the quality of the images which is necessary for human interpretation. Contrast enhancement improves the visibility of an object by enhancing the brightness in the objects and in their backgrounds. The contrast can be altered by mapping the gray level values to new values in an image through a gray-level transform.

#### 2) *Resizing and cropping*

Image can be resized using image scaling. This scaling will stretch an image without changing the actual pixels. Resizing actually changes the PPI (Pixel per inch) number of the image without changing the appearance of image. With bitmap graphics, the size of an image can be reduced or enlarged.

Cropping is done to remove the unwanted portions in an image. Cropping removes the areas of a picture by reducing horizontal or vertical edges. Depending on application, cropping is performed on digital images using software, photograph etc. Cropping allows pictures to be viewed clearly for further processing.

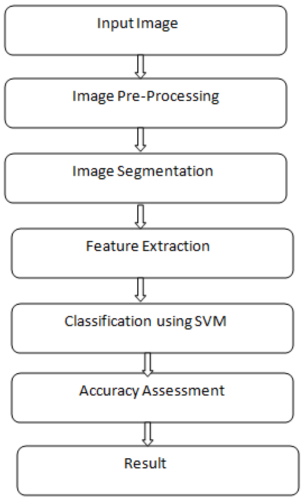


Fig. 3: Block diagram

#### 3) *Filtering*

In image processing, Filters are mainly used to suppress the lower frequencies or higher frequencies in an image and to suppress the noise. Adaptive mean Filter is used to give better output image. The filtering performs processing to determine the pixel that has been affected by noise. The noise in the pixel can be found by comparing each pixel in an image with the nearest neighborhood pixels. The noise pixels are replaced by median pixel value of pixels in the neighborhood.


Fig. 4(a): Fig. 4(b):

Fig.4(a) and fig.4(b) shows the original and preprocessed image of bleeding.

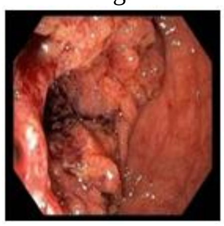
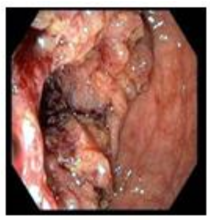

Fig. 5(a) Fig. 5(b)

Fig. 5(a) and fig.5(b): shows the original and preprocessed image of Cancer.

### C. *Image Segmentation:*

Image segmentation is the method of dividing image into numerous segments, this represented as pixel or sub-pixels. Main aim of segmentation is to determine the boundary of interested region. In other words Image segmentation is the process of dividing an image into multiple segments (sets of pixels, also known as super pixels). The main motive of image segmentation is to modify the representation of an image that is easy to analyze.

In this paper, segmentation is done with K-means clustering. The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. In K-means clustering the number of clusters to be partitioned must be specified and allow clusters data by iteratively computing a mean intensity for each class and segmentation of image is done by classifying each pixel with closest mean. The steps in K-means algorithm is, 1) Select K initial clusters $Z_1$ (I), $Z_2$ (I)… $Z_k$(I).2)At the $K^{th}$ iterative step, distribute the samples x among the K clusters.3)To compute the new cluster centers $Z_j(K+1)$,j=1,2,…,k, such that sum of the square distance from all points in $C_j(K)$ to the new cluster is reduced. 4) If $Z_j$ (K+1), j=1,2…K the procedure is terminated.

### D. *Feature Extraction*

To identify abnormalities or to classify pictures into totally different grades of diseases, feature extraction plays an important role. Feature extraction techniques are applied to get features that will be useful in recognition and classification of images. Feature extraction techniques are helpful in various image processing applications. Generally features describe the behavior of an image they show its place in terms of storage taken, efficiency in classification and in time consumption also.

Fig. 6: shows the original image of tumor

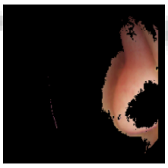

Fig.6(a)

Fig.6(b)

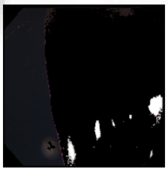

Fig.6(c)

Fig.6(a) & Fig. 6(b) and Fig.6(c) shows the segmented images of tumor with three clusters by using K means clustering.

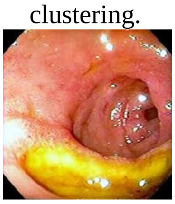

Fig.7 shows the original image of ulcer.

Fig.7(a)

Fig.7(b)

Fig.7(c)

Fig. 7(a), Fig.7(b) and Fig.7(c) shows the segmented images of ulcer with three clusters by using K means clustering.

### E. *Classification*

It is very important and final stage of every project. Main aim of this classifier is to classify the images according to some parameters which help to identify the disease. According to survey, different classification techniques were used such as SVM (support vector machine), neural network, fuzzy classification and decision tree. In this paper SVM algorithm is used for classification of intestinal diseases.

## IV. SVM CLASSIFIER

SVM is a very popular supervised learning technique among machine learning algorithms. It is used in both classification and regression problems and it has a wide range of applications. SVM algorithms have gained importance over the years due to its robustness, high accuracy and effectiveness [5]. Compared to other competing classification methods, they often perform better in terms of generalization performance [7].

### A. *The Statistical Learning Theory*

SVM formulation is based on the Statistical Learning Theory, which aims to deal with the problem of gaining knowledge from an available set of data. It provides a framework to study how to make inferences, predictions and decisions, and how to construct models from the data. Let X and Y are the input and the output spaces. In the following discussion, we will consider binary classification and use labels Y = {−1, +1} for the two classes, with −1 being a negative example and +1 a positive example. Let (x, y) ∈ (X, Y) be a training set of dimension *l* that is sampled according to some unknown distribution P(x, y). The main goal of a classifier is to find a mapping f: X → Y, while minimizing the expectation of the test error, also called the expected risk or just risk, which is given by,

$$R (f) = w\ c(f(x), y)dP(x,y) \qquad (1)$$

In this expression, c(f(x),y) is called the loss function and is a measure of the test error, that relates the predicted value of x with its actual value y. A common loss function used in classification problems is,

$$c(f(x),y) = 1\ 2|y-f(x)| \qquad (2)$$

This function return 0 if x is correctly classified and 1 otherwise. Since P(x,y) is an unknown distribution, usually it is not possible to minimize the expected risk. One way of getting over this is to use the Empirical Risk Minimization induction principle, which replaces the expected risk by the empirical risk. The empirical risk is defined as the mean error rate on the training set and is given by,

$$Remp(f) = \sum i=1 c(f(x),y) \qquad (3)$$

### B. *Linear SVM*

Let's assume that there is a hyperplane which separates positive points, x ∈ {+1}, from negative points, x∈{−1}. The points lying in this hyperplane satisfy,

$$wTx + b = 0 \qquad (4)$$

where x is a vector point and w is the weight vector, which is perpendicular to the hyperplane and has norm ||w||. The perpendicular distance from origin to hyperplane is represented as |b| ||w||. The separating hyperplane divides the data space into two distinct regions, each one corresponding to one of the classes. In each region, the data points which are nearest to the hyperplane are referred as support vectors.

Support vectors are considered to be the most important data from the training set, since they are the only data points used to determine the equation of the separating hyperplane. Let d+ and d− be, respectively, the perpendicular distances from the separating hyper- plane to the closest positive and negative support vectors. H+ and H− are the hyperplanes which are parallel to the separating hyperplane and contain the support vectors. These hyperplanes are defined by,

$$H+: wTx + b = +1 \quad (5)$$
$$H−: wTx + b = −1 \quad (6)$$

Note that any point from the training set falls between these two hyperplanes. Thus, every training data satisfy,

$$wTxi + b \geq +1, yi = +1 \quad (7)$$
$$wTxi + b \leq −1, yi = −1 \quad (8)$$

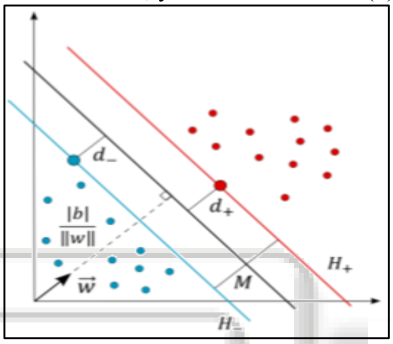


Fig. 8: Linear SVM: The optimal hyperplane.

Combining these two inequations yields,

$$yi(wTxi + b) \geq 1, \forall i \quad (9)$$

The distances from H+ and H− to the origin are, respectively, b+1 ||w|| and b−1 ||w|| . The margin M is defined as the distance between H+ and H−, that is,

$$M =b + 1 ||w||b−1||w||=2 ||w|| \quad (10)$$

The optimal hyperplane allows separating data with the maximum margin possible and is determined by minimizing ||w||2, subject to constraints. This leads to a quadratic optimization problem.

### *C. Rigid-Margin SVM*

Rigid Margin SVM defines a rigid decision boundary and does not allow any data point to lie inside the margin. The optimization problem becomes,

Minimize,

$$2||w||2 \quad (11)$$

Subject to,

$$yi(wTxi + b)\geq 1, \forall i . \quad (12)$$

This quadratic optimization problem is solved by switching to an unconstrained Lagrangian formulation [10, 11]. The introduction of positive Lagrangian multipliers αi, i = 1,...,l yields,

$$LP =1\ 2||w||2−\sum iαi[yi(wTxi + b)−1] \quad (13)$$

LP must be minimized with respect to w,b and maximized with respect to αi. The solution is given by the saddle point. This is a convex quadratic optimization problem, since the objective function is itself convex and the points satisfying the constraints also form a convex set. For this reason, it is possible to make use of the Karush-Kuhn-Tucker (KKT) conditions to solve the problem and, therefore, the gradient of LP should vanish,

$$\partial LP\ \partial w= 0 \Rightarrow w =\sum iαiyixi \quad (14)$$
$$\partial LP\ \partial b= 0 \Rightarrow\sum iαiyi = 0 \quad (15)$$

Replacing these results in equation 2.13 gives:

Maximize,

$$LD =\sum iαi −1\ 2\sum i,jαiαjyiyjxixj \quad (16)$$

Subject to,

$$\sum iαiyi = 0 \quad (17)$$
$$αi \geq 1, \forall i \quad (18)$$

This formulation is called the dual problem, while 13 represents the primal formulation. The most important reason for using the dual formulation is that the data appear as dot products between vectors. This property becomes extremely important as it will allow generalizing the problem to deal with non-linearly separable data. Once the optimization problem is solved for αi, w may be determined from 14. The parameter b is then found from the KKT condition [11],

$$αi(yi(wTxi + b)−1) = 0, \forall i \quad (19)$$

### *D. The Non-Linearly Separable Case*

In many real problems, it is not possible to find a decision boundary that exactly separates the data into two classes. This may happen due to the presence of noise or outliers or even because of the non-linear nature of the problem. Soft-Margin SVM One possible approach to deal with non-linearly separable data is to smooth the classifier boundaries, allowing some of the data to lie inside the margin. The hyperplane constraints are relaxed by introducing positive slack variables ξi,i = 1,...,l. Thus,

$$yi(wTxi + b) \geq 1−ξi, ξi \geq 0, \forall i \quad (20)$$

If 0 < ξi < 1, then xi is well classified, although it is inside the margin. However, if ξi ≥ 1, xi is classified. The upper limit of the number of training errors is∑i ξi. Add this ∑i ξi to the function yields,

$$1\ 2||w||2 + C\sum i\ ξi \quad (21)$$

In this expression, C is called the regularization parameter and represents a penalty factor to the training errors. The optimization problem is,

Minimize,

$$1\ 2||w||2 + C\sum iξi \quad (22)$$

Subject to,

$$yi(wTxi + b) \geq 1−ξi, ξi \geq 0, \forall i . \quad (23)$$

Just like in Rigid Margin SVM, the problem is solved by switching to the Lagragian formulation,

$$LP =1\ 2||w||2 + C\sum iξi –$$
$$\sum iαi[yi(wTxi + b)−1+ i]−\sum iμiξi \quad (24)$$

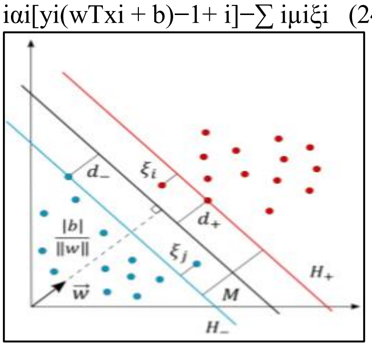


Fig. 9: Soft-Margin SVM: introduction of slack variables.

Again, according to the KKT condition, the derivatives of LP are set to zero,

$$\partial LP\ \partial w= 0 \Rightarrow w=\sum iαiyixi \quad (25)$$
$$\partial LP\ \partial b= 0 \Rightarrow\sum iαiyi = 0 \quad (26)$$
$$\partial LP\ \partial ξi= 0 \Rightarrow C −αi −μi = 0 \quad (27)$$

Replacing these results in 2.24 leads to the dual formulation of the problem,

Minimize,

$$LD = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \quad (28)$$

Subject to,

$$\sum_i \alpha_i y_i = 0 \quad (29)$$

$$0 \leq \alpha_i \leq C, \forall i \quad (30)$$

As before, once $\alpha_i$ is determined, w and b are found, Respectively, from 25 and from the KKT condition [11]

$$\alpha_i(y_i(w^T x_i + b) - 1 + \xi_i) = 0, \forall i \quad (31)$$

### E. Non-Linear SVM

In Soft-Margin SVM, the decision boundary is a linear function of the data. Non- Linear SVM deals in the feature space corresponds to a non-linear model in the input space. This procedure is known as the Kernel Trick. The reason for doing this is based on Cover's Theorem. According to this theorem, an input space with non-linearly separable data can be mapped into a higher dimensional space (possibly infinite dimensional), in which data has high probability of being linearly separable. This will be true as long as the mapping transformation is non-linear and the dimension of the feature space is high enough.

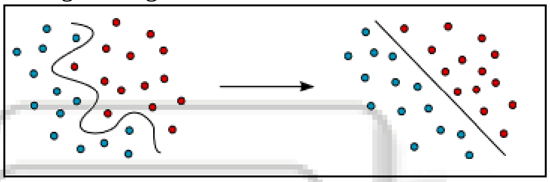

Fig. 10: The kernel trick: mapping the input space into the feature space.

Let Φ be the function which maps the input space T (low dimensional) into the feature space H (high dimensional). Thus,

$$\Phi: T \rightarrow H \quad (32)$$

It is not hard to understand that, if the dimension of the feature space is too high, the computation of the mapping function may become too complex to be done in practice. Thus, in these cases, it is not viable to work with Φ explicitly. However, it is not really necessary to know Φ explicitly, since the only information that is required in the feature space is the dot product between the data. Given this, we use a kernel function K, which receives two data points in the input space and returns their dot product in the feature space,

$$K(x_i,x_j) = \Phi(x_i).\Phi(x_j) \quad (33)$$

Since the kernel function uses an implicit mapping, we can directly apply it in the input space instead of calculating $\Phi(x_i)$ and $\Phi(x_j)$ and then taking the dot product. This makes the procedure much simpler.

The most used kernels are the following,

Polynomial of degree q,

$$(x_i x_j + 1)^q \quad (34)$$

Radial Basis Function (RFB),

$$\exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma}\right) \quad (35)$$

Sigmoid function,

$$\tanh(\kappa x_i x_j - \delta) \quad (36)$$

The choice of the kernel strongly affects the success of an SVM classifier. Although there aren't clear rules for selecting the most effective kernel for a particular classification task, the RBF function usually offers good performance and it is definitely the most popular kernel choice.

## V. Conclusion

The work in this paper discusses the detection of intestinal lumen diseases by using SVM classifier algorithm. In this paper, the images are captured by Wireless Capsule Endoscopy which provides visualization of GI tract by transmitting images to data recorder which is worn by the patient. From the collected images, a single static image is used to detect the disease. In pre-processing resizing of images is done to reduce or enlarge the size of the image, cropping is done to improve framing or aspect ratio and Adaptive mean filter is used to remove noise in the image. Pre-processed image is segmented to detect the accurate portion of the disease in intestine. The advantages of Proposed Methods are: Time consumption is low, able to get the accurate result, Low complexity and easy to detect the diseases. For classification of diseases, Support Vector Machine (SVM) algorithm is employed. The future work is about finding the stages of the diseases in the intestine and 3-D representation of images helps to diagnose the disease better.

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